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EVALUATING COST EFFICIENCY IN LOCAL GOVERNMENTS' PROVISION OF PUBLIC GOODS AND SERVICES: APPLICATIONS TO THE SPANISH CASE

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A mis abuelos.

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List of Abbreviations

AE	Allocative Efficiency
CE	Cost Efficiency
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DMUs	Decision Making Units
FDH	Free Disposal Hull
GDP	Gross Domestic Product
IGAE	Spanish General State Comptroller *(Intervencioón General de la Administración del Estado)*
INE	Spanish Statistical Office (*Instituto Nacional de Estadística*)
KSW	Kneip et al.'s 2008 bias corrected DEA estimator
LAUs	Local Administrative Units
MPI	Malmquist Productivity Index
NUTS	Nomenclature of Territorial Units for Statistics
OLS	Ordinary Least Squares
QR	Quantile Regression

RMSE	Root Mean Squared Error
SFA	Stochastic Frontier Approach
SGP	Stability and Growth Pact
SSCI	Social Sciences Citation Index
TCE	True Cost Efficiency
TE	Technical Efficiency
WoS	Web of Science

Abstract

The present thesis project considers the multidimensional evaluation of different aspects related to the cost efficiency of local governments in Spain, using non-parametric frontier analysis methods. In doing so, the economic crisis scenario that seriously affected Spanish local government revenues and finances in general is taken into account. The thesis contributes to the development of robust tools to evaluate and promote the improvement of the efficiency of local governments. The empirical results provide evidence for a better definition of public policies through the evaluation and identification of the benchmark local governments in order to set potential improvements and, therefore, minimize (cost) inefficiencies which might help to reduce public expenditures.

Specifically, the thesis is structured around five relevant research objectives in the field of local governments performance, in general, and Spanish municipalities, in particular, which are: (1) to assess local governments cost efficiency from a global point of view, taking into account the complexity in the measurement of local services and facilities and the inclusion of quality variables, (2) to examine the evolution of local government efficiency during the period of the economic crisis (2008–2013), (3) to investigate the existence of structural differences in the cost efficiency results between municipalities located in different Spanish regions and provinces as well as differences according to the size of the municipalities, (4) to compare different non-parametric methods to estimate efficiency, considering the difficulties arisen from the methodological selection, as well as to define a consistent method to choose a efficiency estimators which might be more appropriate to measure local governments performance in Spain, and (5) to analyse the impact of external or environmental factors that affect local governments' efficiency results, considering variations in the impact for differing efficiency levels and possible endogeneity issues.

Resumen

El presente proyecto de tesis plantea la evaluación multidimensional de distintos aspectos relacionados con la eficiencia en costes de los gobiernos locales en España, utilizando métodos de análisis frontera no paramétricos. Al hacer esto se tiene en cuenta el escenario de crisis económica vivido en España durante los últimos años y que ha tenido un gran impacto en los ingresos y finanzas locales en general. La tesis contribuye al desarrollo de herramientas robustas para evaluar y promover la mejora de la eficiencia de los gobiernos locales. Los resultados empíricos aportan evidencia para una mejor definición de políticas públicas mediante la evaluación e identificación de los gobiernos locales más eficientes como punto de referencia para establecer mejoras potenciales y, por lo tanto, poder eliminar ineficiencias (en costes) que ayuden a reducir el gasto público.

En concreto, la tesis se estructura en torno a cinco objetivos relevantes en el campo de la eficiencia de las corporaciones locales en general, y de los municipios españoles, en particular, que son: (1) evaluar la eficiencia en costes de los gobiernos locales desde una perspectiva global, teniendo en cuenta la complejidad en la medición de las instalaciones y servicios municipales y la inclusión de información sobre la calidad de los servicios, (2) analizar la evolución de los índices de eficiencia durante el periodo de crisis (2008–2013), (3) investigar la existencia de diferencias estructurales en los índices de eficiencia entre municipios situados en distintas regiones y provincias, así como diferencias relacionadas con el tamaño de los municipios, (4) comparar diferentes métodos no paramétricos para estimar la eficiencia, considerando la complejidad y las las dificultades derivadas de la selección metodológica, y además tratar de definir de una forma robusta y controlada qué metodologías son más adecuadas para medir la eficiencia en los gobiernos locales en España, y (5) evaluar el impacto de factores externos o ambientales que afectan a los niveles de eficiencia, teniendo en cuenta las posibles variaciones en los efectos según los niveles de eficiencia y los posibles problemas de endogeneidad.

Chapter 1

Public sector efficiency and local governments in Spain: an overview

1.1. General context, motivation and objectives

In recent years, improving public management efficiency has been a growing concern in many developed and developing countries, partly due to the new public finance scenarios resulting from the international economic crisis. However, other mechanisms have also operated in certain contexts. This is the case in the European Union, where the Stability and Growth Pact (SGP) stipulates that all governments should prioritise managing their resources *efficiently* in order to contribute to the viability of the European Economic and Monetary Union. Since 2011, the SGP has undergone several reforms in order to better consider each country's specific circumstances, and to strengthen the rules concerning budget deficits or public debt burdens.[1] Therefore, in a context in which the financial crisis has challenged public finances in several euro area and non-euro area countries, leading to unprecedented increases in some

[1]In 2013, the SGP was reformed through a collection of new laws, known as the "Six Pack". It laid down detailed rules for national budgets to ensure EU governments respect the requirements of economic and monetary union and do not run excessive deficits. In 2014 the SGP was further strengthened by new laws, known as the "Two Pack", as well as budgetary targets set by a law known as the "Fiscal Compact". Taken from the History of the Stability and Growth Pact (SGP), https://ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/eu-economic-governance-monitoring-prevention-correction/stability-and-growth-pact/history-stability-and-growth-pact. Last accessed 23.3.17

countries, efficient management of resources at all levels of government (central, regional and municipal) has become essential (Balaguer-Coll et al., 2013).

The present thesis focuses on Spain, a country that has not escaped the effects of this international scenario (Barreiro and Sánchez-Cuenca, 2012). The crisis that started in 2007, together with the bursting of the housing bubble[2] in 2008, led the country into a deep recession and became a priority issue[3,4] for the Eurozone in 2012. Thus, in response to the macroeconomic situation, the Spanish government adopted austerity programmes that advocated higher taxes and reduced public spending in order to meet budgetary stability targets. In a decentralised country such as Spain, the central government's budgeting efforts would be of little use if they were not backed by lower levels of government (Cabasés et al., 2007). The framework for budgetary stability in Spain was therefore enacted in the Law on Budgetary Stability,[5] which introduced more control over public debt and public spending at all levels of government with the aim of achieving a balanced budget. In this law, the principles of economic and financial management include compliance with effectiveness in achieving the objectives, within a framework of transparency and efficiency in the allocation and use of public resources.

Focusing on local governments, they are responsible for a significant number of public powers (Devas and Delay, 2006; Da Cruz and Marques, 2014), although this varies from country to country. For instance, since the approval of the 1978 Constitution, in Spain local governments have played an important role in providing public services, and form a sub-sector whose powers have increased over time—although modestly compared with higher (regional) levels of government (Vilalta Ferrer, 2010). In addition, as local government is the closest level of government to its citizens,

[2]In 2007 the construction sector represented 13% of Spain's gross domestic product (GDP). Low interest rates and the expansion of the Spanish savings banks (Cajas de Ahorros) substantially contributed to a construction boom that turned into a "bubble", which burst when borrowing was severely curtailed after the fall of Lehman Brothers in 2008 (Almendral, 2013).

[3]Traynor, I. and Watt, N. (6 June 2012). "Spain calls for new tax pact to save euro: Madrid calls for Europe-wide plan but resists 'humiliation' of national bailout". *The Guardian*. Retrieved from https://www.theguardian.com/business/2012/jun/06/spain-euro-finished-fiscal-union, last accessed 23.3.17

[4]Forell, C. and Steinhauser, G. (11 June 2012). "Latest Europe Rescue Aims to Prop Up Spain". *Wall Street Journal*. Retrieved from http://www.wsj.com, last accessed 23.3.17

[5]*Ley General Estabilidad Presupuestaria* (2007,2012), or Law on Budgetary Stability.

it has a first-hand impression of society's demands (Martín et al., 2011). However, municipalities have seen their resources severely reduced since the severe impact of the economic crisis on most of their revenues (Pérez López et al., 2013), as well as stricter budget limitations. The decline in municipal revenues combined with harsh budget constraints has therefore made the task of managing available resources with maximum efficiency an even greater challenge. Under these circumstances, in which issues related to Spanish local government efficiency and their contribution to public sector deficit are more relevant than ever, performance measurement may successfully support local public organisations in their effort to increase the value for money in service provision (Lo Storto, 2016) in order to provide the best possible local services (output) at the lowest possible cost (input).

In short, as evidenced by the latest regulatory reforms in Spain where the information demands are much more oriented towards the financial transparency of governments and the sustainability of public services in with the principles of effectiveness and efficiency, the growing need to have adequate management tools to meet the demand of citizens together with the need of public managers to evaluate the activity carried out and comply with current legislation, requires a considerable effort to improve public management.

Conscious of this need, in Spain the General State Comptroller *(Intervencioón General de la Administración del Estado, IGAE)*, a public institution which depend on the Spanish Ministry of the Treasury and Public Administrations (*Ministerio de Hacienda y Administraciones Públicas*), published a document entitled "Management Indicators for Public Organizations", becoming a guide for public entities to implement management indicators in order to evaluate effectiveness, economy, efficiency and quality.[6] In this document, express reference is made to the use of benchmarking techniques, by comparison with other units (in principle homogeneous) of the public sector in order to contribute to an improvement in the provision of goods and services. More specifically, Data Envelopment Analysis (DEA) methodology is accepted as an

[6]One of the most important novelties of the current General Public Accounting Plan (*Plan General de Contabilidad Pública*, PGCP) from 2010 is the inclusion of management indicators, referring to the document entitled "Management Indicators for Public Organizations" published by the IGAE in 20017.

appropriate approach to make this evaluation (pp. 235). Indeed, this methodology has been successfully applied to public services provided by municipalities of several Spanish regions (Prieto and Zofio, 2001; Balaguer-Coll et al., 2007; Balaguer-Coll and Prior, 2009; Bosch-Roca et al., 2012; Benito et al., 2010; Zafra-Gómez and Muñiz-Pérez, 2010).

However, the adequate measurement of local governments efficiency is usually a highly complex issue. First, the measurement of the costs of public activities, the identification and definition of the local public services and facilities and the assessment of their quality are thorny issues. In most cases the problems arise from the difficulties to collect data and directly quantify the provision of public services (Balaguer-Coll et al., 2013). In the Spanish case, we find largely available data on most of the services that municipalities are legally obliged to provide. However, the law only establishes the minimum services and facilities that each municipality must provide according to their size and, as a consequence, municipalities could provide additional services and facilities which might spend a significant part of local resources. Second, despite the high academic interest in efficiency measurement, widely applied in local governments and other public and private organizations, there is still a lack of consensus as to what methodology to perform efficiency analysis. This is not a trivial question because the method selected may affect the efficiency analysis (Geys and Moesen, 2009b) and could lead to biased results.

Finally, the presence of different environmental conditions beyond the control of local managers could affect local governments efficiency, so performance analysis should control for this heterogeneity (Balaguer-Coll et al., 2007). However, although the literature on this topic is extensive, the inclusion of external or environmental factors in previous studies often lacks structure (Da Cruz and Marques, 2014), since there is no well-established theory as to which variables constitute the "environmental conditions" that might impact on local governments' cost structure (Balaguer-Coll et al., 2013). In addition, the evidence from different studies is inconclusive about the direction of some determinants on local governments' cost efficiency. Therefore, these and other challenging questions when analysing technical, cost or other forms of efficiency in local governments provision of public goods and services, make the accurate efficiency evaluation a challenging empirical issue.

In view of these considerations, the main focus of this thesis is to analyse different aspects of the efficiency on local governments in Spain through the application of different non-parametric frontier techniques. In doing so, the economic crisis scenario in Spanish municipalities is taken into account. In addition, this thesis also aims to overcome some of the limitations to measure efficiency found in previous literature. More specifically, we consider six main research objectives related to the analysis of the cost efficiency of local public services:

- To widely review the current state of the efficiency in local governments, to discuss and survey which variables and methodological issues have been applied and to identify problems related to previous literature and ways for further research.
- To accurately define the bundle of services and facilities that municipalities must provide, to consider alternative input-output models in order to assess whether the different choices might explain heterogeneity among local governments and to analyse the possible implications of service quality when measuring local government cost efficiency.
- To examine the evolution of local government efficiency over time, i.e., to analyse whether Spanish local governments have succeeded in reducing their budget expenditures while maintaining public service provision in times of crisis.
- To investigate the existence of structural differences in the cost efficiency results between municipalities located in different Spanish regions and provinces as well as differences according to the size of the municipalities.
- To compare different non-parametric methodologies to assess local governments performance and to use a consistent method to choose an efficiency estimator which might be more appropriate to measure local governments performance in Spain.

- To analyse the impact of a comprehensive set of external or environmental factors that affect local governments' cost efficiency also taking into account possible endogeneity issues, and to obtain a detailed analysis of the relationship between the environmental variables and efficiency by considering variations in the impact across the efficiency distribution.

1.2. Specific aspects of public sector efficiency

Since the efficiency measurement of the provision of public goods and services in local governments is the main topic of this thesis, it is necessary to first give detailed definitions of several concepts. The basic idea of efficiency analysis in public sector can be defined as a comparison among a group of decision-making units or DMUs (in our particular case, Spanish local governments), in order to evaluate how the available resources (or inputs) are employed to produce public services and facilities (or outputs).[7]

As efficiency is defined in terms of a comparison between the observed and the optimal values of inputs or outputs, it can take either input or output orientation forms (Daraio and Simar, 2007a). The output-oriented framework looks at maximize the output levels given a set of inputs, while the input-oriented aims at reducing as much as possible the input levels required to produce at least the given set of outputs. This second orientation is generally adopted when decision makers can control the amount of inputs but not the outputs. Indeed, this is the case of most public sector entities, in general, and local governments, in particular. They are committed to provide a bundle of public services and facilities which are established externally while they are interested in the efficient management of their inputs, in terms of minimisation.

In addition, three different types of efficiency measures can be distinguished, depending on the available data for inputs and outputs (Farrell, 1957; Debreu, 1951). First, *technical efficiency (TE)* requires data on input and output quantities and it refers to the ability to use the productive resources in the most technologically efficient manner (Fried et al., 2008). Second, *allocative efficiency (AE)* requires additional information

[7]See Coelli et al. (2005) and Fried et al. (2008) for an introduction to efficiency measurement.

on input prices because it refers to the ability to combine the productive resources in optimal proportions considering the set of prices (Daraio and Simar, 2007a). Moreover, these two measures can be combined to obtain economic efficiency, also called *cost efficiency (CE)*[8] when the economic objective is cost minimisation (although revenue efficiency and profit efficiency may also be considered). Specifically, cost efficiency refers to the ability to produce a specified level of output in the cheapest possible manner (Worthington and Dollery, 2000a).

In contrast to private sector, it should be noted that public sector goods and services are frequently unpriced due to their non-market nature (Kalb et al., 2012). However, if data on costs are available but data on prices and physical units are not, cost efficiency can be measured but not decomposed (Balaguer-Coll et al., 2007). In this context, since there is no data available on local input prices, the evaluation of local governments efficiency in the following chapters will be based on cost efficiency measures, using data in municipal budgets as input costs. In addition, public goods and services.

Finally, we also should mention that we can distinguish two different stages in the production of public goods and service provision (De Witte and Geys, 2011). In the first stage, inputs (such as employees or equipment) are transformed into outputs (for example, in public sector the tons of waste collected). In the second stage, outputs are transformed into outcomes, which ultimately have welfare effects on consumers (in the waste collection example, perceiving cleanliness in the street). We note that the efficiency of public good provision can be measured at each stage of this production process. However, in practice, it is often very difficult to distinguish between inputs, outputs and outcomes given the unavailability of data. Under this circumstances, the analysis is usually confined to the first stage of the process, i.e., the links between inputs and outputs (Balaguer-Coll et al., 2013).

[8] Cost Efficiency (CE) = Technical Efficiency (TE) · Allocative Efficiency (AE)

1.3. Institutional framework of the local governments in Spain

As stated in section 1.1 the main objective of this thesis is to conduct a multidimensional assessment of the cost efficiency in Spanish public sector, and specifically, local governments in Spain. The institutional context of the Spanish public sector was formally established in the 1978 Constitution. Accordingly, Spain has three levels of government: central, regional and local, and as such, is one of the most decentralised countries in Europe (Balaguer-Coll et al., 2010a). Spain has 17 autonomous communities or regions (NUTS2), 50 provinces (NUTS3) and 8,114 municipalities (NUTS5).[9]

Spanish local governments are characterised by their very diverse populations and territorial distributions. In 2011, almost 83.74% of municipalities had populations below 5,000, and accounted for only 13% of the total population. Despite this diversity, because local governments are responsible for providing the most basic services, they are closer to citizens than other levels of government. Since the approval of the 1978 Constitution, local governments have played an important role in providing public services and their responsibilities have increased over time. However, their share of total public spending has remained relatively stable during this period, at least when compared to regional governments.[10] Table 1.1 shows the distribution of total public expenditures among central, regional and local levels. As can be seen, while regional governments' share of total public spending has increased at the expense of central government, local government spending remains stable at around 15%.

The Constitution also recognises local municipal autonomy to manage their responsibilities, though the local governments constitute the lowest level of government. This principle guarantees their right to participate in the affairs that affect their interests, meaning that municipalities can manage and assume responsibility for a substantial share of public undertakings for the benefit of their inhabitants. Local autonomy is therefore reflected in their financial resources as well as their competencies.

[9] Data from INE (*Instituto Nacional de Estadística*, Spanish Statistical Office), January 2011.

[10] Regional governments have been gaining powers at the expense of central government at a greater rate than local governments (see, Balaguer-Coll et al., 2007, 2010a).

Table 1.1: Distribution of total public expenditures among central, regional and local administrations in Spain (%)

	1995	2000	2005	2010
Central	62.05	53.81	46.31	45.68
Regional	24.19	30.91	38.22	38.60
Local	13.76	15.28	15.48	15.72
Total	100.00	100.00	100.00	100.00

Source: IGAE, Ministry of the Treasury and Public Administrations (*IGAE, Ministerio de Hacienda y Administraciones Públicas*).

With regard to their financial structure, local government revenues come mainly from local taxes, the most relevant being property taxes (*IBI, Impuesto de Bienes Inmuebles*), transfers received from central government, and fees paid for the use of public infrastructures or provision of public services. Table 1.2 shows the most important revenue categories in municipal budgets for the years 2008–2013. Note that although municipalities are considered financially autonomous by law, they only generated 54.07% of their total revenues in 2008–2013 from their own resources (i.e., through taxes, fees, property incomes and sale of fixed assets) while transfers from other levels of government accounted for 27.08% and financial transactions, 19.98%.

As regards local government competencies, the distribution of basic municipal powers is established in the 1985 Spanish local government law (*Ley 7/1985 Reguladora de Bases de Régimen Local*). Article 26 of this law establishes the minimum services and facilities that each municipality must provide, according to their size. In addition, articles 25, 27 and 28 of the law consider that local powers also depend on central or regional government legislation, and state that municipalities can take the initiative to exercise complementary activities for other specific purposes. This open framework may therefore lead to disparities in the services municipalities provide. The law only establishes the minimum services; however, it does not prevent municipalities from going beyond this legal minimum and offering not only more quantity or improved quality of a particular compulsory service, but also additional services and facilities (Balaguer-Coll et al., 2013). Table 1.3 reports the services and facilities Spanish local

Table 1.2: Structure of local revenues in Spain during the period 2008–2013 (%)

		Revenues[a](%)
Current revenues		81.09
Direct taxes		32.23
	Property tax[b]	21.32
	Motor Vehicle tax[c]	4.48
	Tax on the Increase in the Value of Urban Land[d]	2.77
	Tax on Business Activities[e]	2.80
	Other direct taxes	0.86
Indirect taxes		2.39
	Tax on Construction, Installations and other Works[f]	1.60
	Other indirect taxes	0.79
Fees and other revenues		16.14
	Fees	10.35
	Public fares	1.15
	Other revenues	4.64
Current grants received		28.05
	From central government	17.59
	From regional government	6.79
	From provincial council (*Diputaciones*)	2.91
	Other grants	0.75
Property incomes		2.28
Capital revenues		11.00
	Sale of fixed assets	1.03
	Capital transfers	9.98
Non-financial revenues		92.09
Financial revenues		7.91
Total revenues		100.00

Sources: Data from Ministry of the Treasury and Public Administrations (*Ministerio de Hacienda y Administraciones Públicas*).
[a] Share of total revenues averaged over the period 2008-2013.
[b] IBI, *Impuesto de Bienes Inmuebles*.
[c] IVTM, *Impuesto sobre Vehículos de Tracción Mecánica*.
[d] IIVTNU, *Impuesto sobre el Incremento de Valor de los Terrenos de Naturaleza Urbana*.
[e] IAE, *Impuesto de Actividades Económicas*.
[f] ICIO, *Impuesto sobre Construcciones, Instalaciones y Obras*.

governments provide as stipulated by law.

Table 1.3: Municipal powers in Spain (*Ley 7/1985 Reguladora de Bases de Régimen Local, LRBRL)*

Article 26	Articles 25, 27 and 28
Public street lighting	Powers exercised in the conditions defined by State and Regional laws:
Cemetery	Public safety
Waste collection	Traffic management
Street cleaning	Civil protection, fire prevention and extinction
Drinking water to households	Management of parks and garden
Sewage system	Urban policies
Access to population centres	Cultural heritage
Paving of public roads	Protection of the environment
Regulation of food and drink	Fairs and related activities
Public parks	Protection of public health
Public library	Participation in the management of primary healthcare
Market	Cemeteries and funeral services
Treatment of collected waste	Social services, promotion of social reinsertion
Civil protection	Local public networks (waste and water supply, public lighting)
Provision of social services	Public transport
Fire prevention and extinction	Cultural or sport activities and facilities
Public sports facilities	Tourism
Urban passenger transport	Participation in the design of education programmes and facilities
Protection of the environment	Any delegated competence
	Complementary activities from other levels of government (related to education, culture, promotion of equality for women, housing, health and environmental protection).

1.4. Structure and contents

This thesis is organised as follows: chapter 2 presents an extensive and comprehensive review of the existing empirical literature on local governments' efficiency from a global point of view, covering all articles from 1990 up to the year 2016. The chapter shows a detailed overview of the studies on local governments' efficiency across various countries, comparing the data and samples employed, and the main results obtained. Moreover, it summarises the inputs, outputs and the environmental variables used, as well as the methodologies applied to measure efficiency in the context of local governments. Given that the efficiency results depend heavily on the variable selection and the methods used, this chapter provides a good basis for researchers in the field of local governments' efficiency. Finally, at the end of chapter, we give some operative directions and considerations for further research in the field.

Chapter 3 investigates different aspects of the cost efficiency in Spanish local governments during the period of the economic crisis (2008–2013). Specifically, we attempt to learn whether Spanish local governments have succeeded in reducing their budget expenditures while maintaining public service provision; in other words, whether local government cost efficiency has improved in times of crisis. Moreover, regardless of the context of the analysis, chapter 3 attempts to address some common problems from previous literature earlier discussed in chapter 2, such as the accurate definition of output variables as well as the selection of methodologies to measure efficiency. For this, in order to assess whether the different choices might explain the differences between local governments, we consider several output models and different non-parametric methodologies, namely, Data Envelopment Analysis (DEA), Free Disposal Hull (FDH), order-m frontier and the bias corrected DEA estimator proposed by Kneip et al. (2008).

Finally, this chapter also investigates the existence of structural differences in the efficiency scores between municipalities located in different Spanish regions and provinces as well as the variation of the efficiency scores according to the size of the municipalities. The results suggest that the efficiency of Spanish local governments has improved over the crisis period 2008–2013 since they have reduced their budget expenditures (inputs or costs) while maintaining local public services and facilities (outputs). In addition, the further results show that the efficiency scores also vary according to the size of the municipalities as well as the location in different Spanish regions and provinces.

Chapter 4 compares the estimation techniques previously explained in chapter 3 using an extension of the experiment developed in the study of Badunenko et al. (2012). Since the method chosen to perform efficiency analysis may affect the efficiency results, this chapter aims to uncover which techniques are more appropriate to assess cost efficiency in Spanish local governments. We carry out an experiment via Monte Carlo simulations and we discuss the relative performance of the efficiency estimators under various scenarios. Then, from the simulation results, we determine in which scenario our data lies in, and we follow the suggestions related to the performance of the estimators for this scenario. The findings show that there is no one approach suitable for all efficiency analysis. When using these results for policy decisions, local regulators must be aware of which part of the distribution is of particular interest and if the interest lies in the efficiency scores or the rankings estimates. From a technical point of view, the analytical tools introduced in this chapter would represent an interesting contribution that examine the possibility of using a consistent method to choose an efficiency estimator, and the obtained results give evidence on how efficiency could certainly be assessed to provide some additional guidance for policy makers.

Chapter 5 analyses local governments' cost efficiency in Spain while explicitly accounting for external or environmental influences that might affect municipalities' performance. Based on the classification provided for the different types of determinants of local governments' efficiency in chapter 2, we identify a set of environmental variables that are associated with better/worse economic performance of local governments in Spain. Afterwards, the relationship between these environmental variables and the efficiency scores is assessed in a two-stage analysis. In a first stage, cost efficiency results are measured via the non-parametric methods developed in chapter 3. In the second stage, when the factors causing inefficiency are included in the analysis, a instrumental variable quantile regression is considered.

In contrast to previous two-stage initiatives, this technique contributes to the literature by providing an alternative basis for considering the impact of the environmental variables on local governments' efficiency according to the differing levels of efficiency, while allowing to control for the possible endogeneity of some of our explanatory variables. Results show an asymmetry regarding the determinants of efficiency for the best and worst local governments. Indeed, for the worst local governments, performance is a result not only of their managers' decisions but also other factors related to their environment, such as such as tax revenues, the debt levels, transfers from higher levels of government, share of retired people or the electoral participation.

Finally, chapter 6 gives a short summary of the main results and conclusions.

Chapter 2

Local governments' efficiency: a systematic literature review

2.1. Introduction

Over the last 30 years there have been many empirical studies that have focused on the evaluation of efficiency in local governments from multiple points of view and contexts. Following De Borger and Kerstens (1996a), it is possible to identify two strands of empirical research. On the one hand, some studies concentrate on the evaluation of a particular local service, such as refuse collection and street cleaning (Worthington and Dollery, 2000b, 2001; Bosch et al., 2000; Benito-López et al., 2011, 2015), water services (García-Sánchez, 2006a), street lightning (Lorenzo and Sánchez, 2007), fire services (García-Sánchez, 2006b), library services (Stevens, 2005) and road maintenance (Kalb, 2012) among others. On the other hand, other studies evaluate local performance from a "global point of view" considering that local governments supply a wide variety of services and facilities.

In this chapter we provide a systematic review of the existing literature on local government efficiency from a global point of view, covering all articles from 1990 up to the year 2016. More specifically, it contributes to the literature in three major aspects. First, it presents a detailed review of the studies investigating local government efficiency across various countries, comparing the data and samples employed as well as the main results obtained. Second, it describes which techniques have been used for measuring efficiency in the context of local governments. Finally, it suggests classifications for the input, output as well as the operational environment. In local government efficiency measurement, the selection of variables is a complex task, due to the difficulty to collect data and the measurement of local services (Balaguer-Coll et al., 2013). Indeed, different studies use diverse measures, even those which analyse efficiency using data from the same country. Moreover, many investigations have attempted to determine whether external factors affect local governments' performance. However, the inclusion of these environmental variables is not unanimous since there is a lack of a clear and standard classification (Da Cruz and Marques, 2014). Here, we identify all variables used in previous literature according to the classifications proposed, and we comment their correlation with efficiency.

Our review starts from five previous works that referred to local government literature. First, Worthington and Dollery (2000a) provided a survey of the empirical analysis on efficiency in local government until 1999. Second, Afonso and Fernandes (2008) reviewed some relevant studies that evaluated both non-parametric and global local governments efficiency. Third, Kalb et al. (2012) collected 23 studies which analysed local government efficiency and made a comparison across various countries. Fourth, Da Cruz and Marques (2014) suggested a general classification for the determinants of local government performance. Finally, De Oliveira Junqueira (NA) reviewed some empirical studies on local government efficiency and identified the main inputs and output variables included in the analysis. However, to the best of our knowledge, the literature review presented in this chapter is the most complete source of references on local government efficiency analysis. We show a complete overview of the existing literature, the variables selection, the methodologies employed as well as some considerations for further work.

The remainder of the chapter is organised as follows: section 2.2 provides the bibliographic selection process to construct the systematic literature review. Section 2.3 presents an extensive review of the existing literature on local governments efficiency at country level. Section 2.4 reports which techniques have been used for measuring efficiency, while section 2.5 describes the input and output variables most commonly used. Section 2.6 provides the methodologies used to incorporate environmental variables in the analysis, while section 2.7 proposes a classification and comments the impact of the different variables over efficiency. Finally, section 2.8 discuss the main conclusions and suggest operative directions for future researchers in the field.

2.2. A systematic review on local government efficiency

In this review, we have used the search engines Web of Science (WoS)[1], Scopus[2] and Google Scholar. The search was limited to the Social Sciences Citation Index (SSCI) in WoS and to the Social Sciences and Humanities area in Scopus to reduce the likelihood of retrieving articles that were not related to the topic, like energy or health efficiency. Also, we have restricted the literature search to English language. We included empirical papers until August 2016.

As the main focus is local governments' efficiency, the initial search was done using combinations of the keywords "efficiency", "performance measurement", "local government" and "municipality". Using these keywords, the databases provided us more than 250 books, papers and unpublished working papers. To limit the total number of results, we excluded the presentations given at conferences as well as dissertations. Next, the results retrieved were filtered qualitatively to ensure they addressed the research question. As a criterion for inclusion we included studies which present empirical data, measuring efficiency at local government level (LAU-2)[3], with a selection of inputs and outputs, and excluding studies addressed to international comparisons and studies addressed to measure a particular service, such as refuse

[1]Web of Science (WoS) is an scientific citation indexing database and search service maintained by Thomson Reuters. It allows for in-depth exploration of specialized sub-fields within an academic or scientific discipline.

[2]Scopus is a bibliographic database maintained by Elsevier. It contains abstracts and citations for academic journal articles, books and conference proceedings.

[3]Local administrative units (LAUs) are basic components of the Nomenclature of Territorial Units for Statistics (NUTS) for referencing the subdivisions of countries regulated by the European Union. Specifically, LAU-2 is a low level administrative division of a country, ranked below a province, region, or state. So, we exclude studies focused on intermediate level of local governments, such as those of Nold Hughes and Edwards (2000), Hauner (2008), Nieswand and Seifert (2011) and Otsuka et al. (2014), among others.

collection, water services, road maintenance, education, etc. Finally, we obtained 84 studies. Note that in the second part of the chapter, when we only take into account those studies which included environmental variables in the analysis, i.e., 63 studies.

2.3. Country level analysis

As mentioned in the introduction, there have been many empirical studies that have focused on the evaluation of the overall efficiency in local governments covering several countries. Table A.1 in the appendix A summarises the empirical contributions focused on local government efficiency from a global point of view, listed by countries and chronological order of publication. As we can observe, some of these studies also attempted to analyse the relationship between local government efficiency and other important topics, such as the municipal size, the effect of amalgamation of the municipalities, the impact of fiscal decentralization, the effects of political competition and the influence of the spatial closeness between municipalities, among others. The differences in the average efficiency scores found between the studies are remarkable due to differences in the samples, methodologies and variables included. However, we summarise efficiency scores by countries with the aim to define general trends.

Looking first at Japan, Nakazawa (2013, 2014) evaluated 479 municipalities in 2005 considering the effects that amalgamation had over cost efficiency. Moreover, Nijkamp and Suzuki (2009) evaluated 34 cities in Hokkaido prefecture in 2005, and Haneda et al. (2012) used 92 municipalities in Ibaraki prefecture for the years 1979–2004 to analyse the change in efficiency in the post-merger period. In general, Japanese municipalities show high efficiency levels, scoring from 0.75 to 0.90 depending on the method and the data. Two studies have evaluated local governments in Korea. Seol et al. (2008) analysed 106 local governments in 2003, while Sung (2007) assessed 222 local governments from 1999 to 2001. Both studies examined the impact of information technology on Korean local government performance. Their results vary from 0.57 to 0.97 depending on the specification model and the sample.

In addition, five more studies focused on other Asian countries. Yusfany (2015) analysed 491 Indonesian municipalities in 2010, Liu et al. (2011) measured 22 local governments in Taiwan in 2007, Kutlar and Bakirci (2012) evaluated 27 Turkish municipalities from 2006 to 2008, and Ibrahim and Karim (2004) and Ibrahim and Salleh (2006) analysed 46 local governments in Malaysia in 2000. Efficiency results for Indonesian municipalities are quite low (0.50), while in Taiwan results range from 0.38 to 0.82, in Turkey from 0.53 to 0.86, and in Malaysia from 0.59 to 0.76.

Three studies have evaluated local governments on the Australian context. Specifically, Worthington (2000) measured cost efficiency for municipalities in New South Wales for 1993. Also, Fogarty and Mugera (2013) evaluated efficiency for Western Australia municipalities in 2009 and 2010. Finally, Marques et al. (2015) used a sample of 29 Tasmanian local councils between 1999 and 2008 with the aim to estimate the optimal size on local government. The mean efficiency scores in Australian municipalities range from 0.40 to 0.86, however heterogeneous results were expected since none of the Australian studies used the same dataset and method. Moreover, there are three studies which analysed local governments in Brazil. Sampaio de Sousa et al. (2005) evaluated 3,756 local governments in 1991 while Sampaio de Sousa and Ramos (1999) and Sampaio de Sousa and Stošić (2005) used 4,796 municipalities in 1991 and 2001, respectively. Despite data in these last two studies are 10 years difference, their efficiency scores are quite similar, ranging from 0.52 to 0.92 depending on the method used. In addition, Pacheco et al. (2014) analysed the efficiency of 309 Chilean municipalities from 2008 to 2010, reporting an average efficiency score of around 0.70.

Further, some studies assessed cost efficiency in local governments in the United States. Hayes and Chang (1990) evaluated 191 US municipalities in 1982, studing whether or not the council-management form is more efficient than the mayor-council form of government in formulating and implementing public policies. Moreover, Grossman et al. (1999) examined 49 US central cities for the years 1967, 1973, 1977 and 1982. They measured technical inefficiency in the local public sector based on a comparison of local property values. Finally, Moore et al. (2005) analysed largest cities in the US from 1993 to 1996. Interestingly, despite the different methods and data used, results for the efficiency levels in US local governments are quite consistent, varying between 0.81 to 0.84. Three studies assessed provision of basic services in local municipalities in South Africa from 2005 to 2010 (Dollery and van der Westhuizen, 2009; Mahabir, 2014; Monkam, 2014). In general, they show low efficiency levels, scoring from 0.17 to 0.64.

There exist several studies about performance in Belgian local governments[4]. De Borger et al. (1994) and De Borger and Kerstens (1996a,b) measured cost efficiency for 589 municipalities in 1985, while Eeckaut et al. (1993) analysed 235 Walloon municipalities in 1986. Moreover, Geys and Moesen (2009a,b) and Geys (2006) evaluated 304 Flemish municipalities in 2000, analysing in the last study the existence of spatial interdependence in local government policies. Similarly, Coffé and Geys (2005) evaluated 305 Flemish municipalities, studying the effect of social capital on local government performance, while Ashworth et al. (2014) assessed 308 Flemish municipalities, measuring whether political competition affect local government efficiency. In general, despite many studies have used similar samples for the same years, efficiency results for Belgian municipalities differ from 0.49 to 0.99. These differences might be explained by the different methodologies applied as well as the different topics studied.

In addition, some studies analysed German local governments. Kalb et al. (2012) and Geys et al. (2013) analysed cost efficiency in 1,021 municipalities for data in 2001 and 2004, respectively. The last study considered local government size to measure the effect of economies of scale. Similarly, Bönisch et al. (2011) evaluated local governments in Saxony-Anhalt in 2004 taking into account municipality size. Moreover, Geys et al. (2010) assessed whether voter involvement is related to government performance using 987 German municipalities for the years 1998, 2002 and 2004. Kalb (2010) and Bischoff et al. (2013) studied municipalities from 1990 to 2004, considering the impact of intergovernmental and vertical grants on cost efficiency, while Asatryan and De Witte (2015) evaluated 2,000 Bavarian municipalities in 2011, connecting the efficient provision of local public services with the role of direct democracy. Finally, Lampe et al. (2015) analysed the effect of new accounting and budgeting regimes

[4]See De Borger and Kerstens (2000) for a literature review on Belgian local governments up to the year 1998. They discuss the difficulties to benchmark local governments.

in 396 German municipalities from 2006 to 2008. On average, results on German municipalities showed that inputs or costs should be reduced by 1% to 20% of their current level.

Six studies have analysed local government in Norway. Kalseth and Rattsø (1995) used 407 Norwegian local authorities in 1988, while Borge et al. (2008) and Bruns and Himmler (2011) evaluated between 362 to 374 local governments from 2001 to 2005. The second study investigated whether efficiency in public service provision is affected by political and budgetary institutions, fiscal capacity, and democratic participation, while the last study examined the role of the newspaper market for the efficient use of public funds by elected politicians. Moreover, Sørensen (2014) and Helland and Sørensen (2015) evaluated 430 Norwegian local authorities from 2001 to 2010, both considering whether political variables affect local government efficiency. Finally, Revelli and Tovmo (2007) analysed 205 local governments located in the 12 southern counties of Norway, investigating whether the efficiency exhibits a spatial pattern that is compatible with the hypothesis of yardstick competition. The only study which used frontier techniques to measure efficiency in Norwegian local governments showed efficiency results from 0.74 to 0.84. The others concluded that efficiency values of the ratios between inputs and outputs ranged from 100 to 104.9.

Otherwise, Loikkanen and Susiluoto (2005) and Loikkanen et al. (2011) evaluated cost-efficiency of basic welfare service provision in Finnish municipalities for data from 1994 to 2002. This second study examined whether Finnish city managers' characteristics and work environment, in addition to external factors, explain differences in cost efficiency. On average, the results for Finnish municipalities show a high efficiency level, scoring from 0.75 to 0.89. In addition, two studies have focused on the English case. Revelli (2010) studied 148 main local authorities in England from 2002 to 2007. Moreover, Andrews and Entwistle (2015) analysed 386 local authorities in England in 2007. They investigated the relationship between a commitment to public-private partnership, management capacity and efficiency. In the English case, the efficiency values of the ratios between inputs and ouputs were 1.05.

Furthermore, six papers focused their attention in Italian local governments.

Barone and Mocetti (2011) analysed the links between public spending inefficiency and tax morale using a sample 1,115 municipalities for data from 2001 to 2004. Moreover, Boetti et al. (2012) evaluated 262 Italian municipalities in the province of Turin in 2005, assessing whether efficiency of local governments is affected by the degree of vertical fiscal imbalance. Similarly, D'Inverno et al. (2017) analysed 282 Tuscan municipalities in 2011, while Agasisti et al. (2015) analysed 331 Lombardy municipalities with more than 5,000 inhabitants from 2010 to 2012. Finally, Lo Storto (2013, 2016) used 103 Italian municipalities in 2011 and 2013, respectively. In general, the efficiency scores in Italian municipalities vary drastically (from 0.19 to 0.88), depending on the specification, the sample and the method employed.

Five studies have evaluated local governments in Portugal. The studies of Afonso and Fernandes (2003, 2006) analysed 51 Portuguese municipalities in the regions of Lisbon and Vale do Tejo in 2001. Similarly, Afonso and Fernandes (2008), Da Cruz and Marques (2014) and Cordero et al. (2017) investigated cost efficiency in 278 Portuguese local governments' for data from 2001 to 2014. In general, the efficiency results shown in Portuguese municipalities are quite low, scoring from 0.22 to 0.76. Otherwise, there are two studies which assessed cost efficiency in Greek local governments. Athanassopoulos and Triantis (1998) analysed municipalities with more than 2,000 inhabitants for 1986 data, while Doumpos and Cohen (2014) focused on the period 2002-2009, exploring optimal reallocation of the inputs and outputs. Mean efficiency on Greek municipalities differs from 0.5 to 0.85 depending on the method applied as well as the sample analysed. In addition, El Mehdi and Hafner (2014) analysed the efficiency of 91 rural districts in the oriental region of Morocco from 1998/1999, showing average efficiency scores ranging from 0.38 to 0.50.

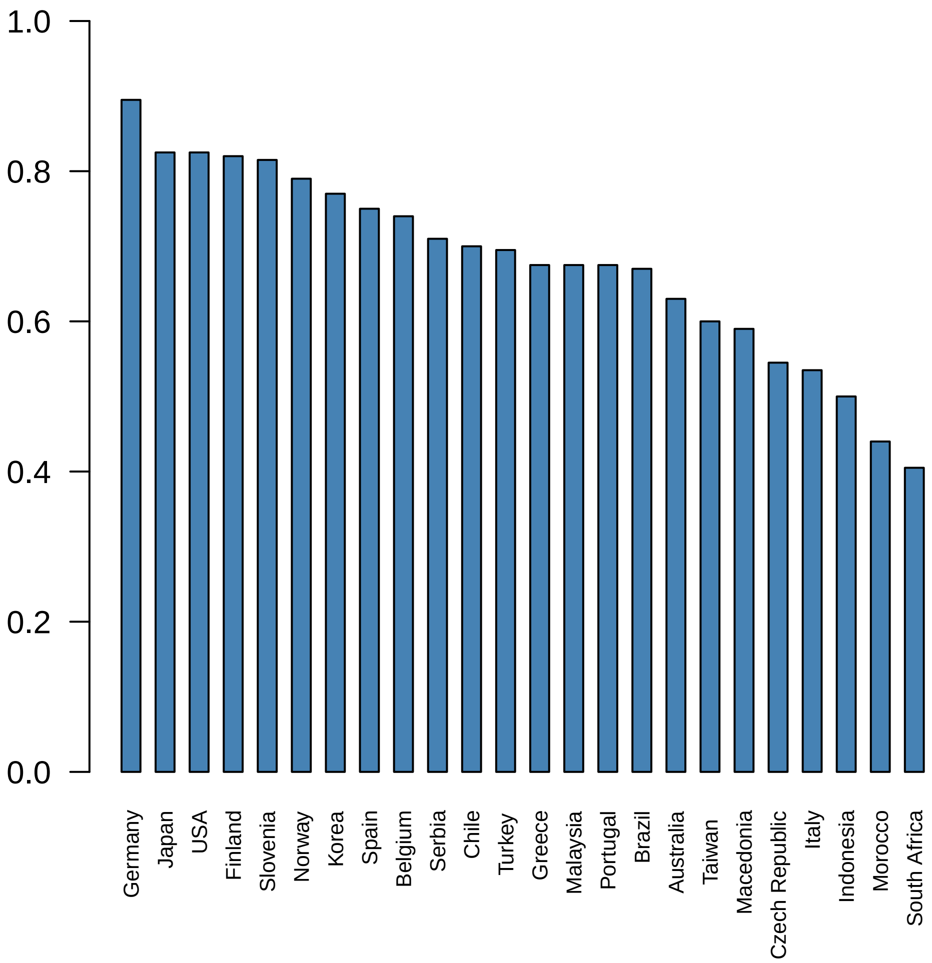
Moreover, Štastná and Gregor (2011, 2015) compared 202 local governments in the Czech Republic in the transition period of 1995-1998 and the post transition period of 2005-2008. Their results show low efficiency levels, scoring from 0.30 to 0.79 depending on the method used. In addition, other studies focused on data in Central and East European countries. Pevcin (2014a,b) measured efficiency in 200 Slovenian municipalities in 2011. Their results suggested that mean technical inefficiency should be approximately 12-25% above the estimated best-practice frontier. Moreover, Radulovic and Dragutinović (2015) measured efficiency for 143 Serbian local governments in 2012, and Nikolov and Hrovatin (2013) analysed 74 municipalities in Macedonia. This last study took into account the ethnic fragmentation of municipalities to explain efficiency. Their results show that mean efficiency scores are quite low in Macedonia (0.59), while Serbian local governments should reduce their inputs by 15% to 33%.

Finally, some studies analysed the case of Spanish municipalities (13 papers). Balaguer-Coll et al. (2007) and Balaguer-Coll and Prior (2009) measured local governments in the Valencian Region for data from 1992 to 1995. The last study considered a temporal dimension of efficiency and applied different output specifications. Similarly, the study of Giménez and Prior (2007) evaluated 258 Catalonian municipalities for data in 1996, decomposing the total cost efficiency into short and long term, while Bosch-Roca et al. (2012) evaluated 102 Catalonian municipalities between 5,000 and 20,000 inhabitants in 2005, connecting efficiency of local public services with citizen's control in a decentralized context. Moreover, Benito et al. (2010) analysed the efficiency in 31 municipalities of the Murcia Region in 2002, Prieto and Zofio (2001) analysed 209 municipalities of less than 20,000 people in Castile and Leon Region in 1994, and Arcelus et al. (2015) measured efficiency in small municipalities (fewer than 20,000 inhabitants) from Navarre Region in 2005.

Differently, other studies focused on Spanish data covering most part of the Spanish territory. For instance, Balaguer-Coll et al. (2010a,b) analysed the links between overall cost efficiency and the decentralization power in Spain with more the 1,164 Spanish local authorities over 1,000 inhabitants for data from 1995 to 2005. Moreover, Cuadrado-Ballesteros et al. (2013) used 129 Spanish municipalities with populations over 10,000 from 1999 to 2007 and Zafra-Gómez and Muñiz-Pérez (2010) measured the cost efficiency of 923 municipalities for the years 2000 and 2005 together with their financial condition. Finally, in Balaguer-Coll et al. (2013) and Pérez-López et al. (2015) an analysis of local government performance is assessed with a sample of municipalities between 1,000 and 50,000 inhabitants for the years from 2000 to 2010. The first study splits municipalities into clusters according to various criteria (output mix, environmental condition and level of powers). The last study analysed the long term effects of the new delivery forms over efficiency. Broadly speaking, efficiency results for Spanish municipalities are really heterogeneous, scoring from 0.53 to 0.97 depending on the different variables specifications, methodologies used and the data.

To summarise, figure 2.1 presents the average efficiency scores by country, measured as the average between the maximum and the minimum scores found in previous literature. We observe that Germany presents the highest average efficiency results (0.90), while South Africa presents the lowest (0.40).

Figure 2.1: Average efficiency scores by country.



2.4. Methodological approaches to measure efficiency

The literature uses different techniques to analyse local governments' efficiency[5]. It is possible to distinguish two main branches of best practice frontiers: the non-parametric and the parametric methods. Table 2.1 provides a review of the studies using the different approaches to measure efficiency in local governments.

On the one hand, the most commonly non-parametric tools used in local government efficiency literature are Data Envelopment Analysis (DEA) (Charnes et al., 1978) and its non-convex version Free Disposal Hull (FDH) (Deprins et al., 1984). Non-parametric methods have received a considerable amount of interest mainly because they have less restrictive assumptions and greater flexibility than parametric methods. Moreover, they can easily handle multi-input and multi-output analysis in a simple way (Ruggiero, 2007). As observed in table 2.1, in total 41 papers used DEA, 13 used FDH and 2 used the super-efficiency DEA model of Andersen and Petersen (1993).

Nevertheless, the traditional non-parametric methods also present several drawbacks: their deterministic nature (all deviations from the frontier are considered as inefficient and no noise is allowed), the difficulty to make statistical inference, and the influence of outliers and extreme values. In this setting, other recent techniques in the non-parametric field have been used to solve these problems. First, bootstrap methods based on sub-sampling (Simar and Wilson, 1998, 2000, 2008) have been used to correct DEA or FDH bias[6]. They allow for statistical inference (consistency analysis, bias correction, confidence intervals, hypothesis testing, etc) in the non-parametric setting. We found 6 papers which used bias-corrected methods. Moreover, Sampaio de Sousa et al. (2005) and Sampaio de Sousa and Stošić (2005) introduced a method known as DEA or FDH with "jackstrap" that combines bootstrap and jackknife resampling to eliminate the influence of outliers and possible measurement errors in the data.

Second, partial frontiers such as order-m (Cazals et al., 2002) are more robust to

[5]See Coelli et al. (2005) and Fried et al. (2008) for an introduction to efficiency measurement.

[6]As stated by Simar and Wilson (2008), DEA and FDH estimators are biased by construction, which means that the true frontier would be located under the DEA-estimated frontier.

Table 2.1: Approaches to measure efficiency in local governments

A. NON-PARAMETRIC APPROACHES AND SEMI-PARAMETRIC APPROACHES
1. DEA
Eeckaut et al. (1993); Kalseth and Rattsø (1995); De Borger and Kerstens (1996a); Athanassopoulos and Triantis (1998); Sampaio de Sousa and Ramos (1999); Worthington (2000); Prieto and Zofio (2001); Ibrahim and Karim (2004); Coffé and Geys (2005); Moore et al. (2005); Loikkanen and Susiluoto (2005); Afonso and Fernandes (2006); Balaguer-Coll et al. (2007); Afonso and Fernandes (2008); Geys and Moesen (2009b); Seol et al. (2008); Nijkamp and Suzuki (2009); Dollery and van der Westhuizen (2009); Balaguer-Coll and Prior (2009); Bosch-Roca et al. (2012); Benito et al. (2010); Zafra-Gómez and Muñiz-Pérez (2010); Štastná and Gregor (2011); Loikkanen et al. (2011); Bönisch et al. (2011); Boetti et al. (2012); Nikolov and Hrovatin (2013); Lo Storto (2013); Fogarty and Mugera (2013); Monkam (2014); Ashworth et al. (2014); Pevcin (2014b); D'Inverno et al. (2017); El Mehdi and Hafner (2014); Marques et al. (2015); Yusfany (2015); Lo Storto (2016)
1.2. Malmquist index with DEA Doumpos and Cohen (2014); Haneda et al. (2012); Sung (2007); Kutlar and Bakirci (2012)
1.3. DEA super-efficiency Da Cruz and Marques (2014); Liu et al. (2011)
2. FDH
Eeckaut et al. (1993); De Borger et al. (1994); De Borger and Kerstens (1996a,b); Sampaio de Sousa and Ramos (1999); Afonso and Fernandes (2003); Balaguer-Coll et al. (2007); Giménez and Prior (2007); Geys and Moesen (2009b); Balaguer-Coll et al. (2010a); El Mehdi and Hafner (2014); Mahabir (2014)
2.2. Malmquist index with FDH Balaguer-Coll et al. (2010b)
3. DEA or FDH Bias-corrected
Bönisch et al. (2011); Fogarty and Mugera (2013); Bischoff et al. (2013); El Mehdi and Hafner (2014)
3.2. Malmquist index with DEA Bias-corrected Cuadrado-Ballesteros et al. (2013); Agasisti et al. (2015)
4. DEA or FDH with "Jackstrap"
Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005)
5. Order-m
Balaguer-Coll et al. (2013); Pérez-López et al. (2015)
6. Conditional efficiency
Asatryan and De Witte (2015); Cordero et al. (2017)
B. PARAMETRIC APPROACHES
1. SFA
De Borger and Kerstens (1996a); Athanassopoulos and Triantis (1998); Grossman et al. (1999); Worthington (2000); Geys (2006); Ibrahim and Salleh (2006); Geys and Moesen (2009a,b); Geys et al. (2010); Kalb (2010); Barone and Mocetti (2011); Kalb et al. (2012); Boetti et al. (2012); Geys et al. (2013); Nakazawa (2013); Nikolov and Hrovatin (2013); Nakazawa (2014); Pacheco et al. (2014); Pevcin (2014a,b); Arcelus et al. (2015); Lampe et al. (2015); Radulovic and Dragutinović (2015)
1.2. SFA time variant Štastná and Gregor (2011, 2015)
2. COLS, OLS, Fixed effects regressions Hayes and Chang (1990); Kalseth and Rattsø (1995); De Borger and Kerstens (1996a); Revelli (2010); Sørensen (2014); Helland and Sørensen (2015)
C. RATIOS
Revelli and Tovmo (2007); Borge et al. (2008); Revelli (2010); Bruns and Himmler (2011); Andrews and Entwistle (2015)

extremes or outliers in data and they do not suffer from the curse of dimensionality. We only found 2 studies which employed order-m approach. Finally, Asatryan and De Witte (2015) used the conditional efficiency model (Daraio and Simar, 2005) while Cordero et al. (2017) used the time-dependent conditional frontier model recently developed by Mastromarco and Simar (2015). They are an extension to the traditional FDH and order-m which allow to account for heterogeneity among municipalities.

On the other hand, some studies used parametric approaches. They determine the frontier on the basis of a specific functional form using econometric techniques. The deviations from the best practice frontier derived from parametric methods can be interpreted in two different ways. While deterministic approaches interpret the full deviation from the best practice frontier as inefficiency (standard OLS or corrected OLS method), Stochastic Frontier Approach (Aigner et al., 1977; Meeusen and Van den Broeck, 1977) decompose the deviation of the best practice frontier between the effect of measurement error and inefficiency. In addition, environmental variables can be easily treated with a stochastic frontier. They can adopt different cost or production functions, for instance, the Cobb-Douglas or Translog. As observed in table 2.1, in total 25 papers used SFA, 3 studies used COLS or OLS, 2 studies fixed effects regression and 1 study used standard cost regression.

Otherwise, some studies have applied a dynamic approach in order to reveal the efficiency changes over the time. The most popular method among the non-parametric field is the Malmquist productivity index Caves et al. (1982), which has been used joint DEA, FDH or bootstrap methods. Moreover, two studies assessed the efficiency scores over time with parametric approaches, using the time-variant SFA analysis.

Finally, 4 studies measured efficiency by using a index developed by Borge et al. (2008) instead of traditional frontier techniques. The index is defined as the ratio of the total aggregate output to local government revenues. Finally, the efficiency measure is normalized to 100, so that deviations from the mean can be interpreted as percentage deviations.

2.5. Inputs and outputs indicators

The selection of variables depends on the availability of data and the specific services and facilities that local government provide in each country. Therefore, many variables cannot be used in all countries.

2.5.1. Input variables

We review the input variables most widely used in previous literature to proxy for the municipal resources employed for local service provision. The selection of inputs could vary across countries since they depend on specific accounting practices and characteristics of local governments. Moreover, we note that most studies used input variables in cost terms since data on prices and physical units are not available. Public sector goods and services are frequently unpriced since they have a non-market nature (Kalb et al., 2012). Despite some authors have tried to decompose physical inputs and input prices, most of these input prices variables coincide with the input variables in cost terms. In this setting, in our input classification we do not differentiate input prices. Following, we discuss all variables describing how different studies have measured them. Table A.2 in appendix A also summarises the studies containing local inputs from different areas, using the same structure as the main text.

Financial expenditures

Inputs variables within this category come from local public accounts or budget expenditures. We include indicators such as total expenditures, current expenditures, capital expenditures and financial expenditures.

- Total expenditures (24 papers)

  This variable has been commonly used in local government efficiency analysis to proxy for the total cost of service provision.[7] Mainly, it includes different

[7]Kalseth and Rattsø (1995); De Borger and Kerstens (1996a,b); Prieto and Zofio (2001); Afonso and Fernandes (2003, 2006); Coffé and Geys (2005); Afonso and Fernandes (2008); Balaguer-Coll et al. (2010b); Kutlar and Bakirci (2012); Nakazawa (2013, 2014); Ashworth et al. (2014); Pevcin (2014a,b); Mahabir (2014); Yusfany (2015); Andrews and Entwistle (2015).

expenditures categories such as current (or operational) expenditures, capital and financial expenditures.

In addition, other variants of total expenditures have been used. Some studies measured total local government expenditures excluding personnel expenses since these are measured separately.[8] Similarly, Lampe et al. (2015) and Asatryan and De Witte (2015) measured total government expenditures net of transfers from the central government to municipalities arguing that municipalities have no discretion to make decisions on their use.

- Current expenditures (46 papers)

  Current expenditures or operating expenses are the most widely used input indicators to measure the costs incurred by local governments to provide local services.[9] They do not include capital expenditures since they are highly volatile because of investments in large infrastructures.

  Similarly, some studies have used the total net current expenditures in a municipality. These include all spending on the current budget minus interest and amortization repayments from local public debts. Again, spending from the capital budget is not considered, since this mainly refers to large investment events which inflate total spending in the year they emerge.[10]

  In addition, some studies measured current expenditures as the spending on those issues for which they observed government outputs. They aggregate data on expenditures or costs given a number of local services provided.[11]

[8] Sung (2007); Seol et al. (2008); Nijkamp and Suzuki (2009); Cordero et al. (2017).

[9] Eeckaut et al. (1993); Athanassopoulos and Triantis (1998); Sampaio de Sousa and Ramos (1999); Ibrahim and Karim (2004); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Geys (2006); Ibrahim and Salleh (2006); Balaguer-Coll et al. (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010a); Zafra-Gómez and Muñiz-Pérez (2010); Bosch-Roca et al. (2012); Štastná and Gregor (2011); Kutlar and Bakirci (2012); Nikolov and Hrovatin (2013); Balaguer-Coll et al. (2013); Cuadrado-Ballesteros et al. (2013); Pacheco et al. (2014); Monkam (2014); Marques et al. (2015); Štastná and Gregor (2015); Radulovic and Dragutinović (2015); Arcelus et al. (2015); Pérez-López et al. (2015).

[10] Geys et al. (2010); Kalb (2010); Kalb et al. (2012); Geys et al. (2013); Pacheco et al. (2014); Nakazawa (2014); Lampe et al. (2015).

[11] Hayes and Chang (1990); Loikkanen and Susiluoto (2005); Moore et al. (2005); Geys and Moesen (2009a,b); Benito et al. (2010); Revelli (2010); Barone and Mocetti (2011); Loikkanen et al. (2011); Boetti et al. (2012); Lo Storto (2013); Pacheco et al. (2014); D'Inverno et al. (2017); Agasisti et al. (2015); Lo Storto (2016).

- Personnel expenditures (26 papers)

  Local personnel expenses can be measured as the number of local government employees[12] or as the total personnel costs or wages and salaries[13]. In addition, Sampaio de Sousa and Stošić (2005) and Sampaio de Sousa et al. (2005) used the number of teachers as a proxy for personnel inputs.

- Capital and financial expenditures (17 papers)

  Capital or financial expenses are related to interest payments and loans. Including capital expenditures means considering the investment expenditure that local entities make on a regular basis, such as expenditure on the maintenance of municipal facilities and equipment.[14] Moreover, the study of Liu et al. (2011) used the accumulation of fixed assets as a proxy for capital inputs, and De Borger et al. (1994) employed the surface of building owned by the municipality as a proxy for capital stocks. In addition, the study of Nijkamp and Suzuki (2009) included the amount of outstanding city bonds as a proxy for financial costs, while Hayes and Chang (1990) used the municipal bond rating.

- Other financial expenditures (6 papers)

  In this category, we include physical expenses which consisted on material purchases and inventory, plants and equipment, contract expenses, utility expenses, insurance costs and any other costs grouped as other expenses in the financial statements,[15] as well as resources and intermediate inputs which contained all other current expenditures not related to labour or capital expenditures.[16]

[12]De Borger et al. (1994); Worthington (2000); Moore et al. (2005); Sung (2007); Seol et al. (2008); Nijkamp and Suzuki (2009); Haneda et al. (2012); Da Cruz and Marques (2014).

[13]Hayes and Chang (1990); Worthington (2000); Balaguer-Coll et al. (2007); Giménez and Prior (2007); Balaguer-Coll and Prior (2009); Dollery and van der Westhuizen (2009); Benito et al. (2010); Balaguer-Coll et al. (2010a); Zafra-Gómez and Muñiz-Pérez (2010); Bönisch et al. (2011); Liu et al. (2011); Kutlar and Bakirci (2012); Fogarty and Mugera (2013); Bischoff et al. (2013); Nakazawa (2013); Balaguer-Coll et al. (2013); Cordero et al. (2017).

[14]Worthington (2000); Balaguer-Coll et al. (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010a); Bosch-Roca et al. (2012); Zafra-Gómez and Muñiz-Pérez (2010); Bönisch et al. (2011); Kutlar and Bakirci (2012); Balaguer-Coll et al. (2013); Fogarty and Mugera (2013); Bischoff et al. (2013); Cuadrado-Ballesteros et al. (2013); Da Cruz and Marques (2014).

[15]Worthington (2000); Giménez and Prior (2007); Fogarty and Mugera (2013).

[16]Bönisch et al. (2011); Bischoff et al. (2013); Da Cruz and Marques (2014).

Financial resources

Inputs variables within this category come from local public accounts or budget revenues. We include own revenues as well as transfers.

- Local revenues (7 papers)

  Some studies measured total local government revenues as the available resources in local government, which include own tax revenues (tax revenues, fees and charges) as well as central government grants or subsidies.[17] In addition, El Mehdi and Hafner (2014) used the own receipts of the municipality measured as the total operating receipts less the subsidies.

- Current transfers (8 papers)

  Current transfers represent transfers and grants received from higher levels of government.[18]

Non-financial inputs

We include input indicators not related to local financial statements:

- Public health services (2 papers)

  The studies of Sampaio de Sousa et al. (2005) and Sampaio de Sousa and Stošić (2005) used the number of hospital and health centres (as they are the main providers of health services) to proxy for public health services. Also, they accounted for the rate of infant mortality serves as an input, suggesting that if health services are efficient, this indicator should be as low as possible.

- Area (1 paper)

  Finally, Haneda et al. (2012) included the area in Km2 considering it as a municipal asset.

[17] Revelli and Tovmo (2007); Borge et al. (2008); Bruns and Himmler (2011); Sørensen (2014); Doumpos and Cohen (2014); Helland and Sørensen (2015).

[18] Balaguer-Coll et al. (2007); Giménez and Prior (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010a, 2013); Benito et al. (2010); Kutlar and Bakirci (2012); Zafra-Gómez and Muñiz-Pérez (2010).

2.5.2. Output variables

Measuring local governments' outputs is a complex task which comes from the difficulty to collect data and the measurement of local services (Balaguer-Coll et al., 2013). Indeed, different studies use diverse measures of outputs, even those which analyse efficiency using data from the same country. Also the number of output variables included in the different studies is varied, since some studies aggregate various municipal services in a global index, while others evaluate a set of specific local services. We discuss all variables containing local outputs from 17 different categories. Table A.3 in appendix A also summarises the local outputs, following the same structure as the main text.

Global output indicator (14 papers)

A global output indicator represents an index containing a set of services and facilities that municipalities must provide (such as education, health, roads infrastructure, social services, sports and culture, waste collection, water supply, etc.). Given that the services offered by local governments are varied and not all have the same budgetary weight, each output included in the global output indicator is weighted according to different criteria. In this context, Afonso and Fernandes (2003, 2006, 2008), Nijkamp and Suzuki (2009) and Yusfany (2015) gave the same weighting for the different outputs included in the composed index, Bosch-Roca et al. (2012) weighted each output according to the relative weight in the accounts of each municipality, and Nakazawa (2013, 2014) gave specific numerical weights to each different area of public service included.

In addition, other studies have used official indicators of the provision of local services developed by public institutions. For instance, in Norway the studies of Revelli and Tovmo (2007), Borge et al. (2008), Bruns and Himmler (2011), Sørensen (2014) and Helland and Sørensen (2015) used an aggregate output measure published annually by the Norwegian Advisory Commission on Local Government Finances. This aggregate measure is calculated as the weighted average of the output measures for the individual service sectors using the average spending shares as weights. Moreover, in United Kingdom the studies of Revelli (2010) and Andrews and Entwistle (2015) used an official rating of local government performance (Comprehensive Performance Assessment, CPA) built annually by the Audit Commission (a central government regulatory agency).

Total population (46 papers)

This variable is the output indicator most frequently used in local government efficiency analysis. It reflects the basic administrative tasks performed by municipal governments through the service general administration as well as other services for which more direct outputs do not exist. Eeckaut et al. (1993) was the pioneer study which proposed the use of population as a proxy indicators for public services in the evaluation of local efficiency. The route opened up by the latter study was later expanded by De Borger and Kerstens (1996a,b) and converted as a common standard in governmental efficiency research thus far.[19] Otherwise, the studies of Štastná and Gregor (2011), Haneda et al. (2012) and Pacheco et al. (2014) used population size as a proxy for the scope of services since bigger municipalities should provide more public goods and services.

In addition, some studies used proxy variables for the services delivered to non-resident population. For instance, local governments in areas with tourist visitors would have higher demand for their services. Therefore, variables such the as share of non-residents, tourist presence, number of visitors or number of beds in tourism establishments have been used.[20]

[19] Sampaio de Sousa and Ramos (1999); Worthington (2000); Ibrahim and Karim (2004); Coffé and Geys (2005); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Ibrahim and Salleh (2006); Balaguer-Coll et al. (2007); Giménez and Prior (2007); Balaguer-Coll and Prior (2009); Geys et al. (2010); Kalb (2010); Zafra-Gómez and Muñiz-Pérez (2010); Balaguer-Coll et al. (2010a,b); Bönisch et al. (2011); Kalb et al. (2012); Kutlar and Bakirci (2012); Boetti et al. (2012); Nikolov and Hrovatin (2013); Fogarty and Mugera (2013); Cuadrado-Ballesteros et al. (2013); Nikolov and Hrovatin (2013); Bischoff et al. (2013); Geys et al. (2013); Balaguer-Coll et al. (2013); Lo Storto (2013); Pevcin (2014a,b); D'Inverno et al. (2017); Monkam (2014); Da Cruz and Marques (2014); Lampe et al. (2015); Radulovic and Dragutinović (2015); Agasisti et al. (2015); Pérez-López et al. (2015); Cordero et al. (2017); Lo Storto (2016).

[20] Athanassopoulos and Triantis (1998); De Borger et al. (1994); Kutlar and Bakirci (2012); D'Inverno et al. (2017).

Area of municipality and built area (10 papers)

Municipal area (measured as total municipal surface, urban area or built-up area) has been used as a proxy for the demand of public services delivered to citizens in several studies.[21] It works as an indirect approximation due to the difficulty of quantifying the supply of public services and facilities. In addition, some studies have used the number of properties or households in the local area[22] as a proxy for the demand of urban services.

Administrative services (9 papers)

Many studies have used variables such as "population" to proxy administrative services. However, others have used more direct outputs designed to measure the provision of services linked to administrative tasks. For instance, Arcelus et al. (2015) used an index measuring the provision of administrative services defined by the Local Administration of the Navarre government. Moreover, Kalseth and Rattsø (1995) defined the administrative activities as the administrative costs of central administration and the sectoral administration of different services. In addition, other studies included civil affairs[23], the number of certificates and requested documents handled[24], the number of receipts processed[25], electoral service[26], the number of planning applications[27], the amount of internal reports produced[28], the number of building permits issued[29], and taxes on construction and square feet of city building space available to proxy for urban and building management[30].

[21] Athanassopoulos and Triantis (1998); Giménez and Prior (2007); Šťastná and Gregor (2011); Lo Storto (2013); Cuadrado-Ballesteros et al. (2013); Šťastná and Gregor (2015); Arcelus et al. (2015); Pérez-López et al. (2015); Lo Storto (2016).

[22] Athanassopoulos and Triantis (1998); Šťastná and Gregor (2011); Fogarty and Mugera (2013); Arcelus et al. (2015); Šťastná and Gregor (2015).

[23] Sung (2007).

[24] Seol et al. (2008); Barone and Mocetti (2011).

[25] Marques et al. (2015).

[26] Barone and Mocetti (2011).

[27] Marques et al. (2015).

[28] Seol et al. (2008).

[29] Sung (2007); Barone and Mocetti (2011); Cordero et al. (2017).

[30] Cuadrado-Ballesteros et al. (2013); Moore et al. (2005).

Infrastructures

We include indicators of the basic municipal infrastructures related to street lighting and municipal roads:

- Street lighting (11 papers)

  This variable measures the provision of public street lighting in the municipalities, mostly measured as the number of lighting points.[31]

- Municipal roads (34 papers)

  The length of municipal roads (in km) is a proxy for the provision of local road maintenance services (such as paving or street cleaning), traffic, urban transport and access to the municipality.[32] Similarly, the study of Moore et al. (2005) included the miles of streets serviced as a proxy of street maintenance, Šťastná and Gregor (2011, 2015) used the size of municipal roads measured in hectares, Sung (2007) used the ratio of road length to area, and Lo Storto (2013) used the urban infrastructure development. In addition, Doumpos and Cohen (2014) and Arcelus et al. (2015) used the variable "Pavement" to proxy for municipal roads services, while Prieto and Zofio (2001) measured the pavement shortage as well as the pavement condition. Finally, some studies included the number of vehicles as a proxy for surfacing of public roads.[33]

Communal services

This group of variables related to "network services" include indicators such as waste collection, sewerage system, water supply and electricity as part of municipal

[31] Prieto and Zofio (2001); Balaguer-Coll et al. (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010a,b); Zafra-Gómez and Muñiz-Pérez (2010); Barone and Mocetti (2011); Balaguer-Coll et al. (2013); Doumpos and Cohen (2014); Arcelus et al. (2015); Pérez-López et al. (2015).

[32] Eeckaut et al. (1993); De Borger et al. (1994); De Borger and Kerstens (1996b); Worthington (2000); Ibrahim and Karim (2004); Ibrahim and Salleh (2006); Balaguer-Coll et al. (2007); Geys (2006); Geys and Moesen (2009a,b); Balaguer-Coll and Prior (2009); Zafra-Gómez and Muñiz-Pérez (2010); Balaguer-Coll et al. (2010a,b); Barone and Mocetti (2011); Boetti et al. (2012); Nikolov and Hrovatin (2013); Fogarty and Mugera (2013); Balaguer-Coll et al. (2013); Da Cruz and Marques (2014); D'Inverno et al. (2017); Ashworth et al. (2014); Doumpos and Cohen (2014); Marques et al. (2015); Agasisti et al. (2015); Radulovic and Dragutinović (2015).

[33] Moore et al. (2005); Sung (2007); Giménez and Prior (2007).

outcomes:

- Waste collection (32 papers)

  The municipal waste collection and treatment of waste collected are mainly measured as the amount of waste collected in tons, quintals or kilograms.[34] Moreover, the study of Liu et al. (2011) included the volume of garbage generation measured in kilos as an undesirable output.

  In addition, some studies have used the number of properties receiving domestic waste management service or the population served to proxy for waste collection service.[35] Similarly, Geys and Moesen (2009a,b) used the share of municipal waste picked up through door-to-door collections. Otherwise, Hayes and Chang (1990) and Štastná and Gregor (2011, 2015) used the expenditures on waste collection.

- Sewerage system (10 papers)

  The sewerage network and cleansing of residuals water can be measured as the number of properties receiving sewerage services[36], or as the number of sewerage connections.[37] Similarly, Sung (2007) used the penetration rate of sewage as the share of the households with sewage over all households. In addition, the study of Da Cruz and Marques (2014) measured the waste-water treated in thousands of cubic meters. Finally, Prieto and Zofio (2001) measured the treated flow, the sewerage network shortage as well as the sewerage network condition.

- Water supply (16 papers)

[34]Ibrahim and Karim (2004); Ibrahim and Salleh (2006); Balaguer-Coll et al. (2007); Giménez and Prior (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010a,b); Zafra-Gómez and Muñiz-Pérez (2010); Benito et al. (2010); Barone and Mocetti (2011); Boetti et al. (2012); Balaguer-Coll et al. (2013); Pacheco et al. (2014); Da Cruz and Marques (2014); Ashworth et al. (2014); Pérez-López et al. (2015); Agasisti et al. (2015); Cordero et al. (2017).

[35]Sampaio de Sousa and Ramos (1999); Worthington (2000); Moore et al. (2005); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Benito et al. (2010); Mahabir (2014); Monkam (2014).

[36]Worthington (2000); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Pacheco et al. (2014); Monkam (2014); Mahabir (2014).

[37]Marques et al. (2015).

Different variables have been used to proxy for water supply. Some studies have used the number of properties or consumers receiving water services.[38] In a similar way, Sung (2007) used the penetration rate of water supply measured as the share of households with water supply over all households.

Moreover, other studies used the amount of water supplied or produced in megalitres or thousands of cubic meters.[39] In addition, Benito et al. (2010) used the number of new connections to potable water network conduct while Pérez-López et al. (2015) used the water network length. Finally, Prieto and Zofio (2001) measured the treated flow, the water tanks capacity, the water distribution net shortage as well as their quality condition.

- Electricity (3 papers)

  Only three studies measure the provision of electricity by a municipality, measured as the number of consumer units or households receiving electricity.[40]

Parks, sports, culture and recreational facilities

In this section we include indicators related to leisure and recreational facilities that municipalities must provide. We found five indicators:

- Sport facilities (4 papers)

  This service can be measured as the surface of indoor and outdoor sporting facilities[41], or as the number of users registered in municipal sport activities.[42] Štastná and Gregor (2015) also proxy the expenses related to sport clubs and sporting events. Additionally, Prieto and Zofio (2001) measured the quality of the sport facilities as the indoor sporting facilities condition.

[38] Sampaio de Sousa and Ramos (1999); Worthington (2000); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Moore et al. (2005); Mahabir (2014); Monkam (2014); Radulovic and Dragutinović (2015).

[39] (Moore et al., 2005; Benito et al., 2010; Da Cruz and Marques, 2014; Marques et al., 2015; Cordero et al., 2017).

[40] Dollery and van der Westhuizen (2009); Monkam (2014); Mahabir (2014).

[41] Prieto and Zofio (2001); Benito et al. (2010); Štastná and Gregor (2011, 2015).

[42] Benito et al. (2010).

- Cultural facilities (4 papers)

  This variable is used as a proxy for the expenses related to subsidies for theatres, cinemas, municipal museums and galleries, and the costs of monument preservation Šťastná and Gregor (2011, 2015). Additionally, Benito et al. (2010) employed the number of visits to municipal museums and Šťastná and Gregor (2011, 2015) included the number of monuments and the number of museums and galleries. Finally, Prieto and Zofio (2001) measured the surface of cultural facilities as well as their quality condition.

- Libraries (4 papers)

  Different variables have been used to proxy for the public library services, such as the number of volumes in public libraries and collection turnover[43], total loans [44], and the number of library registrations or visits[45].

- Parks and green areas (16 papers)

  Municipal parks and green areas are mainly measured as the registered surface area of public parks.[46] Similarly, Sung (2007) used the area of urban parks per person, Moore et al. (2005) used the acres of park space in use, Ibrahim and Karim (2004) and Ibrahim and Salleh (2006) used the number of trees planted, and Šťastná and Gregor (2011, 2015) used nature reserves and the size of urban green areas to reflect spending on parks maintenance.

- Recreational facilities (20 papers)

  Some studies included the total surface of public recreational facilities (in hectares) as an indicator of municipalities' surface of parks, sports, leisure and other recreational facilities.[47] In addition, Da Cruz and Marques (2014)

[43] Moore et al. (2005); Benito et al. (2010)

[44] Loikkanen and Susiluoto (2005); Loikkanen et al. (2011)

[45] Moore et al. (2005)

[46] Prieto and Zofio (2001); Balaguer-Coll et al. (2007); Balaguer-Coll and Prior (2009); Benito et al. (2010); Balaguer-Coll et al. (2010a); Zafra-Gómez and Muñiz-Pérez (2010); Balaguer-Coll et al. (2010b, 2013); Pacheco et al. (2014); Pérez-López et al. (2015).

[47] De Borger et al. (1994); De Borger and Kerstens (1996a,b); Coffé and Geys (2005); Geys (2006); Geys and Moesen (2009a); Geys et al. (2010); Bönisch et al. (2011); Kalb et al. (2012); Bischoff et al. (2013); Ashworth et al. (2014); Doumpos and Cohen (2014); Lampe et al. (2015); Asatryan and De Witte (2015).

used the variable "infrastructures" which includes cultural (municipal museums, auditoriums, libraries and cultural and congress centres) and sports facilities (municipal pools, sports halls, courts and race tracks) managed by municipalities, while Balaguer-Coll et al. (2010a,b, 2013) used "Public building surface area" to proxy public libraries and public sports facilities.

Health (6 papers)

Few studies measured basic municipal services in health. Pacheco et al. (2014) captured the provision of health services by the number of health centres, while Kutlar and Bakirci (2012) used the number of beds in hospitals. Moreover, Loikkanen and Susiluoto (2005) and Loikkanen et al. (2011) measured basic health care and dental care as the number of visits and bed wards, and Moore et al. (2005) reported emergency medical services as the response time in minutes. In addition, the study of Marques et al. (2015) used the number of food handling premises inspected as a variable related to community and health safety activities.

Education

The variables included in this category are related to kindergartens provision and primary and secondary education as part of municipal outcomes:

- Kindergartens or nursery places (14 papers)

  The number of students in Kindergartens is assumed to proxy for kindergarten places facilitated by the municipality.[48] In addition, Lo Storto (2013) used the number of nursery schools, Radulovic and Dragutinović (2015) used the number of preschool institutions, Asatryan and De Witte (2015) included "Child population" measured as the ratio of the number of children at kindergartens to population and D'Inverno et al. (2017) and Nikolov and Hrovatin (2013) considered population from 0 to 5 years old proxy the services for kindergarten.

[48] Geys et al. (2010); Štastná and Gregor (2011); Barone and Mocetti (2011); Boetti et al. (2012); Kalb et al. (2012); Geys et al. (2013); Štastná and Gregor (2015); Lampe et al. (2015).

- Primary and secondary education (33 papers)

  The main indicator used for the provision of education services in primary and secondary levels is the number of students enrolled in primary and secondary schools.[49] Similarly, Asatryan and De Witte (2015) used "Pupil population" measured as the ratio of the number of students at secondary schools to population, while Sampaio de Sousa and Ramos (1999), Sampaio de Sousa et al. (2005) and Sampaio de Sousa and Stošić (2005) used literate population to proxy for educational services. Moreover, D'Inverno et al. (2017) considered the school-age population (i.e. from 3 to 13 years old), while Nikolov and Hrovatin (2013) used population ages from 5 to 19 to proxy for primary and secondary schools.

  In addition, other variables have been employed to proxy educational service provision. Pacheco et al. (2014) used the number of public schools in a municipality. Moreover, Loikkanen and Susiluoto (2005) and Loikkanen et al. (2011) included the number of hours of teaching in comprehensive and senior secondary schools. Also, Radulovic and Dragutinović (2015) used the number of school institutions. Finally, Sampaio de Sousa et al. (2005) and Sampaio de Sousa and Stošić (2005) chose schooling variables that reflected problems of the Brazilian education system: the enrolment per school, the student attendance per school, the students who get promoted to the next grade per school and the students in right grade per school.

Social services

We include as social services the indicators related to subsidence grants, care for elderly, care for children and social organizations:

- Beneficiaries of minimal subsistence grants (12 papers)

[49] Eeckaut et al. (1993); De Borger et al. (1994); De Borger and Kerstens (1996a,b); Sampaio de Sousa et al. (2005); Geys (2006); Coffé and Geys (2005); Geys and Moesen (2009a,b); Kalb (2010); Geys et al. (2010); Bönisch et al. (2011); Šťastná and Gregor (2011); Boetti et al. (2012); Kalb et al. (2012); Geys et al. (2013); Bischoff et al. (2013); Ashworth et al. (2014); Pevcin (2014a,b); Pacheco et al. (2014); Šťastná and Gregor (2015); Lampe et al. (2015).

The number of minimal subsistence grants are related to services provided to low-income families.[50] They proxy the extent of social welfare.

- Care for elderly (21 papers)

  Care for elderly reflects the supply of social services to the elderly, such as retirement or geriatric homes, general assistance for the elder, and medical assistance in public hospitals. The main indicators to proxy for provisions for the elderly are the number of senior citizens or the share of populations older than 65 years.[51] In addition, the studies of Loikkanen and Susiluoto (2005) and Loikkanen et al. (2011) used the days of institutional care of the elderly, while Asatryan and De Witte (2015) used the elderly patient population as a proxy to the capacity in public care centres.

- Care for children (4 papers)

  Loikkanen and Susiluoto (2005) and Loikkanen et al. (2011) measured care for children as te days in children's day centres and family day care. Otherwise, Bönisch et al. (2011) and Bischoff et al. (2013) used the number of approved places in childcare centres.

- Social services and organizations (12 papers)

  Social services are considered essential for social welfare. They include areas such as care services, education and economic subsistence. To measure the amount of social services in a municipality, Pacheco et al. (2014) included the variable social organizations, which registers all social organizations by municipality. Moreover, Balaguer-Coll et al. (2010a,b, 2013) measured the provision of social services as the surface area of assistance centres. Sung (2007) included the seating capacity of social welfare institutions per 100 persons. Also, Cuadrado-Ballesteros et al. (2013) used unemployed population as a proxy for social

[50] Eeckaut et al. (1993); De Borger et al. (1994); De Borger and Kerstens (1996a,b); Geys (2006); Coffé and Geys (2005); Geys and Moesen (2009a,b); Ashworth et al. (2014).

[51] Eeckaut et al. (1993); De Borger and Kerstens (1996a,b); Coffé and Geys (2005); Kalb (2010); Geys et al. (2010); Štastná and Gregor (2011); Boetti et al. (2012); Kalb et al. (2012); Kutlar and Bakirci (2012); Nikolov and Hrovatin (2013); Geys et al. (2013); Pevcin (2014a,b); D'Inverno et al. (2017); Ashworth et al. (2014); Lampe et al. (2015); Štastná and Gregor (2015); Arcelus et al. (2015).

services, while D'Inverno et al. (2017) included the immigrant population to proxy the need of these people. In addition, Radulovic and Dragutinović (2015) used the share of social protection users in total resident population Radulovic and Dragutinović (2015). Otherwise, Štastná and Gregor (2011, 2015) included the number of homes for disabled, while Loikkanen and Susiluoto (2005) and Loikkanen et al. (2011) measure the institutional care of the handicapped as the number of days in social centres.

Public safety (9 papers)

Public safety involves municipal police and fire services. Police services pursue the prevention of crimes, patrolling the geographical area of the municipality, while fire service has the objective to reduce the probability of fires and limit losses when fires occur. Different variables have been used to proxy for public safety services. Štastná and Gregor (2011, 2015) used a dummy for municipal police, while Hayes and Chang (1990) used the expenditures on police and fire protection.

Moreover, Eeckaut et al. (1993) used the number of crimes registered in the municipality, and Moore et al. (2005) employed a crime index to proxy for police services. Similarly, Benito et al. (2010) included the number of interventions and detentions made. In addition, Barone and Mocetti (2011) and Agasisti et al. (2015) used kilometres covered by local police, and Cuadrado-Ballesteros et al. (2013) used the number of police vehicles in circulation. Otherwise, Moore et al. (2005) used the number of civilian fire deaths and total losses as fire protection proxies, while Cuadrado-Ballesteros et al. (2013) included population density representing the probability of fire spreading.

Market (5 papers)

Some studies have measured the market surface area to proxy for the provision of local markets.[52] Similarly, Ibrahim and Karim (2004) and Ibrahim and Salleh (2006) used the number of business lots and stall spaces.

[52] Balaguer-Coll et al. (2010a,b, 2013).

Public transport (2 papers)

Only two studies have used direct outputs for measuring public transportation, proxied as the number of bus stations in a municipality.[53]

Environmental protection (5 papers)

This variable includes services related to environmental protection and regulations in matter of health, air, soil and water protection, and nature preservation. Different variables have been used to proxy for environmental services. Lo Storto (2013) measured the urban ecosystem quality. Moreover, Cuadrado-Ballesteros et al. (2013) used the number of economic activities as a proxy for health services related to environmental protection and business regulations in matters of health and consumer protection. Also, Athanassopoulos and Triantis (1998) included the heavy industrial area since it reflects the need to provide pollution measurement due to the heavy industrial activities. Finally, Štastná and Gregor (2011) used the variable "Pollution area" that includes environmentally harming areas such as built-up area and arable land, while Liu et al. (2011) employed "Air pollution" as an undesirable output measured by the emissions of ozone and sulfur dioxide per year.

Business development (12 papers)

Business development account for the government's role in the need to offer infrastructure to companies. As a proxy for infrastructure and business development services, some studies have included the number of employees paying social security contributions in a municipality based on the idea tha such services are associated with employment, i.e., the number of jobs in a municipality are correlated with the need to provide production related to infrastructure and services.[54] Otherwise, the study of Liu et al. (2011) included the unemployment rate as an undesirable output.

In addition, Athanassopoulos and Triantis (1998) included the average industrial

[53] Štastná and Gregor (2011, 2015).

[54] Geys et al. (2010); Kalb (2010); Bönisch et al. (2011); Kalb et al. (2012); Bischoff et al. (2013); Geys et al. (2013); Pevcin (2014a,b); Asatryan and De Witte (2015); Lampe et al. (2015).

size area to reflect the spatial concentration of industrial activities in local government, while Arcelus et al. (2015) used the percentage of inhabitants employed in manufacturing due to the more industrialized is a town, the more and costlier services will be demanded.

Quality index (5 papers)

Some studies have included a quality indicator designed to measure not only the quantity but also the quality of the services provided, measured as a weighted average quality and the number of physical units of each service and infrastructures.[55] In addition, Balaguer-Coll and Prior (2009) also included the number of votes as a variable to proxy the level of citizen satisfaction, and Haneda et al. (2012) used the number of employees per 10,000 residents, since the familiarity between local government and the residents implies that the local administration can give careful instructions to residents.

Others (6 papers)

Finally, we include other outputs which are not classified in previous subcategories. Athanassopoulos and Triantis (1998) included the average house area as an indication of wealth, suggesting that wealthier population would pressure municipalities to provide more services related to recreation, the development and maintenance of local parks, repairs and maintenance, and street lighting and cleaning. Moreover, Grossman et al. (1999) used the aggregate market value of residential and business property as an indicator of municipal services. They argue that if a city is generates the highest attainable market value of aggregate property within its boundaries given the local fiscal choices that it has made, then it is producing local government in a technically efficient manner. In addition, Pérez-López et al. (2015) included the municipal cemetery area to proxy for cemetery service provision.

Otherwise, two studies included variables related to local revenue to proxy for

[55] Balaguer-Coll et al. (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010b); Zafra-Gómez and Muñiz-Pérez (2010).

local service delivery. El Mehdi and Hafner (2014) used the financial autonomy, defined as ratio of the own receipts of the municipality and its operating expenses, while Nijkamp and Suzuki (2009) used local revenues by local governments. Finally, Doumpos and Cohen (2014) employed the cost of services as a proxy of the value of resources used to provide citizens with all sorts of municipality services, assuming that the higher the net book value of assets as well as the value of goods and services rendered, the higher the quality and the range of options offered to citizens.

2.6. Methodological approaches to include environmental variables

Municipalities face different environmental conditions in terms of social, economic, political and financial, among others. These external factors, also known as determinants or environmental variables, can have a huge impact on the inefficiency scores because they are beyond the control of local managers. In this context, many studies have dealt with estimating how the contextual variables that face municipalities affect their performance. Table 2.2 provides a review of the studies using the different approaches to incorporate environmental variables in the efficiency estimation.

On the one hand, the empirical studies on local government efficiency which used traditional non-parametric methodologies (such as DEA or FDH) usually include external or environmental variables focusing on three main families of models[56]: the two-stage approaches (including the semi-parametric bootstrap-based approach), the frontier separation or meta-frontier approach and conditional models.

The first category is based on the two-stage analysis, the most popular method used to include environmental variables in local government efficiency. The efficiency scores are estimated in a first stage and a set of determinants are included in a second stage, using techniques such as Tobit censored regression model, OLS (Ordinary Least Squares) or single and double bootstrap methods (Simar and Wilson, 2007). The multi-stage approaches assume (implicitly) a separability condition where the operational environment would not influence the input or output levels, but only

[56]For a comprehensive review on methods used to include environmental variables in non-parametric efficiency analysis see the studies of Fried et al. (2008) and De Witte and Kortelainen (2013).

Table 2.2: Approaches to incorporate environmental variables in the efficiency estimation in local governments

A. NON-PARAMETRIC APPROACHES
1. Two stage approach
1.1. Tobit De Borger et al. (1994); De Borger and Kerstens (1996b,a); Worthington (2000); Ibrahim and Karim (2004); Moore et al. (2005); Sung (2007); Giménez and Prior (2007); Seol et al. (2008); Afonso and Fernandes (2008); Balaguer-Coll and Prior (2009); Bosch-Roca et al. (2012); Boetti et al. (2012); Monkam (2014); D'Inverno et al. (2017); Da Cruz and Marques (2014); Yusfany (2015)
1.2. OLS De Borger and Kerstens (1996a); Athanassopoulos and Triantis (1998); Loikkanen and Susiluoto (2005); Revelli and Tovmo (2007); Borge et al. (2008); Bruns and Himmler (2011); Loikkanen et al. (2011); Fogarty and Mugera (2013); Sørensen (2014); Da Cruz and Marques (2014); Andrews and Entwistle (2015)
1.3. Single and double bootstrap methods (Simar and Wilson, 2007) Bosch-Roca et al. (2012); Bönisch et al. (2011); Bischoff et al. (2013); Cuadrado-Ballesteros et al. (2013); Fogarty and Mugera (2013); Da Cruz and Marques (2014); Doumpos and Cohen (2014); Ashworth et al. (2014); Agasisti et al. (2015); Pérez-López et al. (2015); Lo Storto (2016)
1.4. Other approaches: non-parametric Kernel regression (Nadaraya-Watson), bivariate density functions, Generalised Least Squares, Kendall τ test, linear regression model, quantile regression Sampaio de Sousa et al. (2005); Balaguer-Coll et al. (2007); Benito et al. (2010); Nikolov and Hrovatin (2013); Helland and Sørensen (2015)
2. Metafrontier
Balaguer-Coll et al. (2013)
3. Conditional efficiency (Cazals et al., 2002; Daraio and Simar, 2005, 2007b; Mastromarco and Simar, 2015)
Asatryan and De Witte (2015); Cordero et al. (2017)

B. PARAMETRIC APPROACHES
1. Single stage approach
Hayes and Chang (1990); Grossman et al. (1999); Geys and Moesen (2009a); Geys et al. (2010); Kalb (2010); Štastná and Gregor (2011); Kalb et al. (2012); Boetti et al. (2012); Nikolov and Hrovatin (2013); Geys et al. (2013); Nakazawa (2013, 2014); Pacheco et al. (2014); Pevcin (2014a,b); Lampe et al. (2015); Štastná and Gregor (2015); Radulovic and Dragutinović (2015); Arcelus et al. (2015)
2. Two stage approach
2.1. Tobit De Borger and Kerstens (1996a); Athanassopoulos and Triantis (1998); Worthington (2000)
2.2. OLS De Borger and Kerstens (1996a); Geys (2006)

efficiency. As observed in table 2.2, in total 17 papers used Tobit analysis in a second stage, 12 used OLS methods and 11 bootstrapped truncated regressions.

In addition, some studies compared results from different methodologies when they introduced determinants of efficiency in the analysis. For instance, Da Cruz and Marques (2014) compared Tobit, OLS and double bootstrap. Also, Fogarty and Mugera (2013) employed OLS and single bootstrap method, Athanassopoulos and Triantis (1998) used Tobit and fuzzy k-means cluster analysis. De Borger and Kerstens (1996a) used Tobit and OLS, Borge et al. (2008) used OLS and random effects, and Bosch-Roca et al. (2012) used Tobit and bootstrap methods. Otherwise, the study of Benito et al. (2010) used Kendall τ test. Finally, in contrast to previous two-stage research studies, the studies of Balaguer-Coll et al. (2007) and Nikolov and Hrovatin (2013) used non-parametric smoothing techniques instead of econometric methods, which focus on graphical aspects of efficiency results, while Helland and Sørensen (2015) used linear regression and Sampaio de Sousa et al. (2005) used linear regression as well as quantile regression.

The second category refers to the frontier separation or meta-frontier approach. It evaluates separate efficiency performance for different groups according to the environmental characteristics (De Witte and Marques, 2009). In this context, the study of Balaguer-Coll et al. (2013) evaluated the efficiency of Spanish municipalities after splitting them into clusters according to the output mix, environmental conditions and the level of powers.

The third category for including environmental factors is called conditional efficiency, based on a probabilistic formulation of the efficient process formulation. It incorporates the operational environment by conditioning on the external characteristics (Cazals et al., 2002; Daraio and Simar, 2005, 2007b). Its main advantage is that it avoids the problem related to the separability condition from two stage analysis. We found only one study in the literature using this technique (Asatryan and De Witte, 2015). In addition, the study of Cordero et al. (2017) used the time-dependent conditional frontier models recently developed by Mastromarco and Simar (2015).

On the other hand, the empirical studies which used parametric methodologies to estimate local government efficiency (such as SFA) usually include environmental variables focusing on two main families of approaches: the single-stage approach and the two-stage analysis.

First, the single-stage approach jointly estimates the efficiency scores including the environmental variables in one stage. As shown in table 2.2, in total 19 papers have included environmental variables by using a single-stage approach. Second, as commonly used with non-parametric two-stage models, the efficiency scores obtained in a first step via parametric methodologies are regressed in a second step with a set of determinants, using techniques such as OLS or Tobit censored regression. In fact, 3 studies used Tobit analysis in a second step and 2 used OLS.

2.7. Environmental variables

The efficiency analysis literature does not provide a clear and standard classification of the external or environmental variables to include in the analysis. In contrast to the study of Da Cruz and Marques (2014), who proposed a classification for the different type of determinants, we classify the observed variables in six main categories: social and demographic, political, financial, economic, geographical or natural and, institutional or managerial. Table 2.3 shows the classification of the environmental variables included.

Additionally, we notice that in many cases the effects of the determinants present ambiguous effects over efficiency, i.e., results from different studies are mixed. These unclear effects can be explained by the different characteristics of each country and the availability of data. We discuss every single variable used, describing the results shown in previous studies and the expected impact of each variable over efficiency. Table A.4 in the appendix A also summarises the studies containing the variables included in the proposed classification, using the same structure as the main text.

Table 2.3: Classification of non-discretionary variables considered on local governments efficiency

Category	Variables
1. Social and demographic determinants	Population density Population growth Population size Age distribution population (Share of young people, Share of retired people, Aging index) Education level Immigration share and Ethnic diversity Share of homeowners Other related social and demographic characteristics
2. Economic determinants	Unemployment Citizen's income or purchasing power Economic status Tourism Commercial activity Industrial activity Other related economic characteristics
3. Political determinants	Ideological position Political concentration/fragmentation and strength (Herfindahl index, Coalition parties, Majority, Strength) Voter turnout and potential electors Re-election and number of years for elections Other related politic characteristics
4. Financial determinants	Self-generated revenues Transfers or grants Debt or financial liabilities Fiscal surplus Infrastructure investments Other related financial characteristics
5. Geographical and natural determinants	Distance from the centre and localization effects Area Type of municipalities (Sea, Mountain) Other related to geographical or natural characteristics
6. Institutional and management determinants	Informatization or level of computer usage Mayor and local government employees characteristics Amalgamation Managerial forms (Municipal cooperation, Externalization, Mixed firms, Agentification) Other related to institutional or management characteristics

2.7.1. Social and demographic determinants

This group of environmental variables is composed by citizens' related characteristics. It is explained by eight indicators: population density, population growth, population size, age distribution of the population, education level, share of immigrants, share of homeowners and others.

- Population density (37 papers)

  The population density is measured as the number of inhabitants of each municipality divided by its extension, mostly expressed in squared kilometres. Based on previous empirical studies, the influence of this variable is not, *a priori*, clear and we have alternative hypothesis on the effect that population density has on efficiency. On the one hand, it affects the cost of providing public services, i.e., economies of scale could exist when population concentration rises (cost advantages). Hence, it would enhance efficiency.[57] Moreover, some studies included "urbanization rate" as a variable to capture scale effects.[58] They suggested that an increase in the urbanization rate leads to higher levels of efficiency. Similarly, Balaguer-Coll et al. (2013) used the total surface area divided by population as a proxy for urban sprawl as well as urbanised municipalities.

  On the other hand, if the population concentration is larger, the cost of providing public services can become higher (problems of agglomeration and higher complexity). Thus, the provision of the service would be less efficient.[59] However, there are also research studies which found that population density is not statically significant.[60] Additionally, the studies of Kalseth and Rattsø (1995) and Revelli and Tovmo (2007) introduced the variable "settlement pattern",

[57]De Borger and Kerstens (1996a); Sampaio de Sousa et al. (2005); Sung (2007); Afonso and Fernandes (2008); Geys et al. (2010); Kalb (2010); Bönisch et al. (2011); Boetti et al. (2012); Fogarty and Mugera (2013); Bischoff et al. (2013); D'Inverno et al. (2017); Yusfany (2015); Agasisti et al. (2015); Radulovic and Dragutinović (2015); Lo Storto (2016).

[58]Sampaio de Sousa et al. (2005); Loikkanen and Susiluoto (2005); Loikkanen et al. (2011); Bruns and Himmler (2011).

[59]Athanassopoulos and Triantis (1998); Geys (2006); Geys and Moesen (2009a); Kalb et al. (2012); Geys et al. (2013); Doumpos and Cohen (2014); Da Cruz and Marques (2014); Lampe et al. (2015).

[60]Giménez and Prior (2007); Revelli and Tovmo (2007); Revelli (2010); Ashworth et al. (2014); Pevcin (2014a,b); Arcelus et al. (2015); Andrews and Entwistle (2015); Cordero et al. (2017).

calculated as the travelling distance to the administration centre of the local authority, to measure sparseness of population. The first study found that a decentralized settlement pattern seems not to be an important factor, while the second suggested that more sparsely populated areas manage to attain higher levels of efficiency.

- Population growth (6 papers)

  Total population growth is the variation of inhabitants (in percentage) which municipalities face over the years. If the population growth is high, municipalities must increase local services and infrastructures proportionally because population's demand has also increased. If they do it properly, efficiency levels would improve. For instance, Afonso and Fernandes (2008) showed a positive and significant relation with efficiency—but only in the North Region of Portugal. In contrast, if they do not keep pace with the proportional increase of services and infrastructures, they might face an imbalance and we will expect a negative relation with efficiency.[61] Otherwise, some studies concluded that a demographic change does not cause significant efficiency effects.[62]

- Population size (24 papers)

  Population size is mostly measured as the total population for each local government as well as dummy variables representing different population groups. The effect of this variable over efficiency is, *a priori*, ambiguous. A common intuition is that economies of scale and agglomeration externalities typically make larger municipalities more efficient.[63] However, the negative effects of having a larger population (scale inefficiencies) were also confirmed by some studies.[64] Otherwise, results in the study of Doumpos and Cohen (2014) did not

[61] Kalseth and Rattsø (1995); Balaguer-Coll et al. (2013).

[62] Bönisch et al. (2011); Bischoff et al. (2013); Monkam (2014); Andrews and Entwistle (2015).

[63] De Borger et al. (1994); Kalseth and Rattsø (1995); Grossman et al. (1999); Balaguer-Coll et al. (2007); Giménez and Prior (2007); Benito et al. (2010); Revelli (2010); Bruns and Himmler (2011); Boetti et al. (2012); Nakazawa (2013); D'Inverno et al. (2017); Nakazawa (2014); Pérez-López et al. (2015); Asatryan and De Witte (2015).

[64] Loikkanen and Susiluoto (2005); Sung (2007); Geys and Moesen (2009a); Šťastná and Gregor (2011); Loikkanen et al. (2011); Sørensen (2014); Ashworth et al. (2014); Šťastná and Gregor (2015).

follow a linear pattern (the coefficient was negative for small municipalities and positive for medium and large municipalities). Finally, Andrews and Entwistle (2015) did not find population size related to efficiency.

- Age distribution of the population (10 papers)

  The different age distribution of the population can have an impact on the different needs that local governments have to satisfy. Mainly, two variables are included: share of young people (18 years old or below) and share of retired people (over 65 old). First, higher percentages of young population demand higher levels of social and recreational services to the public administrations (for instance, kindergartens, gyms or playing fields among others), so there is an incentive for municipal administrators to improve efficiency.[65] However, this higher spending on public services could also affect efficiency negatively.[66] Other studies found the share of young population not statistically significant.[67]

  Second, retired people could have higher control over council performance because they take part in organizations of local nature.[68] However, the share of retired people over population could have a negative effect since this population group is more likely to use health care and nursing services.[69] Otherwise, some studies concluded that the share of retired people has no statistical significance.[70] Finally, the study of Radulovic and Dragutinović (2015) included an "ageing index", i.e., a ratio between the number of people over 65 and the number of people under 18, while Andrews and Entwistle (2015) included the age diversity. Only Radulovic and Dragutinović (2015) found significant results, showing a negative relation between the age index ratio and efficiency.

- Education level (17 papers)

  Education level includes primary, secondary and tertiary education. On the

[65] Agasisti et al. (2015).
[66] Nakazawa (2013, 2014).
[67] Giménez and Prior (2007); Bruns and Himmler (2011); Asatryan and De Witte (2015).
[68] Bosch-Roca et al. (2012).
[69] Bönisch et al. (2011); Bischoff et al. (2013); Nakazawa (2013, 2014); Da Cruz and Marques (2014).
[70] Giménez and Prior (2007); Bruns and Himmler (2011); Agasisti et al. (2015).

one hand, highly educated citizens might be more effective in demanding more efficient governments since education has an effect on political participation and control. Moreover, municipalities with larger proportion of educated people may imply a more qualified labour force. Therefore, it would have a positive correlation with efficiency.[71] Moreover, the study Da Cruz and Marques (2014) found that higher illiteracy is related to inefficiency.

In contrast, the studies of De Borger and Kerstens (1996a) and Štastná and Gregor (2011, 2015) showed a negative correlation with efficiency. Finally, some the studies found that the education level is not related to local government efficiency.[72]

- Immigration share and ethnic diversity (7 papers)

  The share of immigrants is the percentage of foreign inhabitants related to the total population of a municipality. This variable is assumed to decrease cost efficiency because foreign population does not have right to vote[73] or are less interested in politics[74]. In addition, the study of Lampe et al. (2015) introduces the migration rate (measured as the immigration rate less the migration rate) to measure the municipality's popularity. They found that migration rate is positively correlated to efficiency since it increases the population and the services of a municipality in a short term, while expenditures will not increase in the same proportion (in the respective year).

  Otherwise, Nikolov and Hrovatin (2013) studied "ethnic fragmentation", arguing that more ethnically fragmented municipalities exhibit less efficiency. Similarly, Revelli (2010) and Andrews and Entwistle (2015) included indicators of ethnic composition (percentage of the population that is white) and ethnic diversity (16 groups), concluding that higher ethnic diversity has a negative correlation with

[71] De Borger et al. (1994); De Borger and Kerstens (1996b); Loikkanen and Susiluoto (2005); Afonso and Fernandes (2008); Revelli (2010); Loikkanen et al. (2011); Da Cruz and Marques (2014); Monkam (2014); Radulovic and Dragutinović (2015).

[72] Ibrahim and Karim (2004); Geys and Moesen (2009a); Bruns and Himmler (2011); Bosch-Roca et al. (2012).

[73] Bosch-Roca et al. (2012).

[74] Bruns and Himmler (2011).

efficiency. Also, Hayes and Chang (1990) used the percentage of the population that is minority, however they did not find significant correlation with efficiency.

- Share of home-owners (3 papers)

  Share of home-owners represents the amount of owner-occupiers over local government population. Home-ownership entails a significant financial investment, so home-owners demand more efficient government behaviour and monitor local politicians.[75] Otherwise, the study of Geys and Moesen (2009a) did not find significant relation to local government efficiency.

- Other determinants related to social and demographic characteristics

  Finally, we include other determinants related to social and demographic characteristics which are not classified in the previous subcategories. Agasisti et al. (2015) included the number of families, suggesting that the more families within the municipality, the more services different from the essential ones will be asked, so it has a positive correlation with efficiency. Moreover, Bruns and Himmler (2011) included the average household size as well as the commuter share, however they did not find significant results. Nakazawa (2013) included the ratio of daytime to night-time population, which had negative effects over efficiency, and Revelli (2010) used the share of disabled workers but they did not find significant results.

  In addition, Andrews and Entwistle (2015) included the social class diversity (however, they did not find significant results). Lo Storto (2016) and Da Cruz and Marques (2014) included the crime rate, suggesting that when the level of urban crimes grow, the municipality efficiency increases. Finally, Revelli (2010) and Bruns and Himmler (2011) included the share of religious population. While the first study suggested that religious people are associated with better government performance, the second one argued that a higher share of religious population is associated with lower levels of efficiency since they are possibly less interested in local politics.

[75] Hayes and Chang (1990); Geys (2006).

2.7.2. Economic determinants

This group of environmental variables is composed by variables related to the economic situation of each local government. It is explained by seven indicators: unemployment, citizen's disposable income, economic status, tourist index, commercial activity, industrial activity and others.

- Unemployment (15 papers)

  The variable unemployment is measured as the percentage of unemployment related to the working population of each municipality. A difficult socio-economic municipal situation (i.e., a high unemployment rate) implies higher spending on social and housing benefits, so it tends to decrease efficiency ("cost effect").[76] However, unemployment could imply lower demand for high-cost or high-quality public services ("preference effect"), so it will be expected to have higher levels of efficiency.[77] Other studies indicated that unemployment is not related to municipal efficiency.[78]

- Citizen's income level or purchasing power (26 papers)

  The variable income per capita represents the citizen's economic level estimated for each municipality. On the one hand, municipalities which have richer local residents have an increased population pressure to provide efficient local services. These higher-income citizens might pay greater taxes and, as a consequence, they will have more requirements on local services and facilities. Therefore, higher citizen's incomes would increase efficiency.[79] Similarly, Agasisti et al. (2015) used a taxable income per capita (a progressive tax on all the income of a person called IRPEF) as a proxy of the average income per capita. The higher it is, the more citizens' supervision on municipal administrators, so it is

[76]Loikkanen and Susiluoto (2005); Revelli (2010); Loikkanen et al. (2011); Kalb et al. (2012); Pevcin (2014a,b); Radulovic and Dragutinović (2015); Pérez-López et al. (2015).

[77]Geys et al. (2010); Kalb (2010); Lampe et al. (2015).

[78]Geys and Moesen (2009a); Balaguer-Coll and Prior (2009); Bönisch et al. (2011); Geys et al. (2013); Cordero et al. (2017).

[79]Ibrahim and Karim (2004); Afonso and Fernandes (2008); Afonso et al. (2010); Boetti et al. (2012); Asatryan and De Witte (2015).

positively related to efficiency. Also, Balaguer-Coll et al. (2013) and Da Cruz and Marques (2014) proxied the economic status with the capita GDP, however, only Balaguer-Coll et al. (2013) found a positive relation with efficiency.

On the other hand, if local governments have higher financial resources (because they collect higher incomes), interest of the politicians in reaching efficiency in the provision of local services and facilities is reduced. In addition, citizens from high income municipalities may be less motivated to monitor expenditures. So, it would be negatively related to efficiency.[80] In a similar way, Cuadrado-Ballesteros et al. (2013) measured income level using the variable GDP per capita, and their results present a negative correlation with efficiency. Other studies concluded that citizen's income did not have a significant relation with efficiency.[81]

Additionally, Geys and Moesen (2009a) and Ashworth et al. (2014) included "income inequality" to assess the effect of income heterogeneity in the population. Only Ashworth et al. (2014) found negative significant results.

- Municipal economic situation (6 papers)

The determinants within this subcategory refer to variables related to the economic situation of each municipality. Sampaio de Sousa et al. (2005) used the average earnings as a poverty proxy as well as a dummy variable for those municipalities which took part in the Alvorada Program (a federal program for low income municipalities). They found that poor cities, specially those participating in the Alvorada Program, tend to be more efficient. Similarly, Lo Storto (2016) used the value added per inhabitant as a proxy of the economical context, suggesting that higher efficiency is associated to less rich contexts. Otherwise, Revelli (2010) and Andrews and Entwistle (2015) included a deprivation index to capture the levels of disadvantage in: income, employment, health, education,

[80] De Borger et al. (1994); De Borger and Kerstens (1996a,b); Loikkanen and Susiluoto (2005); Sampaio de Sousa et al. (2005); Giménez and Prior (2007); Bruns and Himmler (2011); Bosch-Roca et al. (2012); Nikolov and Hrovatin (2013); Monkam (2014); Ashworth et al. (2014); Da Cruz and Marques (2014).

[81] Geys (2006); Geys and Moesen (2009a); Balaguer-Coll and Prior (2009); Benito et al. (2010); Yusfany (2015); Cordero et al. (2017).

housing, crime, and environment. They showed a negative relationship with efficiency, indicating that providing public services in disadvantaged areas is an especially challenging task. Fogarty and Mugera (2013) measured the relative socio-economic disadvantage. They hypothesised that councils with higher socio-economic disadvantage would have lower efficiency scores, however, they do not find significant results. Finally, Balaguer-Coll et al. (2013) included the number of bank branches to proxy for the economic level of the municipality.

- Tourist activity (13 papers)

  Tourism measures the importance of the tourist activity of each municipality. On the one hand, seasonal population has an impact on the provision of services because local governments must face higher investments during some periods of the year. Moreover, tourists have a greater demand for higher quality public services that increase the costs. Hence, we will expect that an increase in the tourist index has a negative correlation with efficiency.[82] On the other hand, Giménez and Prior (2007) and Pérez-López et al. (2015) found a positive relation between this variable and efficiency, concluding that the more tourism activity, the lower the cost excess. Finally, some studies found that tourism is not statistically significant.[83]

- Commercial activity (4 papers)

  This variable measures the importance of the commercial activity of each municipality. High commercial activity means more pressure over local managers to improve efficiency because traders exercise more control. Therefore, we expect a positive relation to efficiency.[84] However, Sung (2007) showed that an increase in the number of establishments and service-related establishments may reduce efficiency since more time and effort by local servants is required.

[82]Geys and Moesen (2009a); Kalb (2010); Bosch-Roca et al. (2012); Kalb et al. (2012); Cuadrado-Ballesteros et al. (2013); D'Inverno et al. (2017); Da Cruz and Marques (2014).

[83]Sampaio de Sousa et al. (2005); Balaguer-Coll and Prior (2009); Benito et al. (2010); Lampe et al. (2015).

[84]Giménez and Prior (2007); Balaguer-Coll and Prior (2009); Bosch-Roca et al. (2012).

- Industrial activity (2 papers)

  This variable measures the importance of industrial activity of each municipality. We can hypothesize that more efficient municipalities will attract business, so it will enhance efficiency.[85] On the contrary, the study of Giménez and Prior (2007) concluded that the industry activity has no relation with efficiency.

- Other determinants related to economic characteristics

  Finally, we include other determinants related to economic characteristics which are not classified in the previous subcategories. Sampaio de Sousa et al. (2005) measured the municipalities that receive substantial royalty revenues (on oil and water), suggesting that extra revenues, rather than encouraging the optimal use of resources, contribute to increase inefficiency. Moreover, the study of Revelli (2010) included the percentage of self-employed population, which had a negative correlation with efficiency. Also, Revelli (2010) included the property tax base to capture income effects on the demand for public services, which were estimated to have a positive effect on performance. Otherwise, Balaguer-Coll et al. (2013) and Geys and Moesen (2009a) indicated whether it is a rural municipality (whose needs might differ from others with different sectoral specializations), while Balaguer-Coll et al. (2013) also included municipalities where construction was higher. Finally, Da Cruz and Marques (2014) included the automotive fuel consumed and new vehicles sold as a measure for the economic consumption levels, showing a positive correlation with efficiency.

2.7.3. Political determinants

We have focused on the impact of political and legal determinants on efficiency including five indicators: ideological position, political concentration/fragmentation or strength, voter turnout, re-election and others.

- Ideological position (26 papers)

[85] Geys and Moesen (2009a).

The ideological position represents local governments' political sign. The basic hypothesis is that left-wing parties prefer a larger public sector which, in general, is associated with low efficiency levels.[86] Similarly, the study of Sørensen (2014) concluded that electoral polarization (distance between the socialist and non-socialist party blocs) cause lower government performance. Moreover, Geys (2006) and Šťastná and Gregor (2015) introduced measures for the ideological fragmentation of the governing coalition. Only Šťastná and Gregor (2015) found significant evidence, concluding that the strength of a left-wing mayor seems to further increase cost inefficiency.

However, the available evidence is not entirely uni-directional, since the studies of De Borger et al. (1994) and De Borger and Kerstens (1996a,b) concluded that the presence of the socialist party is associated with higher efficiency. Similarly, Andrews and Entwistle (2015) suggested that Labour vote shares are positively related to productive efficiency, suggesting that whether is a greater support to public services, local authorities may find less difficult to make the best use of their resources. Also the studies of Geys et al. (2010) and Agasisti et al. (2015) concluded that a low share of left-wing parties is associated with lower efficiency. Other studies, however, concluded that the ideological position did not have a significant influence on efficiency.[87] Additionally, Boetti et al. (2012) and Bruns and Himmler (2011) measured governing coalitions with a civic list, which are not identified with any ideological position and are associated with higher efficiency, while Šťastná and Gregor (2011) introduced a dummy for parliamentary parties (less votes for parliamentary parties implies more votes for local parties with no ideology).

- Political concentration/fragmentation and political strength (25 papers)

Most part of the studies which measure political concentration in local govern-

[86] Revelli and Tovmo (2007); Borge et al. (2008); Kalb (2010); Revelli (2010); Šťastná and Gregor (2011); Loikkanen et al. (2011); Kalb et al. (2012); Doumpos and Cohen (2014); Da Cruz and Marques (2014); Ashworth et al. (2014); Helland and Sørensen (2015).

[87] Geys and Moesen (2009a); Benito et al. (2010); Boetti et al. (2012); Sørensen (2014); Asatryan and De Witte (2015); Pérez-López et al. (2015); Cordero et al. (2017).

ment calculate the Herfindahl index. It takes values between 0 and 1, indicating a higher degree of political concentration (or a lower degree of political fragmentation) and, as a result, a higher degree of political strength (or lower degree of competition). On the one hand, when the degree of political concentration is higher, there exist a lower political opposition and it is easier to implement policies and impose budget constraints, so it is expected to increase efficiency.[88] On the other hand, a low political competition makes more difficult to other parties to control expenditures and therefore efficiency can be reduced.[89] Finally, some studies found no statistical significance.[90]

In addition, other variables related to political concentration and strength different from the Herfindahl index have been used. For instance, De Borger et al. (1994) introduced the number of coalition parties, while Ashworth et al. (2014) introduced variables reflecting different aspects of the local government competition as well as the variables "single party government" and "number of coalition parties" to capture the effect of government fragmentation. The first study argues that political coalitions may affect technical efficiency because arbitrage in the bargaining process may require more payments, however, they did not find significant results. The second one found that government fragmentation and coalitions have a significant negative correlation with efficiency. Similarly, Eeckaut et al. (1993) measured political majorities from different parties as well as coalitions, concluding that local governments with multiple-party coalitions are more efficient than municipalities governed by a single party. Otherwise, the studies of Athanassopoulos and Triantis (1998) and Nikolov and Hrovatin (2013) measured the coalition between central government and local government, while the study of Pacheco et al. (2014) used the percentage of council representatives who belongs to the governmental coalition. The first two studies presented contrary results, leading Athanassopoulos and Triantis (1998) to lower levels of

[88]Revelli and Tovmo (2007); Borge et al. (2008); Bruns and Himmler (2011); Šťastná and Gregor (2011); Doumpos and Cohen (2014); Pacheco et al. (2014); Yusfany (2015).

[89]Balaguer-Coll et al. (2007); Geys et al. (2010); Kalb (2010); Loikkanen et al. (2011); Kalb et al. (2012); Geys et al. (2013); Helland and Sørensen (2015).

[90]Geys (2006); Revelli (2010); Sørensen (2014).

efficiency and the Nikolov and Hrovatin (2013) to higher levels, while Pacheco et al. (2014) did not show significant results.

In addition, Sørensen (2014) included "electoral dominance" as the share of election periods wherein a party bloc received more than 60% of the votes. They concluded that party competition leads to higher levels of efficiency. Also, Cuadrado-Ballesteros et al. (2013) introduced variables reflecting different aspects of the local government competition (difference between the percentages of votes obtained by the parties coming in first and second place) as well as political strength (percentage of seats obtained by the governing party). Similarly, Pérez-López et al. (2015) introduced "political strength", concluding that parties governing with an absolute majority present lower levels of efficiency. Finally, the study of Balaguer-Coll et al. (2007) found a negative correlation between efficiency and the relative importance of votes held by the governing party, while Monkam (2014) revealed a positive coefficient of the percentage of council seats held by the majority.

- Voter turnout and democratic participation (9 papers)

The variable voter turnout represents the political participation of the citizens in local elections, i.e., the voter turnout related to the citizens entitled to vote. This variable affects the degree of control that inhabitants have over politicians with their votes in local elections, so we expect an improvement in the efficiency of the municipalities.[91] However, results in Da Cruz and Marques (2014) and Asatryan and De Witte (2015) suggested a negative correlation with efficiency, supporting that less efficient governments motivate more citizen participation. Finally, some studies concluded that voter turnout do not explain efficiency differences.[92]

Moreover, additional variables related to democratic participation are considered. Bosch-Roca et al. (2012) and Geys et al. (2010) employed the variable "potential electors" (citizens entitled to vote related to total population), which is expected

[91] Borge et al. (2008); Geys et al. (2010); Šťastná and Gregor (2011, 2015).
[92] Revelli and Tovmo (2007); Loikkanen et al. (2011).

to increase efficiency. Moreover, Geys et al. (2010) included the variable "free voter unions" as an indicator of voter involvement, arguing that their existence improves efficiency since citizens actively participate in politics. Finally, Asatryan and De Witte (2015) considered dummies for citizens initiatives, associated with higher government efficiency.

- Re-election and number of years for elections (5 papers)

  Re-election or second mandate represents a municipal mayor that has been re-elected at the municipal elections. Similarly, "new government" represents when a different government has been elected. On the one hand, re-election can have a positive effect on efficiency because at the second mandate the municipality's government has become more competent on local issues. On the other hand, in a second mandate local administrators could tend to spend in a less prudent manner, since they have been elected again.[93] Other studies found re-election not statistically significant.[94]

  In addition, variables related to the number of years for elections are considered. Boetti et al. (2012) used the variable "electoral mandate" which represents the number of years since the mayor and the governing coalition were elected, in order to test the presence of opportunistic behaviour by local politicians attributable to the electoral budget cycle, however they did not find significant results. Similarly, Agasisti et al. (2015) measured the years that remain until the end of municipal term, which is positively related to efficiency.

- Other determinants related to political characteristics

  Finally, we include other determinants related to political characteristics which are not classified in the previous subcategories. Bruns and Himmler (2011) introduced the number of municipality council seats per 1,000 inhabitants, which was found positively related to efficiency. They also included local newspaper reach, which is associated with higher efficiency, arguing that newspapers are

[93] D'Inverno et al. (2017).
[94] Doumpos and Cohen (2014); Da Cruz and Marques (2014).

a major provider of the political information that voters use to monitor their elected officials. Moreover, Grossman et al. (1999) included both the Mayor-council form of government and Mayor elected in a general election, however, they showed no significant results. Finally, Helland and Sørensen (2015) included the variables "partisan bias" (voters that vote for party labels and do not care about performance) and "electoral volatility". Their main hypothesis is that non-partisans want better performance and care little about ideology, while partisans vote for labels and care little about high performance. They found that efficiency decreases when the relative partisan bias of the incumbent increases, particularly in municipalities with large electoral volatility.

2.7.4. Financial determinants

We have included a group of environmental variables related to fiscal and financing mechanisms of the local governments. It is explained by five indicators: self-generated, grants and transfers, debt or financial liabilities, surplus and others.

- Self-generated revenues (25 papers)

  Self-generated revenues are the total amount of taxes, fees and charges collected by each local government. On the one hand, when local councils are more able to generate revenues (by collecting higher taxes), politicians are less motivated to manage them properly. Moreover, these local governments will have good services even if they are not efficient. As a consequence, this variable would have a negative correlation with efficiency.[95] Similarly, Agasisti et al. (2015) measured the incidence of the proceeds of public services suggesting that higher revenues different from taxes influence negatively the efficiency of the local administrations. Moreover, D'Inverno et al. (2017) used the ratio of total revenues over total resident population arguing that the more resources are available for a municipality, the greater is the possibility to waste resources. On the other hand,

[95] Grossman et al. (1999); Athanassopoulos and Triantis (1998); Moore et al. (2005); Balaguer-Coll et al. (2007); Revelli and Tovmo (2007); Sung (2007); Borge et al. (2008); Balaguer-Coll and Prior (2009); Štastná and Gregor (2011); Bosch-Roca et al. (2012); Boetti et al. (2012); Nikolov and Hrovatin (2013); Ashworth et al. (2014); Pérez-López et al. (2015); Štastná and Gregor (2015).

higher taxes will increase citizen control on public management, so it will be expected better levels of efficiency.[96] Other studies showed that tax revenues are not correlated with efficiency.[97]

Additionally, some studies used the share of own taxes in local governments' total revenues as a proxy of fiscal autonomy.[98] They found that fiscal autonomy has a positive correlation with efficiency supporting that the higher the revenues from fees and taxes (i.e., from citizens contribution), the higher the responsibility of the local government.

- Transfers or grants (26 papers)

  Transfers or grants represent the municipal revenues which come from transfers or grants received from higher government levels. Also, the financial independence from central governments (i.e., less transfers and grants received) is employed. Local governments which have greater security in obtaining resources via grants are less efficient because politicians will take less care in managing them adequately. Moreover, there will be less citizen control over public management because the cost of inefficient performance is shared by regional and national taxpayers (i.e., they do not pay these revenues directly). Hence, we will expect a negative correlation with efficiency.[99]

  On the contrary, some studies showed a positive association with efficiency, explaining that transfers and grants are linked to a more accurate control of local expenditures by higher levels of government control.[100] Moreover, Bischoff et al. (2013) found that the relationship between vertical grants and efficiency is mixed, since they found a positive relationship between grants and efficiency

[96] De Borger and Kerstens (1996a,b); Benito et al. (2010).

[97] Fogarty and Mugera (2013); Doumpos and Cohen (2014); Arcelus et al. (2015); Yusfany (2015).

[98] Boetti et al. (2012); Da Cruz and Marques (2014); Monkam (2014); D'Inverno et al. (2017).

[99] De Borger and Kerstens (1996a,b); Athanassopoulos and Triantis (1998); Grossman et al. (1999); Loikkanen and Susiluoto (2005); Balaguer-Coll et al. (2007); Borge et al. (2008); Balaguer-Coll and Prior (2009); Geys et al. (2010); Kalb (2010); Štastná and Gregor (2011); Bosch-Roca et al. (2012); Pacheco et al. (2014); Doumpos and Cohen (2014); Da Cruz and Marques (2014); Pérez-López et al. (2015); Yusfany (2015); Agasisti et al. (2015); Štastná and Gregor (2015).

[100] Worthington (2000); Geys (2006); Geys and Moesen (2009a); Bönisch et al. (2011); Ashworth et al. (2014).

but a negative one between fiscal capacity and efficiency. Finally, some studies indicated that transfer grants have no statistical significance.[101]

- Debt or financial liabilities (14 papers)

  Outstanding debt is the value of the financial unresolved liabilities at the financial year. When local governments have an excess on expenditures over revenues they will need to take out loans. The first hypothesis is that local governments which make loans are those with low fiscal revenue capacity. These local governments might be more concerned about cost saving due to their financial problems. Moreover, debt can be the result of past investments on equipment that enhance current efficiency. Therefore, considering these reasons, debt would be positively related to efficiency.[102]

  On the contrary, if the amount of local government debt is higher, there will be more resources employed to attend debt interests and amortization payments and, as a consequence, less resources will be employed in the provision of local services. Hence, the variable would be negatively related to efficiency.[103] Other studies showed that debt is not statically significant.[104] In addition, Balaguer-Coll et al. (2007) consider also financial deficit. If deficit rises, local governments will have a financial weaker situation to face their present and future responsibilities. Hence, deficit affects negatively to efficiency.

- Surplus (6 papers)

  Fiscal surplus is the excess from the year's budget. The main hypothesis is that municipalities that have higher surpluses have better financial performance and also witness higher government efficiency ratings.[105] Similarly, Pérez-López et al. (2015) used the "Non-financial Current Budgetary result Index", which

[101]Worthington (2000); Boetti et al. (2012).

[102]Worthington (2000); Benito et al. (2010).

[103]Geys (2006); Geys and Moesen (2009a); Šťastná and Gregor (2011); Bönisch et al. (2011); Bischoff et al. (2013); Ashworth et al. (2014); Da Cruz and Marques (2014); Cordero et al. (2017).

[104]Balaguer-Coll et al. (2007); Revelli and Tovmo (2007); Balaguer-Coll and Prior (2009); Benito et al. (2010); Pérez-López et al. (2015).

[105]Geys (2006); Geys and Moesen (2009a); Ashworth et al. (2014); Agasisti et al. (2015).

presented a positive and significant relationship with municipal cost efficiency. On the contrary, Yusfany (2015) showed a negative and significant correlation between surplus and efficiency, stating that local bureaucrats in every year's budget tend to maximize the size of the budget in order to create opportunities to take advantage of local budgets freely according to his personal wishes.

- Infrastructure investments (7 papers)

  Infrastructure investments and capital expenditures aim at measuring the effect of a higher level of investments on the use of the financial means. High capital investment in a given year encourages cost savings on current expenditures. Therefore, higher investment expenditure would increase municipal efficiency.[106] Similarly, Arcelus et al. (2015) considered that municipalities with higher accumulated past investments in infrastructures are expected to have more modern endowments and, therefore, more efficient performance. On the contrary, the study of Šťastná and Gregor (2011) found a negative correlation with efficiency. Moreover, Agasisti et al. (2015) included the variables "propensity to invest per capita" and "incidence of capital expenditures on total expenditures". They found that investment was negatively correlated with efficiency, while capital was positively since municipalities exposed to long-term expenditures would be more careful managing the current ones.

  Additionally, Doumpos and Cohen (2014) employed the annual depreciation to cumulative depreciation ratio as an indicator of the assets' age. The higher the value of the ratio, the newer the infrastructure used for rendering services to citizens. They found a statistically significant positive correlation, arguing that new assets have less maintenance and less operating expenses compared to their older counterparts.

- Other determinants related to financial characteristics

  Finally, we include other determinants related to financial characteristics which are not classified in the previous subcategories. Kalb (2010) included dummy

[106] Athanassopoulos and Triantis (1998); Pacheco et al. (2014); Šťastná and Gregor (2015).

variables for abundant and financially weak municipalities to control for financial power of a municipality. Both variables are positive and statistically significant, supporting that abundant or financially weak municipalities have (in relation to financially very weak municipalities) more money to spend and it enables to afford more or qualitatively higher public goods and services. Pérez-López et al. (2015) introduced the variable "cash index". They concluded that the greater the availability of resources, the more efficiency requirements will be relaxed since municipalities can cover their cost increases. Benito et al. (2010) used working capital as an indicator of the local government short-term financial situation.

Moreover, Andrews and Entwistle (2015) included the Formula Spending Share (FSS) per resident was used as a measure of quantity of service needs (this index is used by central government to distribute grant funding to local authorities), as well as the discretionary resources available to each local authority, derived by dividing its total expenditure by its FSS in the same year. They concluded that councils spending beyond the needs of a local population could be seen as an indicator of poor financial performance. Revelli (2010) used the excess spending defined as local public spending per capita minus standard spending per capita set by central government. They suggested that local public expenditures in excess of centrally set spending standards have a detrimental effect on performance. Otherwise, Da Cruz and Marques (2014) and Agasisti et al. (2015) measured the average payment period to suppliers an the speed of payment of current expenditures. Only Da Cruz and Marques (2014) found significant negative results. Finally, Worthington (2000) showed that the higher the level of current assets and current assets relative to current liabilities, the higher the level of technical efficiency.

In addition, some studies included variables related to financial constraints. Boetti et al. (2012) included the effect of the Domestic Stability Pact (DSP), a mechanism of fiscal discipline which leads to cuts in excess spending. They found that municipalities subject to the DSP are more efficient due to the higher control from central government on spending through fiscal rules. Also, Borge et al. (2008) included a dummy variable for centralized budgetary procedure, which was found to be correlated with low efficiency. Finally, Doumpos and Cohen (2014) introduced the administrative expenses to own revenues ratio to assess the burden imposed to municipalities by their administrative costs. They found that municipalities which spend more funds to sustain their bureaucracy status are less efficient.

2.7.5. Geographical or natural determinants

This group of environmental variables is related to geographical, spatial or natural characteristics. It is explained by four indicators: distance from centre, area, type of municipality and others.

- Distance from centre and localization effects (11 papers)

  This variable measures the geographical distance of the municipality from the regional or district centre. The main hypothesis is that the smaller the distance between the municipality and the centre, the higher the competition between municipalities. Also the access to local public goods provided by the region gets easier. Hence, municipalities closer to the centre would be more efficient.[107] However, Štastná and Gregor (2015) found that proximity to the regional centre increases efficiency, while distance to district centre has the opposite sign. Otherwise, there are also studies which found that distance from the centre is not statically significant.[108]

  Otherwise, the study of Sampaio de Sousa et al. (2005) used the variable "capital" as a location aspect, arguing that there is a clear efficiency premium for state capitals since those cities tend to present higher efficiency scores relative to other localities with similar characteristics. Similarly, Andrews and Entwistle (2015) introduced a dichotomous variable for local authorities within London, however they did not find significant results. Moreover, Grossman et al. (1999) introduced

[107] Loikkanen and Susiluoto (2005); Afonso and Fernandes (2008); Loikkanen et al. (2011); Štastná and Gregor (2011); Pacheco et al. (2014).
[108] Boetti et al. (2012).

the number of cities in city's metropolitan statistical area. They found that a greater number of cities in a central city's metropolitan area increase competition and, as a consequence, more technically efficient is the central city. Finally, the study of Radulovic and Dragutinović (2015) introduced the variable "distance to Route E75 (Motorway A1)" as a location factor, supporting that municipalities closer to the E75 would be more efficient.

- Area (5 papers)

  Some studies included the size of local government area measured in squared kilometres. The main hypothesis is that larger areas would have higher costs of infrastructure services. Moreover, smaller administrative areas also tend to be easily managed than bigger ones. So, it is expected to have a negative correlation with efficiency.[109] Other studies found that city size is not significant in explaining efficiency.[110]

- Type of municipality (5 papers)

  It comprises natural geographical factors that affect the level of municipal efficiency, such as sea, mountain or municipalities located in islands. The first group relates to coastal or sea variables. Coastal municipalities are better able to achieve higher levels of economic efficiency due to their higher levels of development and their greater ability to increase tax receipts. So, a coastal location would have a positive relation to efficiency.[111] However, the sea municipalities can be subject to seasonality, which could have a negative correlation with efficiency.[112] In addition, Da Cruz and Marques (2014) included a dummy variable to difference municipalities located in islands as well as municipalities located in the mainland near the coast (littoral area). They argue that municipalities located in islands have higher costs when providing some public services and equipment because of its natural constraint, however they showed a positive correlation

[109] Ibrahim and Karim (2004); Sung (2007); Nakazawa (2013); Da Cruz and Marques (2014).
[110] Moore et al. (2005).
[111] Cordero et al. (2017).
[112] D'Inverno et al. (2017).

with efficiency, explaining that in the Portuguese islands there exists a regional government that substitutes the municipality in some of their responsibilities.

The second group relates to mountain or hill variables. The main hypothesis is that municipalities located in the mountain have higher spending levels than non-mountain municipalities, so it is negatively correlated with efficiency.[113] Similarly, Boetti et al. (2012) found the same results using a dummy for altitude over 600 meters. Otherwise, Da Cruz and Marques (2014) included the variable topography (difference between the maximum and minimum altitude) and Agasisti et al. (2015) used the geographical conformation as the range of altitude mountains, however neither studies found significant results.

- Other determinants related to geographical or natural determinants characteristics

  Finally, we include other determinants related to geographical or natural characteristics which are not classified in the previous subcategories. Sampaio de Sousa et al. (2005) introduced spatial correlation effects showing the relevance of the neighbourhood in the spatial distribution of the efficiency scores. They found positive spatial correlation, thus indicating that higher efficiency levels tend to spread out to the surrounding localities. Also, Arcelus et al. (2015) included a dummy for the municipalities located in the north of the territory, however it was not significant.

  Otherwise, Sampaio de Sousa et al. (2005) also found that municipalities located in drought areas were less efficient than their counterparts in more clement areas since these municipalities have more difficulties to provide the required public services to their population. Agasisti et al. (2015) introduced a dummy variable to measure the seismic risk. They concluded that lower seismic risk reduces the expenditures of the municipalities for taking anti-seismic measures, i.e., it affects positively to efficiency. Finally, Moore et al. (2005) included variables related to weather such as the average precipitation, the average snowfall, the average

[113] D'Inverno et al. (2017).

temperature, the maximum temperature and the minimum temperature. Only average temperature and average snowfall were found significant.

2.7.6. Institutional and management determinants

In this section, we have included a group of environmental variables related to institutional and management characteristics of the local governments. It is explained by five indicators: informatization or level of computer usage, mayor and local government employees characteristics, amalgamation, managerial forms and others.

- Informatization or level of computer usage (4 papers)

  The variables in this subgroup measure the level of technology used by local government. Ibrahim and Karim (2004) and Sampaio de Sousa et al. (2005) used the level of computer usage, suggesting that it is a powerful tool for management, thus being indicative of a superior and more effective decision-making process since computer utilization eases administrative tasks. Both studies found a positive relationship between the efficiency scores and the level of computer utilization. Moreover, Sung (2007) and Seol et al. (2008) attempted to examine the impact of "informatization technology" on local government efficiency. They constructed an index containing variables such as investments and equipments, share of informatization technology personnel and the application of informatization technology to administrative process, among others. Their results confirm a positive and significant correlation between "informatization technology" and efficiency.

- Mayor and local government employees characteristics (10 papers)

  On the one hand, some studies included characteristics related to local government's mayor. Loikkanen et al. (2011) studied whether Finnish city managers' characteristics and work environment explain differences in cost efficiency. They included variables such as age, education level, gender and work environment (cooperation, contact intensity etc.). City manager's education level, attitudes towards the participation of workers, attitude concerning the efficiency advantage of private sector relative to public sector and positive view on cooperation with partners were correlated with higher efficiency. Moreover, Boetti et al. (2012) considered mayor's gender and age, arguing that the presence of older mayors significantly reduces inefficiency, while gender is not statistically significant. Also Agasisti et al. (2015) found mayors' gender not statistically significant. In addition, Ibrahim and Karim (2004) introduced the job vacancies in local government and the education level of the municipal managers, however they did not find significant results. Finally, Grossman et al. (1999) included a variable representing the number of years for the mayor's term, however it is not significant.

On the other hand, some studies included variables related to council employees. Worthington (2000) included the staff per capita, Revelli (2010) used the percentage of employment in financial and real estate services, and Sampaio de Sousa et al. (2005) and Fogarty and Mugera (2013) used the employee expenses per capita. Higher employee expenses or higher level of staff per capita were negatively correlated with the efficiency scores. In addition, Loikkanen and Susiluoto (2005) considered the age of council employees, suggesting that of employees of 35 to 49 seem to be most beneficial to cost efficiency compared to younger or older groups.

- Amalgamation (5 papers)

  Amalgamation measures the process where municipalities of some countries were merged in one municipality. Geys (2006) and Geys and Moesen (2009a) assessed the effect of the large-scale municipal amalgamation operation in Belgium in 1976 by incorporating a variable equal to the number of communities that were united in one municipality in that year. Only Geys (2006) found significant results, suggesting that a higher number of merging municipalities in one municipality was negatively correlated with efficiency. They argue that their inhabitants are still identified with their old community and the resulting "intra-municipality" competition reduces overall efficiency.

Moreover, Nakazawa (2013) introduced the number of Japanese municipalities that participated in an amalgamation while Nakazawa (2014) measured municipal amalgamation by absorption and by consolidation. They showed that amalgamation has a negative correlation with efficiency because it causes integration costs (slack) for an administrative organization. Finally, Da Cruz and Marques (2014) and Cordero et al. (2017) included the number of parishes in local governments regarding to the administrative reform of civil parishes in Portugal which aimed to reduce the number of local council representatives. Cordero et al. (2017) suggested that the process of amalgamation enhanced the efficiency of more divided municipalities, i.e., those with a higher number of civil parishes.

- Managerial forms (11 papers)

  As management factors, different studies have included variables related to municipal association (or cooperation), privatization (or externalisation), mixed companies and decentralization (agentification). The first category relates to the associated management between two or more municipalities and it includes variables such as municipal association, participation in municipal consortia, joint provision and inter-municipal cooperation. On the one hand, members of a municipal association pool their resources in order to realise economies of scale without giving up their status as autonomous municipalities. Moreover, while local authorities are only controlled by a individual voters, the municipal association is also and primarily controlled by the politicians of the member municipalities. So, the joint provision of municipal services would have a positive impact over efficiency.[114] On the contrary, Sampaio de Sousa et al. (2005) found that participation in intermunicipal consortia has a negative impact over efficiency, arguing that only the municipalities that operate on a scale below the optimum, have an incentive to join those consortia in an attempt to reduce average costs. Similarly, Loikkanen and Susiluoto (2005) concluded that a big

[114] Bischoff et al. (2013); Arcelus et al. (2015).

share of services produced by joint municipal organizations tends to reduce efficiency, and Pérez-López et al. (2015) found that intermunicipal cooperation also affects negatively to efficiency. Other studies did not find statistically significant results.[115]

The second category is related to the privatisation management process and it includes variables such as purchases from private producers, private management or externalization. In this context, some studies found that a big share of privately produced services enhances efficiency.[116] On the contrary, Cuadrado-Ballesteros et al. (2013) showed that externalisation and the adoption of contracting-out are harmful to efficiency. Finally, some studies did not find significant differences in efficiency according to the way of management used by the local government.[117]

The third category is related to mixed management which is measured as mixed companies/firms, or joint service delivery. The adoption of mixed firms, featuring collaboration between the public sector and the private sector, contributes to higher levels of efficiency.[118] Cuadrado-Ballesteros et al. (2013) also included the variables total decentralization (measured as the number of functional decentralised agencies created in each municipality such as companies, autonomous organizations, public business entities and foundations), while Pérez-López et al. (2015) measured the agentification level. Both studies showed a negative impact over efficiency.

Additionally, Boetti et al. (2012) and Agasisti et al. (2015) studied the effects of different managerial forms of waste collection. Boetti et al. (2012) indicated a positive significant correlation only for the cooperative organization among municipalities, suggesting that cost savings result from the advantage of sharing large fixed costs combined with the benefit of increasing expenditure control, while Agasisti et al. (2015) showed that only external service company is associ-

[115]Bönisch et al. (2011).
[116]Loikkanen and Susiluoto (2005); Andrews and Entwistle (2015).
[117]Benito et al. (2010).
[118]Cuadrado-Ballesteros et al. (2013); Pérez-López et al. (2015).

ated with efficiency, which is negatively correlated.

- Other determinants related to institutional or managerial characteristics

  Finally, we include other determinants related to institutional or managerial characteristics which are not classified in the previous subcategories. Sampaio de Sousa et al. (2005) studied the decision power of municipal councils. They found that the more power yielded to municipal councils, the better the resource utilization since those councils tend to increase the transparency of the budgeting process, which contributes to more effective control over corruption and over the misuse of local funds. Moreover, Hayes and Chang (1990) included the fire rating arguing that local government has the authority to hire and fire other city officials outside the merit system, however they do not find significant results. Andrews and Entwistle (2015) measured the managerial capacity as the expenditure on central administration per resident. Sampaio de Sousa et al. (2005) also included the degree to which the real estate register is up-to-date, which was found to have a negative correlation with efficiency. Moreover, Arcelus et al. (2015) took into consideration the existence of a public comptroller in the municipality. The hypothesis is that higher degree of local supervision should lead to better management practices and more efficiency in the provision of local services. Finally, Lampe et al. (2015) analysed the effect of new accounting and budgeting regimes. They found that due to the accrual accounting adoption, municipalities' cost inefficiency decreases.

2.8. Conclusion

In this chapter we have presented a systematic review of the existing literature on local government efficiency from a global point of view. We identified 84 empirical studies on the subject, being the most complete source of references on local government efficiency analysis up to now. We summarised the inputs, outputs and the environmental variables used in previous literature, as well as the methodologies applied. As the efficiency results depend heavily on the variable selection and methods used, this chapter provides a good basis for researchers in the field of local governments' efficiency.

The literature review leads us to seven main considerations and ways for further research. First, we found differences in the popularity of local governments' efficiency analysis across countries. The best studied countries are in Europe, being Spain the most analysed country (13 papers), followed by Belgium (9 papers) and Germany (8 papers). Some studies have also attempted to analyse the relationship between local government efficiency and other important topics, which converts it in a multidisciplinary subject. The most important related area is economics, followed by management, public administration, urban studies and political science.

Second, most previous studies have analysed cross-sectional data. A minority of papers has an underlying panel structure in the data but does not exploit this intertemporal variation as they use cross-sectional efficiency techniques. Time period analysis provides interesting managerial and policy-making insights into the efficiency effect of long-term decision. More research is needed in dynamic efficiency analysis in order to investigate the evolution of local government efficiency over time.

Third, there is a wide variety of input and output variables to measure local government efficiency. The accurate definition of local governments' inputs and outputs is a complex task, which comes from the difficulty to collect data and the measurement of local services. The selection of variables depends on the availability of data and the specific services and facilities that local government must provide in each country. Moreover, the number of output variables included in previous literature varies drastically. Some studies aggregate various municipal services in a global index, while others evaluate a set of specific local services.

Given the earlier discussed issues to define the bundle of services and facilities that municipalities must provide, it would be interesting to consider alternative input-output models, in order to assess whether the different choices might explain the heterogeneity among local governments, and to determine how the number of outputs can affect the efficiency scores. Moreover, some measures are too generic or unspecific. It would be necessary to develop better proxy variables for local government services and facilities as well as indicators which measure the quality of local services. The latter are interesting and informative for local governments, since performance decisions may have an impact in their quality and not in their quantity.

Fourth, it is necessary to consider the influence of environmental variables on efficiency. If local governments are affected by factors beyond their control, performance analysis should control for this heterogeneity. Therefore, efficiency estimations which do not account for the operational environment have only a limited value.

Five, there is a wide variety of determinants of local government efficiency. Unfortunately, the literature lacks a clear and standard classification for the inclusion of environmental variables in empirical efficiency analyses. In addition, we note that many determinants present ambiguous effects over efficiency, i.e., results from different studies are mixed. This mixed evidence can be explained by the low external validity of the results due to, e.g., the different micro and macro economic structure, geographical conditions, political and social institutions of countries. In this context, the conclusions and potential policy implications are not necessarily applicable to other jurisdictions, since they are country specific. Our classification of determinants as well as the summary on their impact over efficiency might help to structure future studies on these matters.

Six, past studies interpret their results in a causal way, neglecting the endogeneity issues in the data (e.g., arising from selection bias, unobserved heterogeneity or reversed causality). The issue of endogenous data in local government efficiency literature has received little attention. The large majority of studies tended to omit variables due to the infeasibility to include a large amount of variables in the analysis (arising from methodological and computational issues) as well as data unavailability. Also there is a lack of studies that used municipal or individual fixed effects or considered the reversed causality problem. In general, more research on the issue of causality and on how endogeneity biases the efficiency results is needed.

Finally, the large majority of the previous studies have focused only on one approach, in most cases DEA, FDH or SFA. We must take care when interpreting results from research studies using one particular methodology because the results of the efficiency analysis are affected by the approach taken. Moreover, the most popular methods to include exogenous variables with non-parametric methods are based on the two-stage analysis. In general, it is necessary to apply more advanced techniques to measure efficiency as well as the incorporation of environmental variables.

Given the considerations and conclusions drawn here, in the next chapters we will attempt to address some of the problems from previous literature such as the accurate selection of input and output variables, the selection of methodologies, the inclusion of environmental variables in the analysis and the control of possible endogeneity issues.

Chapter 3

Evaluating local government performance in times of crisis

3.1. Introduction

As explained in chapter 1, in recent years the context of the international economic crisis has highlighted improving efficiency and reducing the costs of local public services as prime area of concern. In the particular case of Spanish local governments, on which we focus, the economic and financial situation that started in 2007 had a huge impact on most local revenues and finances in general, provoking an increase on their deficits. In addition, the huge budgetary limitations become stricter with the law on budgetary stability *(Ley General Presupuestaria)*, which set up more control on public debt and public spending. Under these circumstances, Spanish local governments have come under increasing pressure to accommodate severe economic restrictions while maintaining (or even increasing) their provision of local public services. Taking this premise as our starting point, one of the aims of this chapter is to analyse overall cost efficiency in Spanish municipalities during the economic crisis period (2008–2013), a subject yet to be examined in depth. Specifically, we attempt to learn whether Spanish local governments have succeeded in reducing their budget expenditures while maintaining public service provision; in other words, whether local government cost efficiency has improved in times of crisis.

Regardless of the context of analysis, one of the most significant tasks in efficiency measurement is the proper definition of inputs and outputs (Šťastná and Gregor, 2015). Unfortunately, as stated in chapter 2, a common problem in local government efficiency analysis is the complexity of accurately defining and measuring local governments' inputs and outputs (Balaguer-Coll et al., 2013). This complexity is due to the difficulty of collecting data and measuring local services. Indeed, studies use diverse input and output measures, even when analysing efficiency with data from the same country. In the Spanish case, some studies consider only the minimum services all local governments are obliged to provide (Giménez and Prior, 2007), others analyse the minimum services and a quality variable (Balaguer-Coll et al., 2007; Zafra-Gómez and Muñiz-Pérez, 2010), and a third group examine the complete range of services provided by local governments (Balaguer-Coll et al., 2010a, 2013).

Given how problematic it is to define the bundle of services and facilities that municipalities must provide, we consider it reasonable to propose three separate output models in order to assess whether different choices might explain variations among local governments, and to determine how the number of outputs can affect efficiency scores. We use a comprehensive database, which includes measures of both quantity and quality of the services and facilities provided. The inclusion of quality variables in the analysis is interesting and informative for local governments, since performance decisions may have an impact on their quality, but not on their quantity. In addition, the chapter contributes through the sample selected for analysis. While other studies using Spanish data focus on a specific region or year, our study examines a much larger sample of various regions over several years, specifically, 1,574 Spanish local governments with populations between 1,000 and 50,000 for the period 2008–2013. This sample allows investigation of structural differences in the average efficiency scores between municipalities located in different Spanish regions and provinces for the first time in the literature.

Moreover, other common problem from previous literature earlier discussed in chapter 2 is that the vast majority of previous studies have applied just one frontier technique, in most cases DEA, FDH or SFA. Only a few authors (De Borger and

Kerstens, 1996a; Geys and Moesen, 2009b) apply two or more alternative approaches to analyse public efficiency. In this context in which there is no commonly accepted methodology to measure efficiency, we must be cautious when interpreting results from research studies using one particular method, since their results might be affected by which approach was selected. It is therefore important to assess the robustness of the estimated efficiency by comparing different methodologies (Da Silva et al., 2016). In light of the efficiency estimator selection problem, the present chapter also contributes to the literature by providing a comparative perspective using not only different specifications for inputs and outputs, but also several non-parametric methodologies to measure efficiency, namely, DEA, FDH, order-m frontier and the bias corrected DEA estimator proposed by Kneip et al. (2008).

Our results suggest that Spanish local governments became more efficient over the crisis period 2008–2013 since their budget expenditures (inputs or costs) fell while at the same time they managed to maintain (or even increase) local public services and facilities (outputs). We find statistical evidence that service quality has possible implications when measuring local government cost efficiency. We also detect structural differences in average cost efficiency among municipalities located in different Spanish regions and provinces as well as differences according to the size. Additionally, in line with previous research, our results confirm that the level and variation of efficiency scores are affected by the approach taken. We found large differences in the mean efficiency scores, ranging from 0.44 to 0.96 (also contingent on the model and the year) depending on the reference technology used. Caution is therefore essential when interpreting empirical studies that use just one method and policy-makers must carefully consider their results when taking performance decisions (Badunenko et al., 2012).

The chapter is organised as follows: section 1.3 establishes the institutional framework of Spanish local governments. Section 3.2 gives an overview of the methodologies used to determine cost efficiency. Section 5.2.1 describes the data in detail. Section 5.2.2 presents and comments on the most relevant efficiency results. Finally, section 3.5 summarises the main conclusions.

3.2. Methodologies

In the present chapter, we focus on the *cost efficiency* of local public goods and service provision. We introduce cost notation since we have information relative to specific costs (i.e., we use data in municipal budgets as input costs), although it is not possible to decompose it into technical and allocative efficiency since there is no data available on input prices and physical units (Balaguer-Coll et al., 2007). It should be noted that public sector goods and services are frequently unpriced due to their non-market nature (Kalb et al., 2012).

In addition, we consider four different non-parametric techniques to measure cost efficiency, namely, DEA, FDH, order-*m*, and Kneip et al.'s 2008 bias corrected DEA estimator, henceforth KSW. The former two techniques are the most popular in the non-parametric field, whereas the latter two are relatively recent proposals. We focus on non-parametric as opposed to parametric methodologies, due to their less restrictive assumptions and greater flexibility.[1] In addition, parametric and non-parametric methodologies have not evolved in parallel, and several proposals have leaned towards the non-parametric field, overcoming most of their limitations in the process (Daraio and Simar, 2007a; Bădin et al., 2014).

3.2.1. Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH)

DEA (Charnes et al., 1978; Banker et al., 1984) is a non-parametric methodology based on linear programming to estimate and compare the relative efficiency of DMUs (in our case, Spanish local governments). DEA defines an empirical frontier which creates an "envelope" determined by the efficient DMUs. These units, located on the frontier, are considered "best-practice" units and have an efficiency score equal to 1. In the case of input orientation (which in our case is reasonable, as we will see below), units above the frontier are considered inefficient and have a score lower than 1. The distance between each DMU and the frontier shows the measure of its inefficiency. The most important assumptions of the model are: returns to scale, convexity and free

[1] For a detailed review of the main differences between parametric and non-parametric frontier techniques, see Murillo-Zamorano (2004) and Bogetoft and Otto (2010).

disposability of inputs and outputs.

As indicated above, and similarly to previous studies on local government efficiency, we consider an input-oriented DEA model (Sampaio de Sousa and Stošić, 2005; Balaguer-Coll et al., 2007) because outputs are established externally in the public sector (the minimum services that local governments must provide) and, consequently, it is more appropriate to evaluate efficiency in terms of input minimisation (Balaguer-Coll and Prior, 2009). Moreover, because local governments differ considerably in size, we assume variable returns to scale (Balaguer-Coll and Prior, 2009; Bosch-Roca et al., 2012; Doumpos and Cohen, 2014; Da Cruz and Marques, 2014). This has the added advantage that each municipality is only compared to other municipalities of the same size.

We introduce the mathematical formulation for the cost efficiency measurement (Färe et al., 1994). The minimal cost efficiency can be calculated by solving the following programme for each local government and each sample year:

$$
\begin{aligned}
& min_{\theta,\lambda}\theta \\
& \quad s.t. \quad -y_i + Y\lambda \geq 0 \\
& \qquad\qquad \theta x_i - X\lambda \geq 0 \\
& \qquad\qquad \lambda \geq 0, \\
& \qquad\qquad n1'\lambda = 1 \qquad i = 1, \ldots, n
\end{aligned}
\tag{3.1}
$$

where for n observations (municipalities), X and Y are the input an output matrix which represent the data for all n local governments, x_i and y_i are the observed inputs and outputs corresponding to each unit (municipality) i under evaluation, and λ is the activity vector which describes the importance of the unit considered to determine the virtual reference which is used as a comparison in order to evaluate unit i. The last constraint ($N1'\lambda = 1$) implies variable returns to scale (VRS), which assures that each DMU is compared only with others of a similar size.

A further extension of the DEA model with variable returns to scale, called FDH, was proposed by Deprins et al. (1984). Its main difference from DEA is that it drops the convexity assumption. The FDH linear programming problem is defined as follows:

$$
\begin{aligned}
& min_{\theta,\lambda}\theta \\
& \quad s.t. \quad -y_i + Y\lambda \geq 0 \\
& \qquad\quad \theta x_i - X\lambda \geq 0 \\
& \qquad\quad \lambda \in \{0,1\}, \\
& \qquad\quad n1'\lambda = 1 \qquad i = 1, \ldots, n
\end{aligned}
\tag{3.2}
$$

Finally, by solving linear programming problems (3.1) and (3.2) we obtain the cost efficiency coefficient; in other words we find θ, which is the optimal (minimal) input quantity of producing y_i. Since there is no data available for input prices (due to the difficulty of using market prices to measure public services), all units are assumed to face the same input prices, and we use input variables of input costs (Kalb et al., 2012). Local governments with efficiency scores of $\theta < 1$ are inefficient, while efficient units receive efficiency scores of $\theta = 1$.

3.2.2. Robust variants of DEA and FDH

Although the traditional non-parametric techniques DEA and FDH have been widely applied in efficiency analysis, they present several drawbacks. One limitation of both DEA and FDH is that they are sensitive to outliers and extreme values. Since these techniques envelope all data, the efficient frontier is determined by the observations that are extreme points (Simar and Wilson, 2008) and, as a consequence, any outliers strongly influence the estimated frontier as well as the efficiency scores of all observations. This problem can be addressed by using "partial" frontiers, which are more robust to extremes or outliers in data. Moreover, these "partial" estimators do not suffer from the "curse of dimensionality",[2] a major problem that generally affects efficiency scores obtained using DEA and FDH Daraio and Simar (2007a). Finally, another considerable drawback of traditional non-parametric approaches is the difficulty of making statistical inference. However, bootstrap methods such as those proposed by Simar and Wilson (1998, 2000) enable statistical inferences (consistency analysis,

[2]As Daraio and Simar (2007a) note, the "curse of dimensionality" implies that an increase in the number of inputs or outputs, or a decrease in the sample under analysis (i.e., the number of units for comparison), entails higher efficiencies.

bias correction, confidence intervals, test of hypothesis and so on) about efficiency.

Hence, in this chapter we consider two variants of DEA and FDH estimators that are able to overcome most of the drawbacks of the traditional non-parametric methods. We use the order-m approach, which is a partial frontier that mitigates the influence of outliers, extreme values and the curse of dimensionality; and KSW, which allows for consistent statistical inference by applying bootstrap techniques.

Order-*m*

Order-m frontier (Cazals et al., 2002) is a robust alternative to DEA and FDH estimators that involves the concept of partial frontier, as opposed to the traditional full frontier. The order-m estimators, for finite m units, do not envelope all data points and consequently are less extreme. The benchmark in the input orientation case is the expected minimum input achievable among a fixed number of m units producing at least output level y. Hence, the order-m input efficiency score (Daraio and Simar, 2007a) is given by:

$$\hat{\theta}_m(x,y) = E[(\hat{\theta}_m(x,y)|Y \geqslant y)] \tag{3.3}$$

The value m represents the number of potential units against which we benchmark the analysed unit (i.e., how efficient a local government is compared with m local governments.). If m goes to infinity, the order-m estimator converges to FDH. Daraio and Simar (2005) suggest that the most reasonable value for m is determined as the value for which the number of super-efficient observations becomes constant. In our setting, we consider $m = 350$, although alternative values delivered similar outcomes.

Note that order-m scores are not bounded at 1. A value greater than 1 indicates super-efficiency, showing that the unit operating at level (x,y) is more efficient than the average of m peers randomly drawn from the population of units producing more output than y (Daraio and Simar, 2007a).

Kneip et al.'s (2008) bias-corrected DEA estimator (KSW)

The KSW (Kneip et al., 2008) is a bias corrected DEA estimator which derives the asymptotic distribution of DEA via bootstrapping techniques. Simar and Wilson (2008) note that DEA and FDH estimators are biased by construction, meaning that the true frontier would be located under the DEA estimated frontier. As a consequence, DEA scores (i.e., relative to the estimated frontier) are too optimistic. In the words of Badunenko et al., the bootstrap procedure to correct this bias, based on sub-sampling, "uses the idea that the known distribution of the difference between estimated and bootstrapped efficiency scores mimics the unknown distribution of the difference between the true and the estimated efficiency scores" (Badunenko et al., 2012). In addition, the KSW procedure allows for consistent statistical inference of efficiency estimates (i.e., bias and confidence intervals for the estimated efficiency scores).

Therefore, in order to implement the bootstrap procedure (based on sub-sampling), first let $s = n^k$ for some $k \in (0, 1)$, where n and s are the sample and sub-sample size, respectively. The optimal k depends on the dimensionality of the problem. The bootstrap then considers the following scheme:

1. First, a bootstrap sample $S_s^* = (X_i^*, Y_i^*)_{i=1}^s$ is generated by drawing (independently, uniformly and with replacement) s observations from the original sample, S_n.

2. The DEA estimator is applied, where the technology set is constructed with the sub-sample drawn in step (1), to construct the bootstrap estimates $\hat{\theta}^*(x, y)$.

3. Steps (1) and (2) are repeated B times, using the resulting bootstrap values to approximate the conditional distribution of $s^{2/(p+q+1)}(\frac{\hat{\theta}^*(x,y)}{\theta^*(x,y)} - 1)$, which allows us to approximate the unknown distribution of $n^{2/(p+q+1)}(\frac{\hat{\theta}^*(x,y)}{\theta^*(x,y)} - 1)$. The values p and q are the output and input quantities, respectively. The bias-corrected DEA efficiency score, which is adjusted by the s sub-sample size, is given by:

$$\theta_{bc}(x, y) = \theta^*(x, y) - Bias^* \tag{3.4}$$

where the bias is adjusted by employing the s sub-sample size.

$$Bias^* = \left(\frac{s}{n}\right)^{2/(p+q+1)} \left[\frac{1}{B}\sum_{b=1}^{B}\hat{\theta}_b^*(x,y) - \theta^*(x,y)\right] \tag{3.5}$$

4. Finally, for a given $\alpha \in (0,1)$, the bootstrap values are used to find the quantiles $\delta_{\alpha/2,s}$, $\delta_{1-\alpha/2,s}$ in order to compute a symmetric $1-\alpha$ confidence interval for $\theta(x,y)$

$$\left[\frac{\hat{\theta}(x,y)}{1+n^{-2/(p+q+1)}\delta_{1-\alpha/2,s}}, \frac{\hat{\theta}(x,y)}{1+n^{-2/(p+q+1)}\delta_{\alpha/2,s}}\right] \tag{3.6}$$

3.3. Sample, variables and model specification

We carry out the analysis for a sample of Spanish local governments between 1,000 and 50,000 inhabitants for the 2008–2013 period. The information on inputs and outputs comes from the Spanish Ministry of the Treasury and Public Administrations (*Ministerio de Hacienda y Administraciones Públicas*). Outputs were obtained from a survey on local infrastructures and facilities (*Encuesta de Infraestructuras y Equipamientos Locales*). This survey has only been published annually since 2008 (previously it was five-yearly), so in contrast to previous studies for Spain we have yearly data available for our full sample period. The study is therefore also relevant in terms of the sample analysed. While other studies based on Spanish data focus on a specific region or year, our study examines a sample of Spanish municipalities comprising various regions over several years. Information on inputs was obtained from local governments' budget expenditures.

The final sample contains 1,574 municipalities for every year (representing 19.60%), after eliminating all the municipalities with unavailable data on inputs and outputs for the period 2008 to 2013. Specifically, there was no information for the Basque

Country, Navarre[3], Catalonia and Madrid regions and the provinces of Burgos, Huesca, Guadalajara and Huelva. In Table 3.1 we summarise the number of observations for each region in our sample.

Table 3.1: Distribution of the sample, Spanish regions (*Comunidades Autónomas*)

Region	Number of municipalities
Andalusia	378
Aragon	58
Asturias	42
Balearic Islands	48
Canary Islands	46
Cantabria	45
Castile and Leon	139
Castile La Mancha	170
Extremadura	116
Galicia	211
Murcia	28
La Rioja	24
Valencian Community	269
Total	1,574

3.3.1. Modelling the costs of municipalities

The costs (inputs) are derived from the local governments' budget expenditures and are representative of the cost of the municipal services provided. Using budget expenditures as inputs is consistent with the literature (e.g., Balaguer-Coll et al., 2007, 2010a; Zafra-Gómez and Muñiz-Pérez, 2010; Kalb et al., 2012; Šťastná and Gregor, 2015; Fogarty and Mugera, 2013; Doumpos and Cohen, 2014; Da Cruz and Marques, 2014).[4] Local budget expenditures are divided into two main groups: non-financial transactions and financial transactions. In turn, non-financial transactions comprise two categories: current or ordinary expenditures, and capital expenditures. The first of these categories is divided into personnel expenses, current expenditures on goods and services, financial expenditures (interests and banking expenses) and current transfers

[3]The Basque Country and Navarre are not obliged to present this information to the Spanish Ministry of the Treasury and Public Administrations because they have their own autonomous systems and are therefore not included in the State Economic Cooperation.

[4]See section 2.5.1 in chapter 3 for an accurate summary for the input variables most widely used in previous literature.

(grants and assistance to other entities). The second category, capital expenditures, is divided into real investments and capital transfers (grants or payments to entities for real investments). The second group, financial transactions, is divided into financial assets and financial liability (referring to loans and deposits, and their repayments).

The input measure therefore includes various municipal expenditures. It represents the total local government costs (X_1), by including personnel expenses, expenditures on goods and services, current transfers, capital investments and capital transfers.

3.3.2. Defining the outputs of municipalities

Outputs are related to the specific services and facilities provided by each municipality. Most previous studies in European countries include output variables such as road infrastructure, recreational facilities, waste collection, drinking water supply, social services, primary and secondary education and health care (e.g., Afonso and Fernandes, 2008; Geys and Moesen, 2009a; Kalb et al., 2012; Šťastná and Gregor, 2015).[5] Differences in the Spanish case concern the area of education, care for elderly, and health services, which are not local government responsibilities.

Our modelling of outputs is based on the minimum services and facilities that each municipality is legally obliged to provide, according to their size. These compulsory services are listed in Article 26 of the Spanish local government law (*Ley reguladora de Bases de Régimen Local*[6]). Specifically, all local governments must provide public street lighting, cemeteries, waste collection and street cleaning services, drinking water to households, sewage system, access to population centres, paving of public roads, and regulation of food and drink. Furthermore, larger municipalities with populations of over 5,000, 20,000 or 50,000 (the limits that define the groups) must provide additional services in accordance with the size of the specific population. The selection of outputs is consistent with previous studies on efficiency in Spanish local governments (e.g.,

[5]See section 2.5.2 in chapter 3 for an accurate summary for the output variables most widely used in previous literature.

[6]Articles 25 to 28 of this law were amended in 2013*Ley 27/2013, de 27 de diciembre, de racionalización y sostenibilidad de la Administración Local* to clarify municipal powers, rationalise local government organisational structure in accordance with the principles of efficiency, stability and financial sustainability, and ensure more rigorous financial and budgetary control.

Balaguer-Coll et al., 2007; Balaguer-Coll and Prior, 2009; Zafra-Gómez and Muñiz-Pérez, 2010; Bosch-Roca et al., 2012) as well as in other European countries, since for the most part they have similar competencies (e.g., Da Cruz and Marques, 2014; Doumpos and Cohen, 2014). However, article 26 of this law was modified in 1996, removing the obligation to provide an abattoir; we therefore do not include it in this study, in contrast to previous studies in Spain. In addition, we have added four new variables, including measures for sewage system provision (a compulsory service for all local governments which has not previously been taken into account).

In order to generate a balanced set of outputs that reflects all the services and facilities municipalities are legally obliged to provide, we have a final list of 10 output variables.[7] Due to the difficulty of measuring public sector outputs, in some cases proxy variables must be used, a strategy that has been widely applied in the literature. Based on the study of De Borger and Kerstens (1996a,b), many of these output variables should be considered as crude proxies for municipal services because more direct outputs are not available.

Population size (Y_1), is used as a proxy for the following services: cemetery, regulation of food and drink, civil protection and social service provision. Street infrastructure surface area (Y_2) is used as a proxy for street cleaning, access to population centres, paving of public roads, and fire prevention and extinction. Some services have direct output measures such as public street lightning (calculated by the number of lighting points, Y_3), waste collection and treatment of waste collected (calculated by the tons of waste collected, Y_4), supply of drinking water to households (measured by the length of the water distribution network, Y_5), the sewage system (measured by the length of the sewage networks, Y_6), public parks (measured by the surface area of public parks, Y_7), public library (measured by the surface area of public libraries, Y_8), market (measured by the market surface area, Y_9) and public sports facilities (measured by the sport facilities surface area, Y_{10}).

[7] Although the number of output variables is relatively high compared with previous literature, we have, in general, a more complete and much larger database. We have data available containing the services that municipalities must provide and measures of their quality, including several Spanish regions for several years.

Finally, following Balaguer-Coll et al. (2007), Balaguer-Coll and Prior (2009) and Zafra-Gómez and Muñiz-Pérez (2010), we also incorporate service quality into the analysis. These data are not usually included in the literature, although they are of interest to and informative for local governments, since performance decisions may have an impact on their quality and not on their quantity. Because services and facilities for each municipality are classified as "good", "fair" or "bad" according to their condition, we include these categories in the output variables explained above, weighting by the quantity of service provided:

$$Y_{pi}^{quality} = \frac{Y_{pi} Q_{zi}}{\sum_{i=1}^{n} Y_{pi}} \tag{3.7}$$

where for each $i = 1, \ldots, n$ local government, Y_{pi} is the quantity of output p, and Q_{zi} is the quality category, $z = 1, 2, 3$.

Table 3.2 reports the minimum services that each local government must provide according to their size for the period 2008–2013 and the different output indicators used to evaluate the services.

3.3.3. Model specifications

Unlike previous Spanish studies that only consider the minimum services all local governments are obliged to provide (Giménez and Prior, 2007), the minimum services and a quality variable (Balaguer-Coll et al., 2007; Zafra-Gómez and Muñiz-Pérez, 2010), or the total range of services provided by local governments (Balaguer-Coll et al., 2010a, 2013), we compare how different output specifications affect efficiency scores.

Moreover, in relation to the number of outputs included in the efficiency analysis, we must take into account the problem of dimensionality. A general guideline to establish the number of variables is that the number of observations (i.e., local governments) should be at least twice the number of inputs and outputs considered (Golany and Roll, 1989); hence, following this rule, as the number of units increases, more variables can be incorporated in the analysis. However, including a large number of variables can result in a large number of efficient units.

Table 3.2: Minimum services provided and output variables

	Minimum services	Output indicators
In all municipalities:	Public street lighting	Number of lighting points
	Cemetery	Total population
	Waste collection	Waste collected
	Street cleaning	Street infrastructure surface area
	Supply of drinking water to households	Length of water distribution networks (m)
	Sewage system	Length of sewer networks (m)
	Access to population centres	Street infrastructure surface area
	Paving of public roads	Street infrastructure surface area
	Regulation of food and drink	Total population
In municipalities with populations of over 5,000, in addition:	Public parks	Surface area of public parks
	Public library	Surface area of public libraries
	Market	Surface area of markets
	Treatment of collected waste	Waste collected
In municipalities with populations of over 20,000, in addition:	Civil protection	Total population
	Provision of social services	Total population
	Fire prevention and extinction	Street infrastructure surface area
	Public sports facilities	Surface area of public sport facilities (m^2)
In municipalities with populations of over 50,000, in addition:	Urban passenger transport service	Total population, Street infrastructure surface area
	Protection of the environment	Total surface area

We considered it reasonable to specify three output models in order to assess whether different choices might explain the variations between local governments, and to determine how the number of outputs can affect the efficiency scores. The more encompassing the models are (i.e., more outputs are included in the model), the higher the efficiency (since municipalities have more dimensions in which to excel). Therefore, considering different models will provide us with a more precise view of municipalities' efficiency. The three output models are as follows:

Model 1 includes measures of compulsory minimum services for all governments: number of lighting points, total population, tons of waste collected, street infrastructure surface area (m^2), length of water distribution networks (m), and length of sewage networks (m).

Model 2 includes measures of compulsory minimum services for all governments along with additional services that larger municipalities with populations of over 5,000 or 20,000 must provide: number of lighting points, total population, tons of waste collected, street infrastructure surface area (m^2), length of water distribution networks (m), length of sewage networks (m), public parks surface area (m^2), public library surface area (m^2), market surface area (m^2) and sports facilities surface area (m^2).

Model 3 introduces all the services provided by local governments taking into account the quality of the services weighted by their quantity.[8]

Table 5.1 shows the descriptive statistics for inputs and outputs for the period 2008–2013. We include the median rather than the mean to avoid distortion from outliers.

[8]Different definitions can be applied to include service quality. Indeed, the studies of Balaguer-Coll et al. (2007), Balaguer-Coll and Prior (2009) and Zafra-Gómez and Muñiz-Pérez (2010) included service quality as a single output variable. However, since we aim to compare the efficiency scores with and without including service quality in the analysis, we consider it appropriate to weight the quality of each service by its quantity in order to maintain the same number of variables as output Model 2.

Table 3.3: Descriptive statistics for inputs and outputs (2008–2013)

	Mean	**S.d.**
Inputs[a]		
Total costs (X_1)	6,856,864.55	7,990,865.20
Outputs		
Total population (Y_1)	7,555.36	8,460.33
Street infrastructure surface area[b](Y_2)	336,673.55	325,808.07
Number of lighting points (Y_3)	1,519.78	1,567.02
Tons of waste collected (Y_4)	4,216.73	19,720.07
Length of water distribution networks[b](Y_5)	50,503.12	93,877.89
Length of sewer networks[b](Y_6)	29,650.29	32,424.83
Public parks surface area[b](Y_7)	88,339.98	565,984.51
Public library surface area[b](Y_8)	361.38	1,751.10
Market surface area[b](Y_9)	90,746.34	502,781.06
Sport facilities surface area[b](Y_{10})	3,959.79	10,752.72

[a] In thousands of euros.
[b] In square metres.

3.4. Efficiency results

We estimate efficiency scores for 1,574 municipalities for the 2008–2013 period using the methodologies explained in the previous sections. Tables 3.4, 3.5 and 3.6 report overall cost-efficiency results averaged over all municipalities for each year in Models 1, 2 and 3, respectively. They show summary statistics, including the mean and the standard deviation, as well as additional statistics which provide deeper insights into the distributions of efficiency scores. The last column in each table reports the percentage of efficient local governments.

We also provide violin plots to aid further interpretation of results. They include all features of the distribution and offer more thorough information on how each methodology behaves. Figures 3.1, 3.2, 3.3 and 3.4 display the violin plots for DEA, FDH, order-m and KSW approaches, respectively. We report results for the three models considered, in order to assess whether different output specifications might contribute to explain variations between local governments, and to determine how the number of outputs can affect efficiency scores.

Table 3.4: Summary statistics for efficiency results, Model 1[a]

DEA estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.4943	0.4689	0.0437	1.0000	0.1876	2.6048
2009	0.5843	0.5740	0.1257	1.0000	0.1677	2.6684
2010	0.5212	0.4953	0.1312	1.0000	0.1718	1.9695
2011	0.5314	0.5092	0.1359	1.0000	0.1728	1.9060
2012	0.5316	0.5128	0.1079	1.0000	0.1749	1.8424
2013	0.5712	0.5591	0.1138	1.0000	0.1817	2.7954
FDH estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.7444	0.7678	0.0808	1.0000	0.2276	27.0013
2009	0.8186	0.8563	0.2045	1.0000	0.1841	32.8463
2010	0.7761	0.7848	0.1559	1.0000	0.1961	26.1753
2011	0.7453	0.7434	0.2037	1.0000	0.2108	24.3329
2012	0.7630	0.7737	0.1497	1.0000	0.2076	25.4765
2013	0.7619	0.7721	0.1497	1.0000	0.2055	25.0318
Order-*m* estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.8089	0.8255	0.0834	1.9813	0.2353	29.4155
2009	0.8691	0.8926	0.2122	1.7369	0.2005	36.4041
2010	0.8385	0.8515	0.2172	1.8080	0.2032	29.6061
2011	0.8088	0.8100	0.2368	2.0281	0.2197	27.5731
2012	0.8222	0.8358	0.1797	1.8914	0.2169	29.2884
2013	0.8209	0.8328	0.1785	1.9204	0.2175	28.7802
KSW estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.4421	0.4239	0.0400	1.0000	0.1720	0.0000
2009	0.5383	0.5300	0.1179	1.0000	0.1575	0.0000
2010	0.4541	0.4296	0.0563	1.0000	0.1602	0.0669
2011	0.4752	0.4558	0.1178	1.0000	0.1572	0.0000
2012	0.4677	0.4477	0.0134	1.0000	0.1650	0.0000
2013	0.4846	0.4709	0.0118	1.0000	0.1617	0.0669

[a] This model includes minimum services compulsory for all governments (6 outputs variables from Y_1 to Y_6).

Table 3.5: Summary statistics for efficiency results, Model 2[a]

DEA estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.5125	0.4839	0.0446	1.0000	0.1968	2.7954
2009	0.5957	0.5829	0.1268	1.0000	0.1740	3.9390
2010	0.5382	0.5102	0.1421	1.0000	0.1806	3.1131
2011	0.5506	0.5237	0.1359	1.0000	0.1815	3.2402
2012	0.5528	0.5339	0.1269	1.0000	0.1842	3.1131
2013	0.5900	0.5757	0.1299	1.0000	0.1884	4.7014
FDH estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.8900	1.0000	0.0945	1.0000	0.1795	61.8170
2009	0.9251	1.0000	0.3233	1.0000	0.1394	66.4549
2010	0.9112	1.0000	0.3040	1.0000	0.1524	63.2783
2011	0.8923	1.0000	0.2428	1.0000	0.1755	61.8170
2012	0.8957	1.0000	0.2724	1.0000	0.1684	60.6734
2013	0.9023	1.0000	0.2648	1.0000	0.1594	61.3723
Order-*m* estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.9238	1.0000	0.0969	1.8544	0.1903	63.0241
2009	0.9606	1.0000	0.3420	1.7793	0.1541	68.8691
2010	0.9501	1.0000	0.3130	2.0046	0.1657	65.2478
2011	0.9376	1.0000	0.2800	2.2371	0.1874	63.9136
2012	0.9364	1.0000	0.2946	2.3782	0.1823	63.0877
2013	0.9439	1.0000	0.2937	2.4632	0.1813	63.7230
KSW estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.4462	0.4246	0.0310	1.0000	0.1797	0.0000
2009	0.5333	0.5250	0.1044	1.0000	0.1618	0.0000
2010	0.4562	0.4270	0.0373	1.0000	0.1692	0.0000
2011	0.4815	0.4603	0.1163	1.0000	0.1644	0.0000
2012	0.4775	0.4593	0.0013	1.0000	0.1739	0.1271
2013	0.5318	0.5198	0.0982	1.0000	0.1782	0.0669

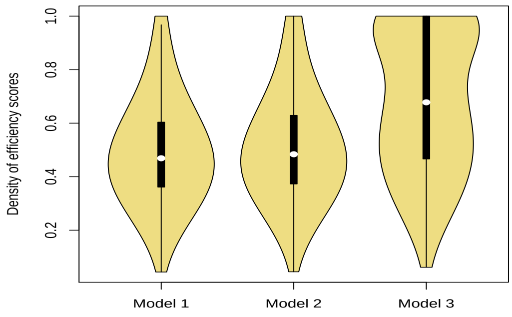
[a] This model includes minimum services compulsory for all governments and additional services that must be provided by larger municipalities with populations of over 5,000 and 20,000 (10 output variables from Y_1 to Y_{10}).

Table 3.6: Summary statistics for efficiency results, Model 3[a]

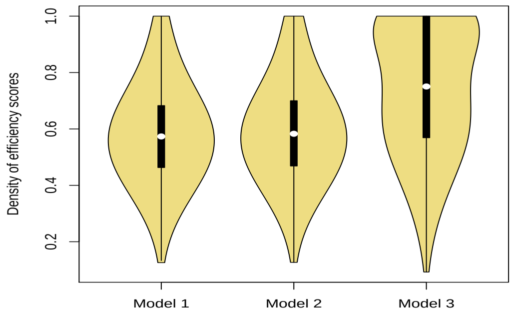
DEA estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.6867	0.6780	0.0614	1.0000	0.2651	28.6531
2009	0.7469	0.7504	0.0925	1.0000	0.2287	30.3685
2010	0.7152	0.6970	0.1141	1.0000	0.2333	27.5731
2011	0.7023	0.6680	0.1257	1.0000	0.2379	26.4295
2012	0.7101	0.7016	0.1073	1.0000	0.2395	27.2554
2013	0.7164	0.7153	0.1043	1.0000	0.2349	26.5565
FDH estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.9210	1.0000	0.2655	1.0000	0.1515	69.6950
2009	0.9285	1.0000	0.2655	1.0000	0.1471	72.4269
2010	0.9291	1.0000	0.2648	1.0000	0.1429	71.3469
2011	0.9230	1.0000	0.2648	1.0000	0.1485	68.8691
2012	0.9212	1.0000	0.2385	1.0000	0.1515	68.4879
2013	0.9226	1.0000	0.2188	1.0000	0.1478	68.6785
Order-*m* estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.9277	1.0000	0.2676	1.3837	0.1502	70.0127
2009	0.9375	1.0000	0.2677	1.4062	0.1474	72.9352
2010	0.9388	1.0000	0.2648	1.8670	0.1454	71.6010
2011	0.9334	1.0000	0.2648	2.0400	0.1506	69.4409
2012	0.9315	1.0000	0.2526	1.7124	0.1507	69.2503
2013	0.9339	1.0000	0.2335	1.6945	0.1503	69.6315
KSW estimator						
Year	Mean	Median	Min	Max	S.d.	% of efficient municipalities
2008	0.5913	0.5608	0.0017	1.0000	0.2558	0.0000
2009	0.5911	0.5641	0.0351	1.0000	0.2492	0.0000
2010	0.6007	0.5649	0.0466	1.0000	0.2410	0.0000
2011	0.6144	0.5748	0.0193	1.0000	0.2350	0.0635
2012	0.6146	0.5848	0.0295	1.0000	0.2352	0.0635
2013	0.6085	0.5783	0.0000	1.0000	0.2311	0.0669

[a] This model includes minimum services compulsory for all governments and additional services that must be provided by larger municipalities with populations of over 5,000 and 20,000 taking into account service quality (10 output variables from Y_1 to Y_{10} weighted by their quality).

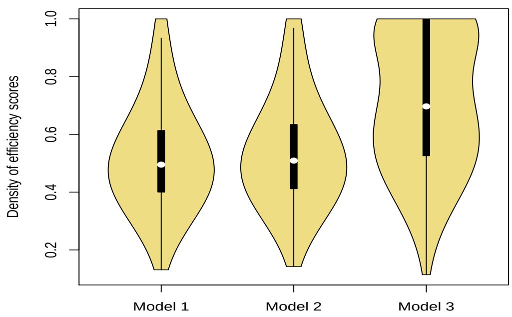
Figure 3.1: Violin plots for efficiency measurement with DEA, the three output specifications per year.



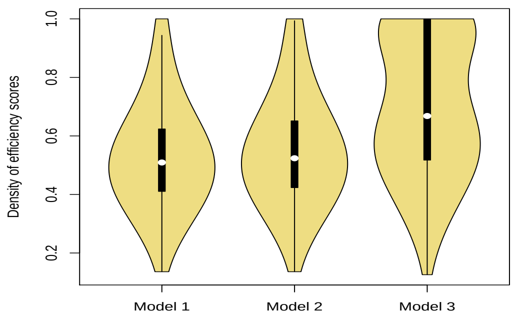
(a) DEA 2008



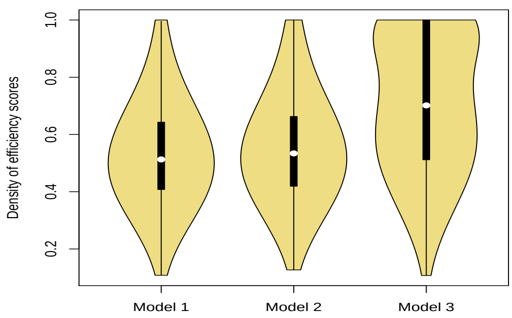
(b) DEA 2009



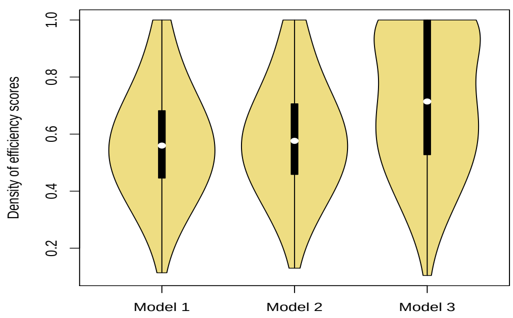
(c) DEA 2010



(d) DEA 2011

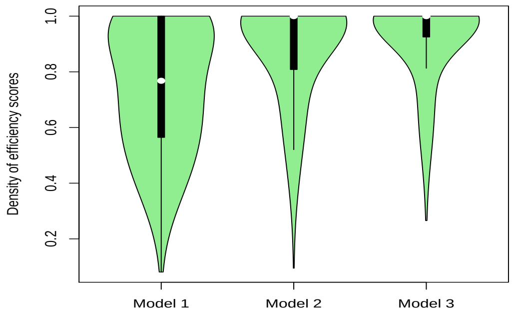


(e) DEA 2012

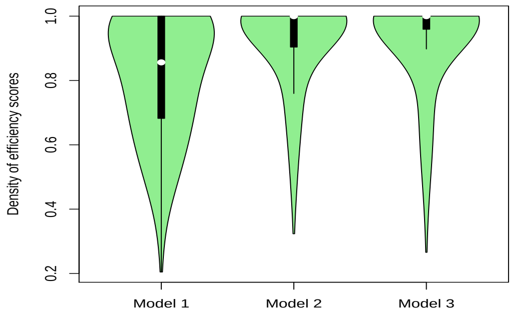


(f) DEA 2013

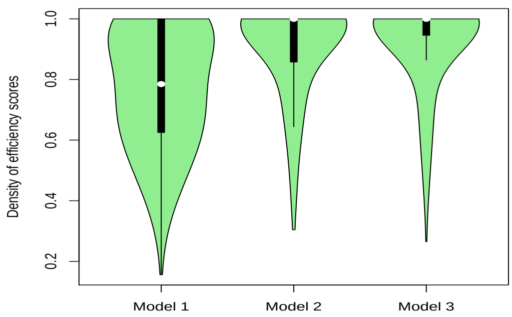
Figure 3.2: Violin plots for efficiency measurement with FDH, the three output specifications per year.



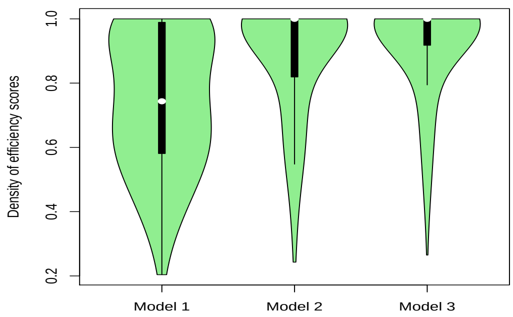
(a) FDH 2008



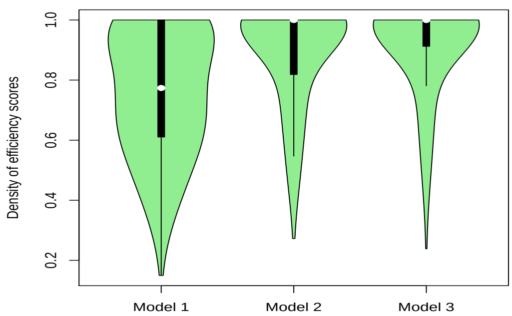
(b) FDH 2009



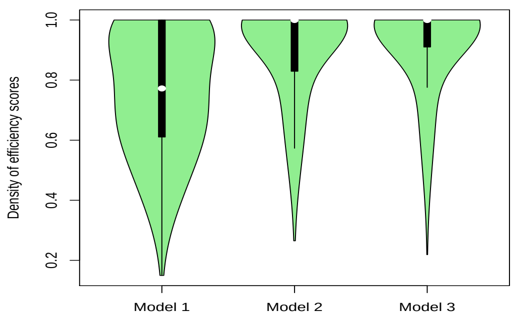
(c) FDH 2010



(d) FDH 2011

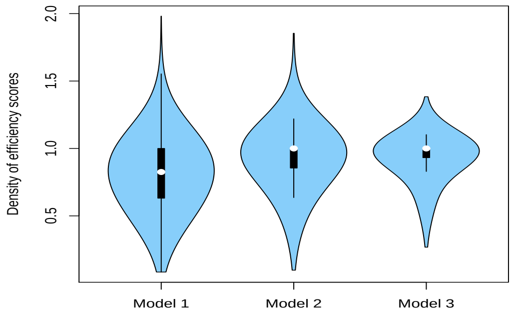


(e) FDH 2012

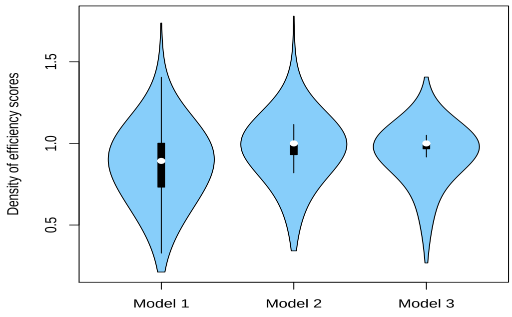


(f) FDH 2013

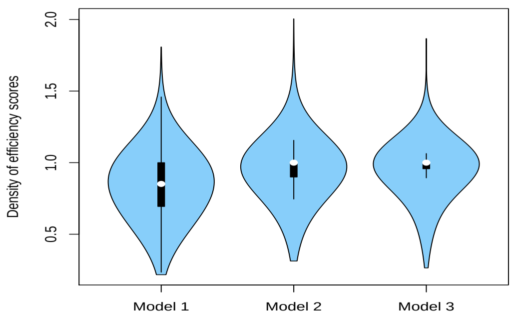
Figure 3.3: Violin plots for efficiency measurement with order-m, the three output specifications per year.



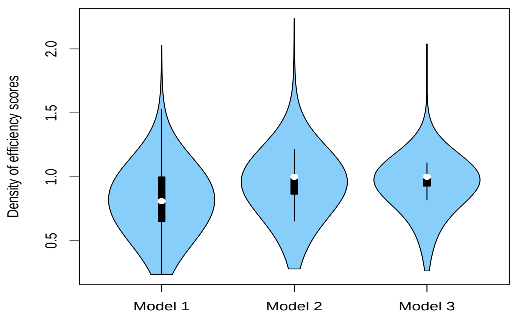
(a) Order-m 2008



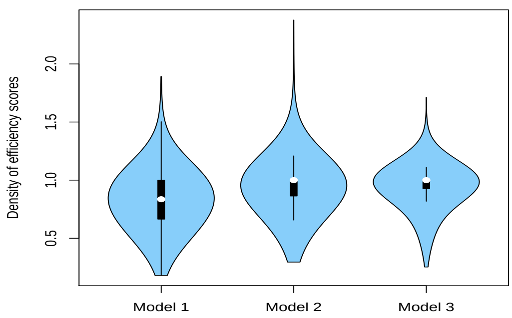
(b) Order-m 2009



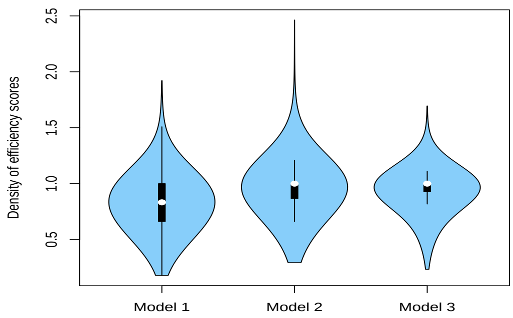
(c) Order-m 2010



(d) Order-m 2011

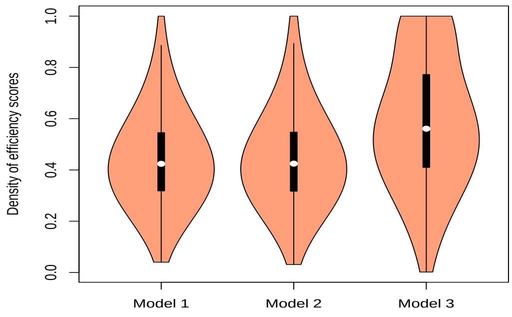


(e) Order-m 2012

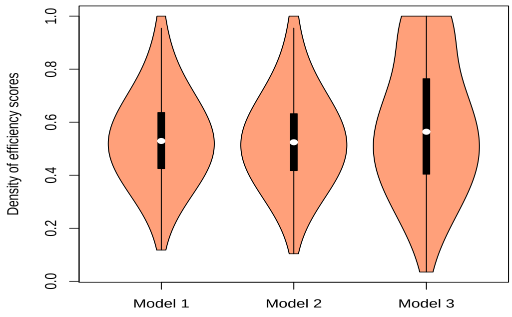


(f) Order-m 2013

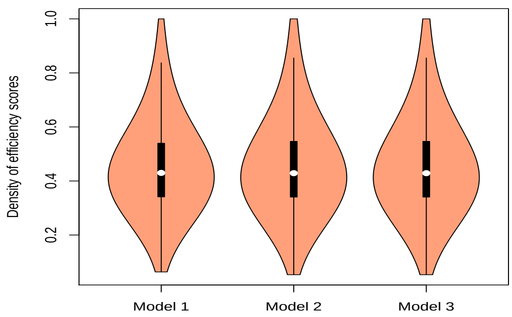
Figure 3.4: Violin plots for efficiency measurement with KSW, the three output specifications per year.



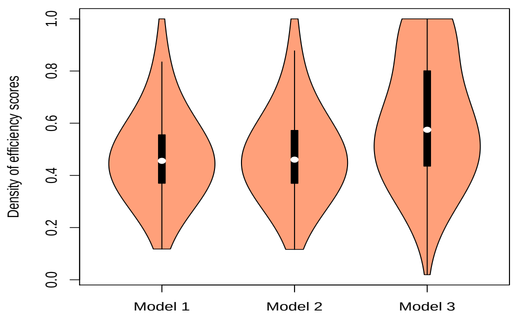
(a) KSW 2008



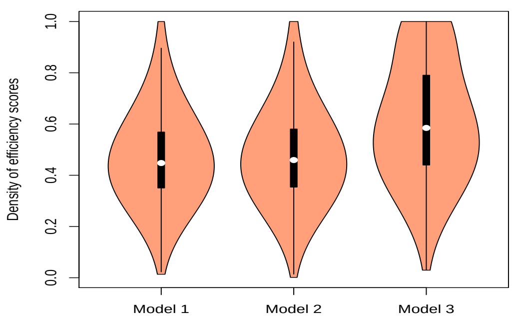
(b) KSW 2009



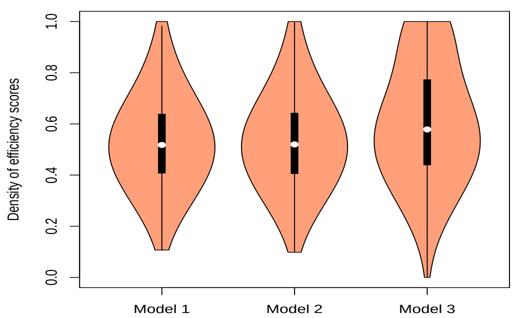
(c) KSW 2010



(d) KSW 2011



(e) KSW 2012



(f) KSW 2013

3.4.1. Evaluating cost efficiency with different non-parametric methodologies

Caution is needed when interpreting results from studies using just one method since the approach taken might lead to different efficiency levels. Therefore, as De Borger and Kerstens (1996a) note, a good strategy is to use different methodologies to check for robust efficiency scores. We now discuss some descriptive statistics for each of the four cost-efficiency measures.

When comparing DEA and FDH, both efficiency scores and the percentage of cost-efficient local governments are higher under FDH than under DEA. Note that FDH drops the convexity assumption underlying DEA and, as a result, it yields a higher number of efficient units. Therefore, all DEA efficient observations are also efficient under FDH (De Borger and Kerstens, 1996a). In addition, the increase in the number of outputs from Model 1 to Models 2 and 3 implies higher efficiency scores for both methodologies, since DEA and FDH estimators notoriously suffer from the "curse of dimensionality" (see Daraio and Simar (2007a), for further discussion).

A comparison of DEA and KSW methodologies shows that the average cost efficiency scores using KSW are lower than those obtained with the DEA approach. Moreover, under KSW most local governments are found to be inefficient (i.e., we observe 0% of efficient local governments in most of the years analysed). By construction, KSW methodology takes the standard DEA estimator to correct its bias and, as a consequence, municipalities considered as efficient when using DEA (i.e., municipalities located in the frontier with an efficiency score of 1), are considered inefficient in KSW because their bias has been corrected (i.e., municipalities could be close to an efficiency score of 1, but they are no longer considered efficient). KSW methodology is therefore useful for ranking the observations (i.e., relative ordering of municipalities) but not for identifying the benchmark units.

The order-*m* approach yields higher efficiency scores and percentages of efficient units than all the other methods. Order-*m* is more robust to extreme values and outliers, giving more prudent results than FDH. Note that order-*m* scores are not bounded by 1, and a value greater than 1 indicates super-efficient units.

Violin plots from Figures 3.1, 3.2, 3.3 and 3.4 support the above descriptive analysis.

DEA figures present uni-modal structures for Models 1 and 2, indicating tighter probability masses of inefficient units around 0.55. In addition, Model 3 shows a bi-modal structure with an additional mode at unity, which are the cost efficient units. In FDH, the tighter probability masses are concentrated at unity, showing the large number of cost-efficient units. Figures from both methods provide evidence that an increase in the number of outputs (from Model 1 to 2 and 3) implies a higher probability mass around unity (i.e., an increase of efficient units). Moreover, although the mode is higher in DEA than in KSW plots, there do not seem to be large differences in the cost structures between the two methods. Finally, order-*m* figures show a higher dispersion of the efficiency scores (there are super-efficient units with efficiency scores greater than 1) with a tighter probability mass around 0.90.

3.4.2. Evaluating cost efficiency with different output models

General discrepancies are observed on comparing the results yielded by the different models (output specifications). As expected, the selection of outputs affects the efficiency results. There are some differences between Model 1 and Models 2 and 3, which can be partly explained by the different number of outputs included. However, when the quality of the services is also included (Model 3), the increase in the efficiency scores might be related to the fact that more cost-efficient municipalities provide better quality services. As Balaguer-Coll et al. (2007) suggest, often local governments cannot directly affect, at least in the short term, the quantity of services and facilities; however, performance decisions may have a decisive impact on their quality.

These tendencies can be more formally tested to uncover whether or not efficiency results differ significantly when service quality is included. The methodology used to determine any significant differences between two different distributions, following Pastor and Tortosa-Ausina (2008), Balaguer-Coll et al. (2010a), Zafra-Gómez and Muñiz-Pérez (2010) or Prior et al. (2016), is based on the Li (1996) test with the variation proposed by Simar and Zelenyuk (2006).[9,10] Since the test compares the

[9]Simar and Zelenyuk (2006) adapted the Li (1996) test when applied to efficiency scores yielded by DEA and FDH via bootstrapping techniques.

[10]Since the analysis considered in this chapter is based on comparing the results yielded by a broad

closeness between two unknown density functions (i.e., it explores the statistical differences between two distributions, in our case distributions of efficiency scores), we compare the efficiency scores from Models 2 and 3. We therefore consider the null hypothesis $H_0 : f(Model2) = g(Model3)$, which means that the distribution of efficiency scores is the same with (Model 3) and without (Model 2) the inclusion of service quality, against the alternative hypothesis $H_1 : f(Model2) \neq g(Model3)$. Results are provided in Table 3.7.

Table 3.7: Effect of including the quality of services based on comparing distributions using Li's 1996 test with the variation proposed by Simar and Zelenyuk (2006)

Estimator	Year	T-statistic (p-value)
DEA	2008	231.2601 (0.0000*)
	2009	256.6770 (0.0000*)
	2010	237.7093 (0.0000*)
	2011	189.2445 (0.0000*)
	2012	204.9543 (0.0000*)
	2013	157.1427 (0.0000*)
FDH	2008	6.1007 (0.0000*)
	2009	2.2549 (0.0340*)
	2010	6.4186 (0.0000*)
	2011	4.8774 (0.0030*)
	2012	3.9812 (0.0050*)
	2013	4.0908 (0.0020*)
Order-m	2008	4.4787 (0.0020*)
	2009	4.4153 (0.0020*)
	2010	2.4271 (0.0100*)
	2011	2.8296 (0.0230*)
	2012	2.5501 (0.0230*)
	2013	1.9678 (0.0350*)
KSW	2008	144.1003 (0.0000*)
	2009	86.4735 (0.0000*)
	2010	140.9611 (0.0000*)
	2011	118.0488 (0.0000*)
	2012	111.1173 (0.0000*)
	2013	45.8914 (0.0000*)

* denotes differences are significant at the 5% level.

category of non-parametric techniques and specification models to measure efficiency, we look at non-parametric techniques to formally test whether the variety of efficiency scores obtained differ significantly. The test is based on the idea of measuring the global distance (closeness) between two density distributions. We consider this tecnique attractive and appropriate because it focuses on entire distributions, instead of comparing summary statistics such as the mean, in the case of the two-sample t-test.

The test reveals significant differences in the efficiency scores when service quality is included, suggesting that for the municipalities in our sample there is a trade-off between cost efficiency and service quality. As a consequence, municipalities which are efficient in terms of output *quantity* can be inefficient in terms of output *quality*. These results reflect the importance of including quality variables in the analysis, since different regulatory policies or managerial decisions could have an impact on the quality of the services and not on their quantity. Violin plots in Figures 3.1, 3.2, 3.3 and 3.4 confirm the results. Note that there seem to be differences in the cost structures when quality is included (Model 3) and when it is not (Model 2), supporting the statistical evidence of the possible implications of service quality when measuring local government cost efficiency.

3.4.3. Evaluating cost efficiency over the period 2008–2013

Tables 3.4, 3.5 and 3.6 also show the evolution in the distribution of efficiency scores over the period 2008–2013. Although we do not set out to analyse the dynamics of efficiency, some tendencies can be seen. The average cost efficiency scores are not constant over the period; specifically, there is a general increase in the efficiency scores over time with all approaches.

In the context of economic crisis, Spanish local governments have been immersed in a process of budgetary reforms. The law on budgetary stability *(Ley General de Estabilidad Presupuestaria)* aims to streamline local expenditures in order to achieve a balanced budget. It establishes annual budgetary stability targets, and expenditure and debt rules. In these circumstances, local governments have been under pressure to accommodate severe economic restrictions while at the same time attending to citizens' needs. Our aim was therefore to analyse whether Spanish local governments have attempted to reduce their budget expenditures while maintaining the provision, and quality, of public services; that is, whether local governments' cost efficiency has improved over time.

In order to analyse the evolution of the efficiency scores for the whole period from 2008 to 2013, we test whether significant differences in efficiency levels took place between the initial and the final period, again using the Li (1996) test with the modification proposed by Simar and Zelenyuk (2006).[11] Therefore, we consider the null hypothesis $H_0 : f(2008) = g(2013)$, which means that the distribution of the efficiency scores in the initial year of the crisis period (2008) is equal to the distribution of the efficiency scores in the final year of the period (2013), against the alternative hypotheses $H_1 : f(2008) \neq g(2013)$. Results are provided in 3.8. The results reveal significant differences in most of the distributions of efficiency during the period 2008–2013, both in quantity and quality output models. This finding confirms that Spanish local governments have improved their efficiency levels in crisis times since they reduced their costs between 2008 and 2013, while maintaining (or even increasing) the level of services and facilities (outputs).

Table 3.8: Comparing efficiency over time (2008 vs. 2013) based on Li's (1996) test with the variation proposed by Simar and Zelenyuk (2006)

Estimator	Model	T-statistic	p-value
DEA	Model 1	66.4750	0.0000*
	Model 2	66.5180	0.0000*
	Model 3	16.2057	0.0000*
FDH	Model 1	6.0456	0.0000*
	Model 2	1.9279	0.0480*
	Model 3	1.1068	0.1560
Order-m	Model 1	2.3448	0.0480*
	Model 2	0.8743	0.2920
	Model 3	0.7925	0.3290
KSW	Model 1	79.9386	0.0000*
	Model 2	80.5064	0.0000*
	Model 3	4.9732	0.0000*

* denotes differences are significant at the 5% level.

[11]Following the same procedure as in previous section, we use non-parametric techniques to formally test whether the variety of efficiency scores obtained differ significantly from 2008–2013. Despite we have pointed out that this is not a specific analysis on the dynamics of efficiency, in the appendix B we also show results for a commonly used approach to analyse the efficiency changes over time: the Malmquist productivity index (MPI).

3.4.4. Evaluating cost efficiency according to the size of municipalities

Additionally, after a global analysis, we now concentrate on the distribution of the coefficients according to size of the municipalities. Table 3.9, 3.10, 3.11 and 3.12 present overall cost-efficiency results by population sizes for each year and method in Model 1, 2 and 3, respectively.

Similarly to Balaguer-Coll et al. (2007, 2010a) and Zafra-Gómez and Muñiz-Pérez (2010), our results indicate that efficiencies vary according to local governments' size. Larger municipalities perform better, that is, mean efficiency scores are higher in municipalities with more than 20,000 inhabitants than in municipalities between 5,000 and 20,000 inhabitants, which in turn are more efficient than the municipalities with fewer than 5,000 inhabitants. This result is robust across time, methodologies and output specifications. Thus, we can conclude that the most inefficient municipalities are found amongst those municipalities with fewer than 5,000 inhabitants, that is, smaller municipalities are further from their efficient frontier, whereas most of larger municipalities are efficient and closer to the frontier. Of special note is that given our variable returns to scale assumption we only compare municipalities of similar sizes, so this inefficiency does not take problems of scale into account.

3.4.5. Evaluating cost efficiency by regions and provinces

A thorough investigation also needs to understand whether there are structural differences in the average cost efficiency between municipalities located in different Spanish regions and provinces. The economic and financial crisis has seriously affected all Spanish public administrations (Balaguer-Coll et al., 2016). However, its impact has not been uniform across territories, since some of them (both regional and local levels of government) have faced higher debt increases along with larger falls in revenues, especially areas hardest hit by the effects of the housing bubble (Portillo Navarro, 2009). Indeed, the most affected areas were located in the eastern part of the Spanish peninsula and, to a greater extent, along the Mediterranean coast. In contrast, the impact was relatively moderate in the Atlantic areas, due to their diversified

Table 3.9: Summary statistics for efficiency results by population sizes for DEA

Model 1

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.4360	0.4093	0.0437	1.0000	1.5766	
2008	>5000 a <=20000	0.5355	0.5182	0.1034	1.0000	0.1623	2.0295
	>20000	0.6983	0.6721	0.3206	1.0000	0.1755	2.9520
	<=5000	0.5440	0.5266	0.1257	1.0000	0.1674	1.9253
2009	>5000 a <=20000	0.6119	0.6095	0.2648	1.0000	0.1405	1.2963
	>20000	0.7196	0.7027	0.3751	1.0000	0.1701	3.3333
	<=5000	0.4758	0.4553	0.1312	1.0000	0.1590	1.0251
2010	>5000 a <=20000	0.5385	0.5247	0.2174	1.0000	0.1493	1.6544
	>20000	0.7191	0.6960	0.3700	1.0000	0.1698	2.3897
	<=5000	0.4882	0.4713	0.1359	1.0000	0.1623	1.1403
2011	>5000 a <=20000	0.5498	0.5414	0.1871	1.0000	0.1491	1.1029
	>20000	0.7135	0.6917	0.3620	1.0000	0.1806	2.5735
	<=5000	0.4707	0.4538	0.1079	1.0000	0.1574	1.0169
2012	>5000 a <=20000	0.5779	0.5689	0.2099	1.0000	0.1485	0.5597
	>20000	0.7224	0.7145	0.2834	1.0000	0.1707	3.3074
	<=5000	0.5148	0.4917	0.1138	1.0000	0.1739	1.9296
2013	>5000 a <=20000	0.6112	0.5999	0.2258	1.0000	0.1501	1.3011
	>20000	0.7522	0.7364	0.3042	1.0000	0.1723	3.8760

Model 2

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.4531	0.4228	0.0446	1.0000	0.1839	2.4775
2008	>5000 a <=20000	0.5539	0.5362	0.1064	1.0000	0.1698	2.3985
	>20000	0.7228	0.7039	0.3282	1.0000	0.1853	4.7970
	<=5000	0.5558	0.5312	0.1268	1.0000	0.1769	3.1710
2009	>5000 a <=20000	0.6228	0.6174	0.2648	1.0000	0.1425	1.6667
	>20000	0.7309	0.7173	0.3881	1.0000	0.1747	4.6296
	<=5000	0.4888	0.4608	0.1421	1.0000	0.1676	2.0501
2010	>5000 a <=20000	0.5609	0.5469	0.2182	1.0000	0.1587	2.2059
	>20000	0.7391	0.7155	0.3706	1.0000	0.1739	3.4926
	<=5000	0.5043	0.4842	0.1359	1.0000	0.1723	2.3945
2011	>5000 a <=20000	0.5729	0.5572	0.2113	1.0000	0.1562	1.6544
	>20000	0.7367	0.7126	0.3736	1.0000	0.1834	3.8603
	<=5000	0.4910	0.4662	0.1269	1.0000	0.1704	1.8079
2012	>5000 a <=20000	0.6020	0.5936	0.2122	1.0000	0.1571	1.4925
	>20000	0.7376	0.7375	0.2875	1.0000	0.1739	4.8638
	<=5000	0.5323	0.5095	0.1299	1.0000	0.1821	3.0647
2013	>5000 a <=20000	0.6325	0.6181	0.2276	1.0000	0.1566	2.9740
	>20000	0.7696	0.7608	0.3058	1.0000	0.1737	6.0078

Model 3

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.6526	0.6106	0.0614	1.0000	0.2572	22.8604
2008	>5000 a <=20000	0.7148	0.7347	0.0745	1.0000	0.2672	31.7343
	>20000	0.7910	1.0000	0.1665	1.0000	0.2669	14.0221
	<=5000	0.7154	0.6936	0.1651	1.0000	0.2159	23.2163
2009	>5000 a <=20000	0.7769	0.8302	0.0925	1.0000	0.2401	35.9259
	>20000	0.8245	1.0000	0.2508	1.0000	0.2288	14.6296
	<=5000	0.6786	0.6408	0.1631	1.0000	0.2234	19.7039
2010	>5000 a <=20000	0.7437	0.7518	0.1142	1.0000	0.2350	32.7206
	>20000	0.8187	1.0000	0.2326	1.0000	0.2406	15.2574
	<=5000	0.6598	0.6186	0.1461	1.0000	0.2256	18.3580
2011	>5000 a <=20000	0.7344	0.7366	0.1257	1.0000	0.2405	31.2500
	>20000	0.8319	1.0000	0.2010	1.0000	0.2342	15.6250
	<=5000	0.6650	0.6350	0.1570	1.0000	0.2334	19.6610
2012	>5000 a <=20000	0.7510	0.7642	0.1073	1.0000	0.2338	31.7164
	>20000	0.8284	1.0000	0.2769	1.0000	0.2290	16.5370
	<=5000	0.6761	0.6512	0.1636	1.0000	0.2279	18.9557
2013	>5000 a <=20000	0.7477	0.7554	0.1044	1.0000	0.2313	29.9257
	>20000	0.8334	1.0000	0.2360	1.0000	0.2334	17.0543

Table 3.10: Summary statistics for efficiency results by population sizes for FDH

Model 1

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.6823	0.6684	0.0808	1.0000	0.2359	20.3829
2008	>5000 a <=20000	0.7985	0.8291	0.1759	1.0000	0.1920	28.4133
	>20000	0.9244	1.0000	0.4436	1.0000	0.1319	16.6052
	<=5000	0.7791	0.7899	0.2087	1.0000	0.1941	24.8018
2009	>5000 a <=20000	0.8605	0.9063	0.3740	1.0000	0.1569	39.8148
	>20000	0.8996	1.0000	0.2045	1.0000	0.1525	15.3704
	<=5000	0.7313	0.7267	0.1559	1.0000	0.1997	17.8815
2010	>5000 a <=20000	0.8143	0.8417	0.3583	1.0000	0.1770	30.8824
	>20000	0.8977	1.0000	0.3636	1.0000	0.1568	15.9926
	<=5000	0.6869	0.6692	0.2037	1.0000	0.2088	14.8233
2011	>5000 a <=20000	0.7945	0.8088	0.2754	1.0000	0.1888	28.6765
	>20000	0.9057	1.0000	0.3975	1.0000	0.1643	17.8309
	<=5000	0.7092	0.6950	0.1497	1.0000	0.2151	18.7571
2012	>5000 a <=20000	0.8114	0.8387	0.2813	1.0000	0.1744	27.4254
	>20000	0.9046	1.0000	0.4344	1.0000	0.1571	17.1206
	<=5000	0.7198	0.7147	0.2247	1.0000	0.2120	19.4098
2013	>5000 a <=20000	0.7971	0.8147	0.2813	1.0000	0.1807	26.0223
	>20000	0.8787	1.0000	0.1497	1.0000	0.1799	16.0853

Model 2

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.8472	1.0000	0.0945	1.0000	0.2023	51.0135
2008	>5000 a <=20000	0.9351	1.0000	0.2742	1.0000	0.1344	71.7712
	>20000	0.9836	1.0000	0.5080	1.0000	0.0679	24.1697
	<=5000	0.8920	1.0000	0.3233	1.0000	0.1616	55.7191
2009	>5000 a <=20000	0.9649	1.0000	0.4763	1.0000	0.0908	78.5185
	>20000	0.9765	1.0000	0.5625	1.0000	0.0757	24.0741
	<=5000	0.8758	1.0000	0.3040	1.0000	0.1750	52.6196
2010	>5000 a <=20000	0.9512	1.0000	0.3874	1.0000	0.1076	74.4485
	>20000	0.9722	1.0000	0.6382	1.0000	0.0747	23.7132
	<=5000	0.8527	1.0000	0.2428	1.0000	0.2000	51.9954
2011	>5000 a <=20000	0.9329	1.0000	0.3803	1.0000	0.1302	70.7721
	>20000	0.9746	1.0000	0.5976	1.0000	0.0750	24.2647
	<=5000	0.8574	1.0000	0.2724	1.0000	0.1902	50.3955
2012	>5000 a <=20000	0.9354	1.0000	0.4106	1.0000	0.1269	69.7761
	>20000	0.9779	1.0000	0.5620	1.0000	0.0729	26.2646
	<=5000	0.8753	1.0000	0.2648	1.0000	0.1772	53.3485
2013	>5000 a <=20000	0.9264	1.0000	0.4106	1.0000	0.1331	67.2862
	>20000	0.9723	1.0000	0.5620	1.0000	0.0844	25.9690

Model 3

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.9037	1.0000	0.2771	1.0000	0.1631	63.1757
2008	>5000 a <=20000	0.9321	1.0000	0.2655	1.0000	0.1425	73.9852
	>20000	0.9863	1.0000	0.5829	1.0000	0.0632	24.9077
	<=5000	0.9139	1.0000	0.3015	1.0000	0.1594	68.0634
2009	>5000 a <=20000	0.9407	1.0000	0.2655	1.0000	0.1340	75.5556
	>20000	0.9701	1.0000	0.2771	1.0000	0.0970	24.2593
	<=5000	0.9112	1.0000	0.2648	1.0000	0.1594	66.1731
2010	>5000 a <=20000	0.9442	1.0000	0.4252	1.0000	0.1241	75.5515
	>20000	0.9781	1.0000	0.5999	1.0000	0.0670	24.0809
	<=5000	0.9024	1.0000	0.2648	1.0000	0.1653	61.6876
2011	>5000 a <=20000	0.9407	1.0000	0.2965	1.0000	0.1284	75.1838
	>20000	0.9777	1.0000	0.5999	1.0000	0.0731	24.6324
	<=5000	0.8995	1.0000	0.2863	1.0000	0.1689	61.4689
2012	>5000 a <=20000	0.9412	1.0000	0.2385	1.0000	0.1294	74.8134
	>20000	0.9761	1.0000	0.5947	1.0000	0.0740	25.8755
	<=5000	0.9073	1.0000	0.2977	1.0000	0.1621	64.1317
2013	>5000 a <=20000	0.9327	1.0000	0.2188	1.0000	0.1336	70.8178
	>20000	0.9751	1.0000	0.5821	1.0000	0.0789	26.1628

Table 3.11: Summary statistics for efficiency results by population sizes for Order-*m*

Model 1

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.7875	0.7724	0.0834	1.9813	0.2659	23.9865
2008	>5000 a <=20000	0.8131	0.8418	0.1800	1.2185	0.1900	29.5203
	>20000	0.9245	1.0000	0.4436	1.0000	0.1318	16.6052
	<=5000	0.8528	0.8501	0.2122	1.7369	0.2319	30.1246
2009	>5000 a <=20000	0.8827	0.9316	0.3782	1.1514	0.1531	40.7407
	>20000	0.9153	1.0000	0.5012	1.0026	0.1306	16.1111
	<=5000	0.8233	0.8148	0.2172	1.8080	0.2280	23.0068
2010	>5000 a <=20000	0.8421	0.8604	0.3611	1.3291	0.1674	31.4338
	>20000	0.9138	1.0000	0.4043	1.0002	0.1424	17.0956
	<=5000	0.7878	0.7718	0.2368	2.0281	0.2440	19.9544
2011	>5000 a <=20000	0.8154	0.8219	0.3022	1.2693	0.1812	29.7794
	>20000	0.9058	1.0000	0.3975	1.0004	0.1642	17.8309
	<=5000	0.8055	0.7884	0.1797	1.8914	0.2450	25.1977
2012	>5000 a <=20000	0.8262	0.8531	0.2967	1.1719	0.1721	27.9851
	>20000	0.9047	1.0000	0.4344	1.0005	0.1570	17.1206
	<=5000	0.8070	0.7912	0.1785	1.9204	0.2464	24.7446
2013	>5000 a <=20000	0.8194	0.8371	0.3041	1.1683	0.1727	27.1375
	>20000	0.9045	1.0000	0.4344	1.0016	0.1555	17.2481

Model 2

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.9054	1.0000	0.0969	1.8544	0.2275	53.1532
2008	>5000 a <=20000	0.9380	1.0000	0.2820	1.0871	0.1323	71.7712
	>20000	0.9836	1.0000	0.5080	1.0000	0.0679	24.1697
	<=5000	0.9488	1.0000	0.3420	1.7793	0.1927	58.7769
2009	>5000 a <=20000	0.9730	1.0000	0.4814	1.1234	0.0842	79.6296
	>20000	0.9861	1.0000	0.5625	1.0004	0.0548	25.0000
	<=5000	0.9401	1.0000	0.3130	2.0046	0.2032	55.2392
2010	>5000 a <=20000	0.9583	1.0000	0.3874	1.4095	0.1055	75.1838
	>20000	0.9782	1.0000	0.6382	1.0000	0.0673	24.4485
	<=5000	0.9307	1.0000	0.2800	2.2371	0.2279	55.7583
2011	>5000 a <=20000	0.9382	1.0000	0.4025	1.1165	0.1262	70.7721
	>20000	0.9746	1.0000	0.5976	1.0000	0.0750	24.2647
	<=5000	0.9273	1.0000	0.2946	2.3782	0.2200	54.6893
2012	>5000 a <=20000	0.9397	1.0000	0.4120	1.1081	0.1249	69.7761
	>20000	0.9779	1.0000	0.5620	1.0000	0.0729	26.2646
	<=5000	0.9433	1.0000	0.2937	2.4632	0.2181	56.6402
2013	>5000 a <=20000	0.9350	1.0000	0.4122	1.1174	0.1282	68.2156
	>20000	0.9778	1.0000	0.5620	1.0000	0.0733	26.5504

Model 3

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.9155	1.0000	0.2771	1.3837	0.1623	63.7387
2008	>5000 a <=20000	0.9322	1.0000	0.2676	1.0002	0.1420	73.9852
	>20000	0.9863	1.0000	0.5829	1.0000	0.0632	24.9077
	<=5000	0.9252	1.0000	0.2771	1.4062	0.1660	67.8369
2009	>5000 a <=20000	0.9449	1.0000	0.2677	1.0010	0.1278	76.2963
	>20000	0.9831	1.0000	0.5999	1.0000	0.0630	25.3704
	<=5000	0.9258	1.0000	0.2648	1.8670	0.1667	65.1481
2010	>5000 a <=20000	0.9474	1.0000	0.4252	1.0030	0.1204	77.0221
	>20000	0.9830	1.0000	0.5999	1.0003	0.0585	25.0000
	<=5000	0.9210	1.0000	0.2648	2.0400	0.1706	62.7138
2011	>5000 a <=20000	0.9409	1.0000	0.3030	1.0029	0.1281	75.1838
	>20000	0.9777	1.0000	0.5999	1.0000	0.0731	24.6324
	<=5000	0.9178	1.0000	0.3049	1.7124	0.1698	62.8249
2012	>5000 a <=20000	0.9414	1.0000	0.2526	1.0037	0.1289	74.8134
	>20000	0.9761	1.0000	0.5947	1.0000	0.0740	25.8755
	<=5000	0.9245	1.0000	0.3050	1.6945	0.1690	64.8127
2013	>5000 a <=20000	0.9360	1.0000	0.2335	1.0026	0.1312	71.9331
	>20000	0.9805	1.0000	0.5832	1.0000	0.0679	26.7442

Table 3.12: Summary statistics for efficiency results by population sizes for KSW

Model 1

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.3769	0.3583	0.0400	0.9227	0.1481	0.0000
2008	>5000 a <=20000	0.4908	0.4742	0.0989	1.0000	0.1458	0.0000
	>20000	0.6441	0.6241	0.1122	1.0000	0.1754	0.0000
	<=5000	0.4940	0.4770	0.1180	0.9573	0.1514	0.0000
2009	>5000 a <=20000	0.5721	0.5725	0.2458	1.0000	0.1339	0.0000
	>20000	0.6676	0.6500	0.3010	1.0000	0.1698	0.0000
	<=5000	0.4064	0.3909	0.0635	0.9359	0.1368	0.0000
2010	>5000 a <=20000	0.4721	0.4626	0.1141	1.0000	0.1439	0.0000
	>20000	0.6542	0.6361	0.2569	1.0000	0.1728	0.0000
	<=5000	0.4340	0.4246	0.1178	0.9287	0.1411	0.0000
2011	>5000 a <=20000	0.4906	0.4840	0.1572	1.0000	0.1355	0.0000
	>20000	0.6455	0.6260	0.2879	1.0000	0.1847	0.0000
	<=5000	0.3994	0.3832	0.0134	0.9142	0.1319	0.0000
2012	>5000 a <=20000	0.5219	0.5147	0.1596	1.0000	0.1447	0.0000
	>20000	0.6573	0.6340	0.2464	1.0000	0.1758	0.0000
	<=5000	0.4673	0.4477	0.1071	0.9440	0.1558	0.0000
2013	>5000 a <=20000	0.5729	0.5700	0.1376	1.0000	0.1483	0.0000
	>20000	0.7016	0.6766	0.2769	1.0000	0.1735	0.0000

Model 2

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.3781	0.3570	0.0310	1.0000	0.1523	0.0000
2008	>5000 a <=20000	0.4964	0.4794	0.1004	1.0000	0.1516	0.0000
	>20000	0.6599	0.6354	0.2426	1.0000	0.1949	0.0000
	<=5000	0.4906	0.4726	0.1040	1.0000	0.1549	0.0000
2009	>5000 a <=20000	0.5671	0.5693	0.2361	1.0000	0.1365	0.0000
	>20000	0.6646	0.6407	0.2996	1.0000	0.1837	0.0000
	<=5000	0.4031	0.3863	0.0531	1.0000	0.1384	0.0000
2010	>5000 a <=20000	0.4835	0.4665	0.0944	1.0000	0.1560	0.0000
	>20000	0.6659	0.6402	0.2264	1.0000	0.1871	0.0000
	<=5000	0.4359	0.4247	0.1163	1.0000	0.1436	0.0000
2011	>5000 a <=20000	0.5017	0.4881	0.1470	1.0000	0.1442	0.0000
	>20000	0.6584	0.6255	0.2220	1.0000	0.1992	0.0000
	<=5000	0.4054	0.3866	0.0013	1.0000	0.1389	0.0000
2012	>5000 a <=20000	0.5379	0.5332	0.1281	1.0000	0.1543	0.1946
	>20000	0.6671	0.6382	0.2343	1.0000	0.1888	0.6623
	<=5000	0.4803	0.4603	0.1375	1.0000	0.1644	0.0000
2013	>5000 a <=20000	0.5708	0.5703	0.1200	1.0000	0.1599	0.1938
	>20000	0.6795	0.6445	0.0982	1.0000	0.1939	0.0000

Model 3

Year	Size	Mean	Median	Min	Max	S.d.	% of efficient municipalities
	<=5000	0.5686	0.5356	0.0064	1.0000	0.2205	0.0000
2008	>5000 a <=20000	0.5948	0.5865	0.0017	1.0000	0.2801	0.0000
	>20000	0.7108	0.8552	0.0609	1.0000	0.3153	0.0000
	<=5000	0.5531	0.5282	0.0357	1.0000	0.2204	0.0000
2009	>5000 a <=20000	0.6164	0.5968	0.0351	1.0000	0.2638	0.0000
	>20000	0.7148	0.7571	0.1109	1.0000	0.2922	0.0000
	<=5000	0.5558	0.5185	0.0636	1.0000	0.2163	0.0000
2010	>5000 a <=20000	0.6379	0.6174	0.0466	1.0000	0.2456	0.0000
	>20000	0.7209	0.8038	0.0817	1.0000	0.2879	0.0000
	<=5000	0.5527	0.5110	0.0193	1.0000	0.2091	0.0000
2011	>5000 a <=20000	0.6662	0.6425	0.0602	1.0000	0.2347	0.0000
	>20000	0.7714	0.8951	0.2308	1.0000	0.2525	0.6623
	<=5000	0.5596	0.5273	0.0295	1.0000	0.2161	0.0000
2012	>5000 a <=20000	0.6590	0.6472	0.0566	1.0000	0.2301	0.1946
	>20000	0.7663	0.8476	0.2257	1.0000	0.2542	0.0000
	<=5000	0.5664	0.5365	0.0000	1.0000	0.2084	0.0000
2013	>5000 a <=20000	0.6363	0.5999	0.0362	1.0000	0.2351	0.0000
	>20000	0.7426	0.8039	0.1130	1.0000	0.2656	0.6536

economies, and in some interior regions such as Castile and Leon, which had not been as heavily involved in the growth of the *real estate* bubble (Méndez Gutiérrez del Valle, 2015).

In addition, territorial differences in the regional financing system could also affect the provision of local public services. Note that local governments receive transfers from regional governments; hence, if the latter are underfinanced, local governments' resources may be affected. On this point, a 2014 report from the Spanish Ministry of the Treasury and Public Administrations concluded that some regions, such as the Balearic Islands, Valencian Community or Murcia, had the lowest rates per capita of funding received by the homogeneous regional powers in 2011, while the regions of Navarre, the Basque Country, La Rioja and Cantabria were the best funded.[12]

Therefore, given that the effects derived from the economic crisis and the regional financing system have not been equal in all Spanish territories, the local governments' location in a given territory could determine the more efficient provision of local public services. Some local entities faced an even more complicated situation, in which they had to continue providing public services with considerably lower resources but attending to their budgetary balance. In this context, we examine the existence of interregional differences showing higher or lower efficiency levels across municipalities located in different areas. Table 3.13 reports the descriptive statistics of the average efficiency scores classified for the Spanish regions and provinces.[13]

When considering the efficiency scores by regions we found that over the whole period municipalities in the region of Galicia seem to have the highest levels of efficiency. Indeed, Table 3.13 shows that better-performing municipalities are concentrated in the north of the country (i.e., Galicia, Cantabria and Asturias). Moreover, a comparison of provinces' efficiency scores reveals that the four provinces making up the region of Galicia are among the most efficient, confirming the higher performance of local

[12]Report from the Spanish Ministry of the Treasury and Public Administrations (*Ministerio de Hacienda y Administraciones Públicas*), July 2014. "Informe sobre la dimensión territorial de la actuación de las Administraciones Públicas, Ejercicio 2011". Retrieved from http://www.minhafp.gob.es

[13]For the sake of simplicity, we focus the analysis on output Model 3 (note that we found statistical evidence of the possible implications of service quality when measuring local government cost efficiency.) However, qualitative results for output Models 1 and 2 are not greatly different and are available upon request.

Table 3.13: Distribution of the efficiency scores grouped by regions and provinces

This table reports the distribution of the efficiency results classified by Regions and Provinces for the years 2008 and 2013 in output Model 3.

	DEA		FDH		Order-*m*		KSW	
Territory	2008	2013	2008	2013	2008	2013	2008	2013
Almería	0.7079	0.7347	0.9369	0.9362	0.9393	0.9400	0.6003	0.6116
Cádiz	0.8572	0.7424	1.0000	0.9578	1.0000	0.9582	0.7548	0.6655
Córdoba	0.6754	0.6350	0.9636	0.9066	0.9666	0.9136	0.5289	0.5616
Granada	0.7028	0.7113	0.9140	0.9427	0.9210	0.9470	0.5440	0.5916
Jaén	0.6538	0.5885	0.9270	0.8890	0.9281	0.8930	0.4869	0.5157
Málaga	0.6048	0.5852	0.8331	0.8323	0.8353	0.8373	0.5597	0.5140
Sevilla	0.7321	0.7518	0.9299	0.9509	0.9304	0.9456	0.5654	0.6442
Andalusia	**0.6977**	**0.6815**	**0.9243**	**0.9184**	**0.9271**	**0.9210**	**0.5632**	**0.5858**
Teruel	0.6065	0.6450	0.9205	0.8814	0.9333	0.9019	0.5782	0.5197
Zaragoza	0.5892	0.5918	0.8962	0.8253	0.9007	0.8330	0.5115	0.5192
Aragon	**0.5927**	**0.6029**	**0.9012**	**0.8369**	**0.9074**	**0.8472**	**0.5253**	**0.5193**
Asturias	**0.7222**	**0.7580**	**0.9551**	**0.9552**	**0.9617**	**0.9671**	**0.5646**	**0.5347**
Balearic Islands	**0.7008**	**0.6577**	**0.8928**	**0.8600**	**0.8950**	**0.8656**	**0.5907**	**0.5820**
Las Palmas	0.5751	0.7979	0.9144	0.9595	0.9144	0.9595	0.4377	0.6796
S.C. de Tenerife	0.5800	0.6217	0.9306	0.8695	0.9317	0.8637	0.5609	0.5571
Canary Islands	**0.5783**	**0.6830**	**0.9250**	**0.9008**	**0.9257**	**0.8970**	**0.5180**	**0.5997**
Cantabria	**0.7680**	**0.8346**	**0.9532**	**0.9639**	**0.9583**	**0.9694**	**0.4285**	**0.4547**
Ávila	0.7509	0.7555	0.9221	0.9452	0.9225	0.9487	0.5566	0.6100
León	0.7386	0.7416	0.9374	0.9443	0.9719	1.0461	0.4687	0.6006
Palencia	0.5371	0.6773	0.9188	0.8378	0.9188	0.8378	0.5403	0.6033
Salamanca	0.6431	0.6929	0.8366	0.8708	0.8558	0.9020	0.5436	0.6044
Segovia	0.7040	0.7998	0.9446	0.9917	0.9647	0.9997	0.6749	0.7306
Soria	0.7170	0.6205	0.8762	0.8412	0.8762	0.9139	0.5897	0.5447
Valladolid	0.6778	0.7287	0.9709	0.9358	0.9922	0.9612	0.5438	0.6166
Zamora	0.7457	0.7054	0.9362	0.9442	0.9983	0.9893	0.5781	0.2801
Castile and Leon	**0.7045**	**0.7273**	**0.9307**	**0.9297**	**0.9555**	**0.9761**	**0.5411**	**0.5815**
Albacete	0.5303	0.6839	0.9121	0.9145	0.9223	0.9403	0.5297	0.5313
Ciudad Real	0.6782	0.7051	0.8774	0.9047	0.8834	0.9214	0.5228	0.5902
Cuenca	0.5566	0.6162	0.8185	0.8350	0.8235	0.8417	0.6111	0.5667
Toledo	0.6917	0.7346	0.9594	0.9499	0.9649	0.9516	0.6070	0.6261
Castile La Mancha	**0.6383**	**0.7027**	**0.9125**	**0.9177**	**0.9191**	**0.9288**	**0.5703**	**0.5902**
Badajoz	0.6646	0.6972	0.9429	0.9521	0.9532	0.9625	0.5527	0.5186
Cáceres	0.5999	0.6196	0.8149	0.8544	0.8275	0.8706	0.5462	0.5532
Extremadura	**0.6406**	**0.6684**	**0.8954**	**0.9159**	**0.9066**	**0.9284**	**0.5503**	**0.5315**
A Coruña	0.9140	0.8517	0.9915	0.9874	0.9919	0.9892	0.7502	0.7022
Lugo	0.9112	0.8064	0.9948	0.9789	1.0009	0.9926	0.4936	0.5997
Orense	0.8606	0.8942	0.9708	0.9721	0.9717	0.9877	0.6660	0.5446
Pontevedra	0.9183	0.8976	0.9745	0.9903	0.9745	0.9948	0.7385	0.7032
Galicia	**0.8987**	**0.8686**	**0.9818**	**0.9823**	**0.9831**	**0.9905**	**0.6859**	**0.6408**
Murcia	**0.5194**	**0.6615**	**0.8585**	**0.8706**	**0.8590**	**0.8716**	**0.5014**	**0.5734**
La Rioja	**0.5135**	**0.5557**	**0.8021**	**0.8108**	**0.8129**	**0.8291**	**0.5211**	**0.5042**
Alicante	0.6717	0.7727	0.9313	0.9522	0.9357	0.9601	0.6085	0.6600
Castellón	0.5988	0.6874	0.8469	0.9296	0.8672	0.9489	0.5702	0.6039
Valencia	0.5569	0.6701	0.8890	0.9027	0.8951	0.9162	0.5304	0.5888
Valencian Community	**0.5961**	**0.7023**	**0.8953**	**0.9209**	**0.9029**	**0.9335**	**0.5586**	**0.6116**

Notes: In our final sample there was no information available for the full period 2008 to 2013 for the Basque Country, Navarre, Catalonia and Madrid regions and the provinces of Burgos, Huesca, Guadalajara and Huelva.

governments located in this region. In contrast, municipalities from La Rioja region show the lowest average efficiency results, followed by the regions of Murcia in 2008 and Aragon in 2013. Efficiency scores considered by provinces again reveal municipalities in La Rioja as having the lowest levels of efficiency, although other provinces such as Cuenca (in Castile La Mancha), Zaragoza (Aragon) or Málaga (Andalusia) also present poor performances in most cases.

The above descriptive analysis gives us an initial insight into the existence of interregional differences, where municipalities with higher or lower levels of efficiency seem to concentrate. In order to statistically support this point, we carry out a Kruskal-Wallis[14] test to determine whether any of the differences between the medians of the regions (or provinces within each region) are statistically significant. We consider the null hypothesis H_0 : *The medians for all regions are equal*, meaning that there is no statistically significant difference between the median efficiency scores of municipalities located in different regions (or provinces within a region), against the alternative hypothesis H_1 : *At least two regions differ*. Results are provided in Table 3.14. The test results show that differences across regions are significant. However, the differences between provinces are significant depending on the region analysed. For instance, there are differences at the 5% level of significance for Andalusia or Castile and Leon, while there are no differences for Galicia, which is in line with our findings in the descriptive analysis.

3.5. Conclusion

In recent years, the context of the international economic crisis has prioritised the improvement of public management efficiency in local governments. In most euro-area countries, the economic and financial situation has had a huge impact on many local governments' incomes, leading to increased deficits. Interest in public efficiency is even higher in countries such as Spain, where municipalities have faced stricter budget limitations with the law on budgetary stability *(Ley General Presupuestaria)*, which tightened control over public debt and public spending. Spain has also experienced

[14]Kruskal-Wallis test is the nonparametric alternative to the one-way ANOVA.

Table 3.14: Testing the differences between the efficiency scores by regions and provinces using Kruskal-Wallis test

We test whether the differences between the medians of the efficiency scores by regions and provinces within a region in output Model 3 are significant. We test the null hypothesis H_0 : *The medians for all regions are equal* (i.e., there is no statistically significant difference between the median efficiency scores of municipalities located in different regions or provinces within a region), against the alternative hypothesis H_1 : *At least two medians differ*.

		Regions	Provinces							
			Andalusia	Aragon	Canary Islands	Castile and Leon	Castile la Mancha	Extremadura	Galicia	Valencian Community
Estimator	Year	*T*-statistic (*p*-value)	*T*-statistic (*p*-value)	*T*-statistic (*p*-value)	*T*-statistic (*p*-value)	*T*-statistic (*p*-value)	*T*-statistic (*p*-value)	*T*-statistic (*p*-value)	*T*-statistic (*p*-value)	*T*-statistic (*p*-value)
DEA	2008	219.0900 (0.0000*)	20.3720 (0.0024*)	0.4537 (0.5006)	0.0565 (0.8121)	3.9705 (0.7832)	14.0730 (0.0028*)	2.5423 (0.1108)	5.7962 (0.1220)	9.1123 (0.0105*)
	2013	149.9200 (0.0000*)	32.3380 (0.0000*)	0.2040 (0.6515)	4.8755 (0.0272*)	5.4782 (0.6018)	6.4061 (0.0934)	3.3879 (0.0657)	10.4730 (0.0149*)	9.5787 (0.0083*)
FDH	2008	85.3350 (0.0000*)	25.5030 (0.0003*)	0.0565 (0.8121)	0.5933 (0.4411)	12.7730 (0.0778)	18.5090 (0.0003*)	11.4710 (0.0007*)	5.7593 (0.1239)	6.3580 (0.0416*)
	2013	101.2500 (0.0000*)	24.6240 (0.0004*)	0.8418 (0.3589)	4.4474 (0.0350*)	12.3410 (0.0899)	14.9170 (0.0019*)	10.6620 (0.0011*)	2.1753 (0.5368)	11.4710 (0.0032*)
Order-*m*	2008	69.9540 (0.0000*)	24.5310 (0.0004*)	0.1857 (0.6665)	0.8025 (0.3703)	15.5840 (0.0292*)	19.4270 (0.0002*)	9.3236 (0.0023*)	10.7990 (0.0129*)	5.5956 (0.0609)
	2013	88.1980 (0.0000*)	24.9840 (0.0003*)	2.3105 (0.1285)	4.5629 (0.0327*)	13.0300 (0.0714)	13.2710 (0.0041*)	7.7553 (0.0054*)	2.6099 (0.4558)	8.7189 (0.0128*)
KSW	2008	66.5620 (0.0000*)	18.8200 (0.0045*)	1.1793 (0.2775)	0.6942 (0.4047)	2.6226 (0.9176)	2.6397 (0.4506)	0.2737 (0.6008)	8.1785 (0.0425*)	3.7539 (0.1531)
	2013	40.9330 (0.0001*)	21.8060 (0.0013*)	0.1331 (0.7152)	2.5439 (0.1107)	4.9938 (0.6607)	3.7912 (0.2849)	0.3301 (0.5656)	3.3298 (0.3435)	5.1765 (0.0752)

* denotes differences are significant at the 5% level.

a deep economic recession since 2007, and came under serious scrutiny within the Eurozone in 2012. In these circumstances, issues related to Spanish local government efficiency and their contribution to public sector deficit are even more relevant. In this chapter, we have analysed the overall cost efficiency of Spanish local governments during the period of the economic crisis (2008–2013) which to date has scarcely been examined, and which has had serious effects on Spanish local governments.

Regardless of the context of the analysis, the current large body of literature evaluating local government efficiency shares two important and still unsolved problems. The first is the complexity of defining local governments' outputs and inputs; the second is the lack of a clear standard methodology to measure efficiency (these two common problems from previous literature were earlier discussed in chapter 2). The present study also contributes to fill these gaps by defining several output models and employing four separate non-parametric approaches to estimate local government cost efficiency. The sample included 1,574 Spanish local governments with populations between 1,000 and 50,000 for the period 2008–2013, the widest-ranging sample based on Spanish data used to date.

Our results point to significant differences in the distribution of the efficiency scores between years 2008 and 2013. In general, efficiency scores improved over the years. In the context of economic crisis, Spanish local governments have come under pressure to accommodate severe economic restrictions while still attending to citizen needs. Thus, we conclude that Spanish local governments have improved their efficiency levels since they reduced their budget expenditures (inputs or costs) while maintaining or increasing local public service provision (outputs) over the crisis period 2008–2013. Additionally, results also vary according to the size of the municipalities. Larger municipalities perform better, i.e., smaller municipalities are further from their efficient frontier, whereas most of larger municipalities are efficient and closer to the frontier.[15] These differences may be related to the quality of public management, given that larger municipalities use more innovative management tools

[15]Of special note is that given our variable returns to scale assumption we only compare municipalities of similar sizes.

(such as financial budgetary control, contracting out of services, etc.) than smaller municipalities (Balaguer-Coll et al., 2007).

Moreover, given the problems of defining the bundle of services and facilities that municipalities must provide, we propose three output models including quantity and quality variables. Our results confirm the importance of considering alternative input-output models in order to assess whether the different choices might explain heterogeneity among local governments. Moreover, in our sample of Spanish local governments we find statistical evidence of the possible implications of service quality when measuring local government cost efficiency. There is a trade-off between cost efficiency and service quality when quality variables are accounted for. In this setting, the inclusion of quality variables in efficiency analysis is particularly interesting and informative for policy-makers, since performance decisions may have an impact on their quality and not on their quantity.

Another important issue concerns the structural differences in the average cost efficiency between municipalities located in different Spanish regions and provinces. This is the first time that local governments' location in a given territory has been investigated in the local government efficiency literature. We found that municipalities with higher efficiency scores are concentrated in the north of the country, while La Rioja and some of the eastern provinces such as Murcia or Aragon present lower efficiency values. These results suggest that these interregional differences should be considered when public policies and fiscal adjustments are being designed to control local governments' budget expenditures since they could affect equality of access to local public services.

Finally, the comparison of results from the four non-parametric methodologies reveals that efficiency scores can vary widely depending on the method applied (Geys and Moesen, 2009b). Since there is no clear standard methodology to measure efficiency, accurately assessing cost efficiency remains difficult. It therefore makes sense to use a variety of methodologies in order to check the robustness of the results. As expected, local managers have some margin to optimise the use of public resources, suggesting that Spanish municipalities could achieve the same level of local output with fewer resources. We found considerable differences in the mean efficiency scores between the various reference technologies, ranging from 0.44 to 0.96 (also depending on the model and the year). Therefore, in line with previous research our results confirm that the level and variation of the efficiency scores are affected by the approach taken.

In the next chapter, since the method chosen to measure efficiency analysis may affect the efficiency results, we compare the estimation techniques explained in this chapter following the method employed in Badunenko et al. (2012). The aim is to uncover which techniques are more appropriate to assess local government cost efficiency in Spain in an attempt to provide a system for assessing local government performance with practical relevance.

Chapter 4

Which estimator to measure local governments' cost efficiency?

4.1. Introduction

Aforementioned in chapter 1, managing the available resources efficiently at all levels of government (central, regional, and municipal) is essential, particularly in the scenario of the current international economic crisis, which still affects several European countries. Given that increasing taxes and deficit is politically costly (Doumpos and Cohen, 2014), a reasonable way to operate in this context is to improve economic efficiency (De Witte and Geys, 2011), which in cost terms means that an entity should produce a particular level of output in the cheapest way. In this setting, since local regulators must provide the best possible local services at the lowest possible cost, developing a system for evaluating local government performance that allows benchmarks to be set over time could have relevant practical implications (Da Cruz and Marques, 2014). However, measuring the performance of local governments is usually highly complex.

As shown in chapter 2, in which an extensive review of the existing literature on local governments efficiency is provided, local government efficiency has attracted much scholarly interest in the field of public administration. However, despite the high number of empirical contributions, a major challenge to analysis of local government performance is the lack of clear, standard methodology to perform efficiency analysis, a common problem from previous literature earlier discussed in chapters 2 and 3. This is not a trivial question as much previous literature has proposed different frontier techniques, both parametric and non-parametric, to analyse technical, cost or other forms of efficiency in local governments.

Although this problem is well-known in the efficiency measurement literature, few studies have attempted to use two or more alternative approaches comparatively. For instance, De Borger and Kerstens (1996a) analysed local governments in Belgium using five different reference technologies, two non-parametric (DEA and FDH) and three parametric frontiers (one deterministic and two stochastic). They found large differences in the efficiency scores for identical samples and, as a consequence, suggested using different methods to control for the robustness of results whenever the problem of choosing the "best" reference technology is unsolved. Other studies compared the efficiency estimates of DEA and SFA,[1] or DEA and FDH or other non-parametric variants,[2] and drew similar conclusions.

Since there is no obvious way to choose an efficiency estimator, the method selected may affect the efficiency analysis (Geys and Moesen, 2009b) and could lead to biased results. Therefore, if local government decision makers set a benchmark based on an incorrect efficiency score, a non-negligible economic impact may result. Accordingly, as Badunenko et al. (2012) point out, if the selected method overestimates the efficiency scores, some local governments may not be penalised and, as a result, their inefficiencies will persist. In contrast, if the efficiency scores are underestimated some local governments would be regarded as "low performers" and could be unnecessarily penalised. Hence, although we note that each particular methodology leads to different cost efficiency results for each local government, one should ideally report efficiency scores that will be more reliable, or closer to the truth Badunenko et al. (2012).[3]

[1] Athanassopoulos and Triantis (1998); Worthington (2000); Geys and Moesen (2009b); Boetti et al. (2012); Nikolov and Hrovatin (2013); Pevcin (2014b)

[2] Balaguer-Coll et al. (2007); Fogarty and Mugera (2013); El Mehdi and Hafner (2014)

[3] We will elaborate further on this *a priori* ambitious expression.

The present chapter addresses these issues by comparing four non-parametric methodologies and uncovering which measures might be more appropriate to assess local government cost efficiency in Spain. The study contributes to the literature in three specific aspects. First, we seek to compare the four non-parametric estimation techniques explained in chapter 3 (see section 3.2), namely DEA, FDH, the order-*m* partial frontier and KSW; the first two are the most popular in the non-parametric field while the latter two are more recent proposals. These techniques have been widely studied in the previous literature, but little is known about their performance in comparison with each other.

Second, we attempt to determine which of these methods should be applied to measure cost efficiency in a given situation. In contrast to previous literature, which has regularly compared techniques and made alternative proposals, we follow the method set out by Badunenko et al. (2012), with the aim to compare the different methods used and identify those that perform better in different settings. We carry out the experiment via Monte Carlo simulations and discuss the relative performance of the efficiency estimators under various scenarios.

As a final contribution, we uncover which methodologies perform better with our particular dataset, i.e., the ones which are more appropriate to measure local governments' efficiency in Spain. From the simulation results, we determine in which scenario our data lies in, and we follow the suggestions related to the performance of the estimators for this scenario. Therefore, we use a consistent method to choose an efficiency estimator, which provides a significant contribution to previous literature in local governments efficiency. We focus on a sample of 1,574 Spanish local governments between 1,000 and 50,000 inhabitants for the period 2008–2013 (for further details, see output specificatin Model 1 from section 5.2.1 in chapter 3).

Note that, as stated in chapters 1 and 3, the sample is also relevant in terms of the period analysed. The economic and financial crisis that started in 2007 has had a huge impact on most Spanish local government revenues and finances in general. Under these circumstances, issues related to Spanish local government efficiency have gained relevance and momentum. Evaluation techniques give the opportunity to identify policy programs that are working well, to analyse aspects of a program that can be improved, and to identify other public programs that do not meet the stated objectives. In fact, giving insight into the amount of local government inefficiency might help to further support effective policy measures to correct and or control it. Therefore, it is obvious that obtaining here a reliable efficiency score would have relevant economic and political implications.

Our results suggest that there is no one approach suitable for all efficiency analysis. When using these results for policy decisions, local regulators must be aware of which part of the distribution is of particular interest and if the interest lies in the efficiency scores or the rankings estimates. We find that for our sample of Spanish local governments, all methods showed some room for improvement in terms of possible cost efficiency gains, however they present large differences in the inefficiency levels. Both DEA and FDH methodologies showed the most reliable efficiency results, according to the findings of our simulations. Therefore, our results indicate that the average cost efficiency would have been between 0.54 and 0.77 during the period 2008–2013, suggesting that Spanish local governments could have achieved the same level of local outputs with about 23% to 36% fewer resources. From a technical point of view, the analytical tools introduced in this chapter would represent an interesting contribution that examine the possibility of using a consistent method to choose an efficiency estimator, and the obtained results give evidence on how efficiency could certainly be assessed to provide some additional guidance for policy makers.

The chapter is organised as follows: section 4.2 shows the methodological comparison experiment and the results for the different scenarios. Section 4.3 gives a suggestion of which methodology performs better with our particular dataset and presents and comments the most relevant efficiency results. Finally, section 4.4 summarises the main conclusions.

4.2. Methodological comparison

In contrast to the previous literature, in this section we compare DEA, FDH, order-m and KSW approaches (for further details, see section 3.2 in chapter 3) following the method proposed by Badunenko et al. (2012).[4] Our aim is to uncover which measures perform best with our particular dataset, that is, which ones are the most appropriate to measure local government efficiency in Spain in order to provide useful information for local governments' performance decisions.

To this end, we carry out the experiment via Monte Carlo simulations. We first define the data generating process, the parameters and the distributional assumptions on data. Second, we consider the different methodologies and take several standard measures to compare their behaviour. Next, after running the simulations, we discuss the relative performance of the efficiency estimators under the various scenarios. Finally, we decide which methods are the most appropriate to measure local government efficiency in Spain.

4.2.1. Simulations

Several previous studies analysing local government cost efficiency with parametric techniques used the SFA estimator developed byAigner et al. (1977) and Meeusen and Van den Broeck (1977) as a model to estimate cost frontiers.[5] These studies considered the input-oriented efficiency where the dependent variable is the level of spending or cost, and the independent variables are output levels. As a parametric approach, SFA establishes the best practice frontier on the basis of a specific functional form, most commonly Cobb-Douglas or Translog. Moreover, it allows researchers to distinguish between measurement error and inefficiency term.

Following this scheme, we conduct simulations for a production process with one input or cost (c) and two outputs (y_1 and y_2).[6] We consider a Cobb-Douglas cost function. For the baseline case, we assume constant returns to scale (CRS) ($\gamma = 1$).[7]

[4]The study of Badunenko et al. (2012) compared two estimators of technical efficiency in a cross-sectional setting. Specifically, they compared SFA, represented by the non-parametric kernel SFA estimator of Fan et al. (1996), with DEA, represented by the non-parametric bias-corrected DEA estimator of Kneip et al. (2008).

[5]See, for instance, the studies of Worthington (2000), De Borger and Kerstens (1996a), Geys (2006), Ibrahim and Salleh (2006), Geys and Moesen (2009a,b), Kalb (2010), Geys et al. (2010), Kalb et al. (2012) or Štastná and Gregor (2015), Lampe et al. (2015), among others.

[6]For simplicity, we use a multi-output model with two outputs instead of six.

[7]In subsection 4.2.4, we consider robustness checks with increasing and decreasing returns to scale to make sure that our simulations accurately represent the performance of our methods.

We establish $a = 1/3$ and $b = \gamma - a$.

We simulate observations for outputs y_1 and y_2, which are distributed uniformly on the $[1, 2]$ interval. Moreover, we assume that the true error term (v) is normally distributed $N(0, \sigma_v^2)$ and the true cost efficiency is $TCE = exp(-u)$, where u is half-normally distributed $N^+(0, \sigma_u^2)$ and independent from v. We introduce the true error and inefficiency terms in the frontier formulation, which takes the following expression:

$$c = y_1^a \cdot y_2^b \cdot exp(v + u), \tag{4.1}$$

where c is total costs and y_1 and y_2 are output indicators. For reasons previously explained in section 3.2 in chapter 3, there is no observable variation in input prices, so input prices are ignored (see, for instance, the studies of Kalb, 2012, and Pacheco et al., 2014).

We simulate six different combinations for the error and inefficiency terms, in order to model various real scenarios. Table 4.1 contains the matrix of the different scenarios. It shows the combinations when σ_v takes values 0.01 and 0.05 and σ_u takes values 0.01, 0.05 and 0.1. The rows in the table represent the variation of the error term (σ_v), while the columns represent the variation of the inefficiency term (σ_u). The first row is the case where the variation of the error term is relatively small, while the second row shows a large variation. The first column is the case where the inefficiency term is relatively small, while the second and third columns represent the cases where variation in inefficiency is relatively larger. The Λ parameter, which sets each scenario, is the ratio between of σ_u and σ_v.

Table 4.1: Combinations of error and inefficiency terms in Monte Carlo simulations to model scenarios

	$\sigma_u = 0.01$	$\sigma_u = 0.05$	$\sigma_u = 0.1$
$\sigma_v = 0.01$	s1: $\Lambda = 1.0$	s3: $\Lambda = 5.0$	s5: $\Lambda = 10.0$
$\sigma_v = 0.05$	s2: $\Lambda = 0.2$	s4: $\Lambda = 1.0$	s6: $\Lambda = 2.0$

Within this context, scenario 1 is the case when the error and the inefficiency terms are relatively small ($\sigma_u = 0.01$, $\sigma_v = 0.01$, $\Lambda = 1.0$), which means that the data has been measured with little noise and the units are relatively efficient, while scenario 6 is the case when the error and the inefficiency terms are relatively large ($\sigma_u = 0.1$, $\sigma_v = 0.05$, $\Lambda = 2.0$), which means that the data is relatively noisy and the units are relatively inefficient.

For all simulations we consider 2,000 Monte Carlo trials, and we analyse two different sample sizes, n= 100 and 200.[8] We note that non-parametric estimators do not take into account the presence of noise, however, we want to check how it affects the performance of our estimators since all data tend to have noise.[9]

4.2.2. Measures to compare the estimators' performance

In order to compare the relative performance of our four non-parametric methodologies, we consider the following median measures over the 2,000 simulations. We use median values instead of the average, since it is more robust to skewed distributions.

- $Bias(TCE) = \frac{1}{n}\sum_{i=1}^{n}(\widehat{TCE_i} - TCE_i)$
- $RMSE(TCE) = [\frac{1}{n}\sum_{i=1}^{n}(\widehat{TCE_i} - TCE_i)^2]^{1/2}$
- $UpwardBias(TCE) = \frac{1}{n}\sum_{i=1}^{n} 1 \cdot (\widehat{TCE_i} > TCE_i)$
- Kendall's τ (TCE)= $\frac{n_c - n_d}{0.5n(n-1)}$

where $\widehat{TCE_i}$ is the estimated cost efficiency of municipality i in a given Monte Carlo replication (by a given method) and TCE_i is the true efficiency score. The bias reports the difference between the estimated and true efficiency scores. When it is negative (positive), the estimators are underestimating (overestimating) the true efficiency. The $RMSE$ (root mean squared error) measures the standard deviation or error from the true efficiency. The upward bias is the proportion of $\widehat{TCE}$ larger than

[8] To ease the computational process, we use samples of n= 100 and 200 to conduct simulations. In subsection 4.2.4, we consider a robustness check with a bigger sample size ($n = 500$) to ensure that our simulations accurately represent the performance of our data.

[9] In subsection 4.2.4, we consider a robustness check with no noise to ensure that our simulations accurately represent the performance of our data.

the true efficiencies. It measures the percentage of overestimated or underestimated cost efficiencies. Finally, the Kendall's τ test represents the correlation between the predicted and true cost efficiencies, where n_c and n_d are the number of concordant and discordant pairs in the data set, respectively. This test identifies the differences in the ranking distributions of the true and the estimated ranks.

We also compare the densities of cost efficiency across all Monte Carlo simulations in order to report a more comprehensive description of the results, not only restrict them to a single summary statistic—the median. So, for example, if we were interested in estimating the poorer performers, we would focus on which estimator perform best at the $5th$ percentile of the efficiency distribution. For each draw, we sort the data by the relative value of true efficiency. Since we are interested in comparing the true distribution for different percentiles of our sample, we show violin plots for 5%, 50% and 95% percentiles.

4.2.3. Relative performance of the estimators

Table 4.2 provides baseline results for the performance measures of the cost efficiency with the Cobb-Douglas cost function. First we observe that the median bias of the cost efficiency scores is negative in DEA and KSW in all cases. This implies that the DEA and KSW estimators tend to underestimate the true cost efficiency in all scenarios. FDH and order-m present positive median bias except for scenario 2 in FDH, implying a tendency to overestimate the true efficiency. Bias for all methodologies tends to increase with the sample size when the bias is negative, and decrease when the bias is positive, except for order-m in scenarios 1, 3 and 5. The RMSE is smaller when σ_v is small, except for FDH in scenario 5 and order-m in scenarios 3 and 5. Moreover, the RMSE of the cost efficiency estimates increases with the sample size for all cases except for FDH in scenarios 1, 3, 5 and 6 and order-m in scenarios 5 and 6.

We also consider the upward bias. This shows the percentage of observations for which cost efficiency is larger than the true value (returning a value of 1). The desired value is 0.5. The values less (greater) than 0.5 indicate underestimation (overestimation) of cost efficiencies. In this setting, DEA and KSW systematically underestimate the

Table 4.2: Baseline results with Cobb-Douglas cost function

	Bias[a]				RMSE[b]				Upward Bias[c]				Kendall's τ[d]			
	DEA	**FDH**	**Order-*m***	**KSW**	**DEA**	**FDH**	**Order-*m***	**KSW**	**DEA**	**FDH**	**Order-*m***	**KSW**	**DEA**	**FDH**	**Order-*m***	**KSW**
s1: $\sigma_v = 0.01$, $\sigma_u = 0.01$																
n=100	-0.0298	0.0074	0.0231	-0.0350	0.0330	0.0096	0.0307	0.0375	0.0500	0.9800	0.9900	0.0100	0.2491	0.1227	0.0615	0.2549
n=200	-0.0348	0.0070	0.0287	-0.0391	0.0376	0.0094	0.0370	0.0415	0.0250	0.9600	0.9850	0.0050	0.2573	0.1590	0.0790	0.2588
s2: $\sigma_v = 0.05$, $\sigma_u = 0.01$																
n=100	-0.0892	-0.0111	0.0049	-0.1006	0.1013	0.0338	0.0399	0.1111	0.0500	0.6400	0.6900	0.0100	0.0681	0.0551	0.0511	0.0687
n=200	-0.1028	-0.0205	0.0043	-0.1130	0.1134	0.0428	0.0466	0.1225	0.0250	0.5000	0.6200	0.0050	0.0707	0.0597	0.0542	0.0705
s3: $\sigma_v = 0.01$, $\sigma_u = 0.05$																
n=100	-0.0182	0.0322	0.0477	-0.0246	0.0238	0.0392	0.0548	0.0285	0.1200	1.0000	1.0000	0.0600	0.6753	0.4443	0.3169	0.6877
n=200	-0.0239	0.0289	0.0512	-0.0293	0.0281	0.0351	0.0581	0.0325	0.0700	0.9900	1.0000	0.0350	0.6843	0.5192	0.3812	0.6911
s4: $\sigma_v = 0.05$, $\sigma_u = 0.05$																
n=100	-0.0707	0.0133	0.0303	-0.0832	0.0857	0.0410	0.0528	0.0960	0.0900	0.7500	0.8100	0.0400	0.3060	0.2547	0.2415	0.3059
n=200	-0.0849	0.0024	0.0279	-0.0963	0.0972	0.0421	0.0565	0.1072	0.0500	0.6300	0.7550	0.0250	0.3132	0.2710	0.2564	0.3123
s5: $\sigma_v = 0.01$, $\sigma_u = 0.1$																
n=100	-0.0101	0.0525	0.0684	-0.0177	0.0203	0.0624	0.0768	0.0238	0.2000	1.0000	1.0000	0.1000	0.8057	0.5928	0.5146	0.8182
n=200	-0.0170	0.0453	0.0689	-0.0232	0.0230	0.0537	0.0763	0.0275	0.1150	0.9950	1.0000	0.0600	0.8174	0.6586	0.5738	0.8254
s6: $\sigma_v = 0.05$, $\sigma_u = 0.1$																
n=100	-0.0580	0.0347	0.0519	-0.0724	0.0755	0.0591	0.0722	0.0869	0.1300	0.8200	0.8800	0.0700	0.4996	0.4170	0.4030	0.4990
n=200	-0.0726	0.0207	0.0485	-0.0854	0.0867	0.0530	0.0717	0.0974	0.0750	0.7200	0.8400	0.0400	0.5065	0.4403	0.4332	0.5065

[a] The bias reports the difference between the estimated and true efficiency scores. When it is negative (positive), the estimators are underestimating (overestimating) the true efficiency.
[b] The *RMSE* (root mean squared error) measures the standard deviation or error from the true efficiency.
[c] The upward bias is the proportion of estimated efficiencies larger than the true efficiencies (returning a value of 1). The desired value is 0.5. The values less (greater) than 0.5 indicate underestimation (overestimation) of cost efficiencies.
[d] Kendall's τ shows the correlation coefficient for the efficiency ranks between true and estimated efficiency scores.

true efficiency. Moreover, as the sample size increases, so does the percentage of underestimated results. In contrast, FDH and order-m tend to overestimate the true efficiency, but as the sample size increases overestimated results decrease. Finally, we analyse Kendall's τ for the efficiency ranks between true and estimated efficiency scores. In each scenario and sample size, DEA and KSW have a larger Kendall's τ; they therefore perform best at identifying the ranks of the efficiency scores.

We also analyse other percentiles of the efficiency distribution, since it is difficult to conclude from the table which methods perform better. Figures 4.1 to 4.6 show results for the 5*th*, 50*th* and 95*th* percentiles of true and estimated cost efficiencies. We compare the distribution of each method with the TCE.

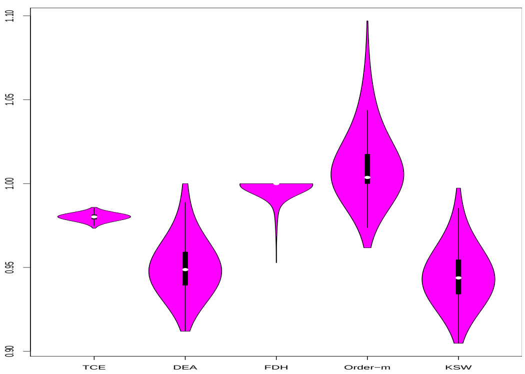
The figures show that results depend on the value of the Λ parameter. As expected, when the variance of the error term increases our results are less accurate (note that non-parametric methodologies assume the absence of noise). In contrast, when the variance of the inefficiency term increases, our results are more precise.

Under **scenario 1** (see Figures 4.1a, 4.1b, 4.1c, 4.1d, 4.1e and 4.1f), when both error and inefficiency terms are relatively small, DEA and KSW methodologies consistently underestimate efficiency (their distributions are below the true efficiency in all percentiles). If we consider median values and density modes, order-m tends to overestimate efficiency in all percentiles, while FDH also tends to overestimate efficiency at the 5*th* and 50*th* percentiles. Moreover, we observe that FDH performs well in estimating the efficiency units in the 95*th* percentile.

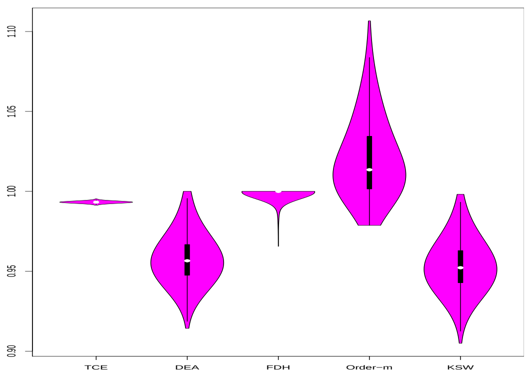
Although **scenario 4** (see Figures 4.4a, 4.4b, 4.4d, 4.4c, 4.4e and 4.4f) is the opposite case to scenario 1, when both error and inefficiency terms are relatively large they have the same value of Λ. As in scenario 1, DEA and KSW methodologies consistently underestimate efficiency. On the other hand, we see from the 5*th* percentile that both FDH and order-m tend to overestimate efficiency. However, at the 50*th* and 95*th* percentiles both methods perform better at estimating the efficiency units since their median values and density modes are closer to the TCE distribution.

Similarly, in **scenario 2** (see Figures 4.2a, 4.2b, 4.2d, 4.2c, 4.2e and 4.2f), when the error term is relatively large but the inefficiency term is relatively small, DEA

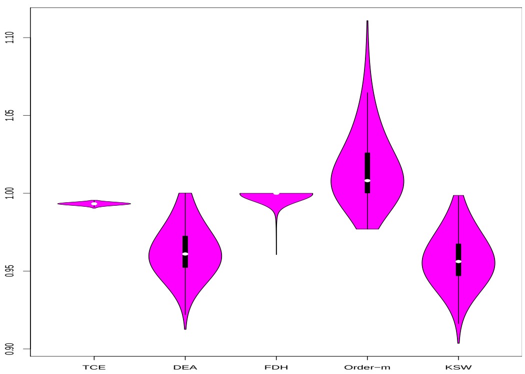
Figure 4.1: Distributions (violin plots) for scenario 1



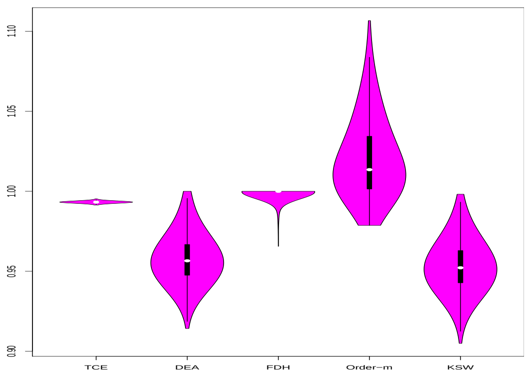
(a) S1, 5th percentile, n=100



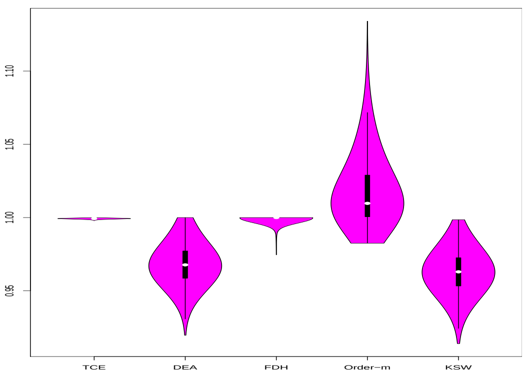
(b) S1, 50th percentile, n=200



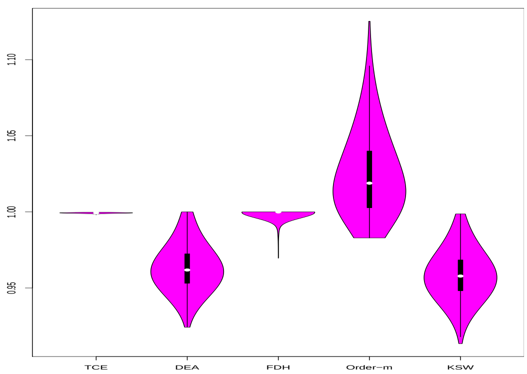
(c) S1, 50th percentile, n=100



(d) S1, 50th percentile, n=200

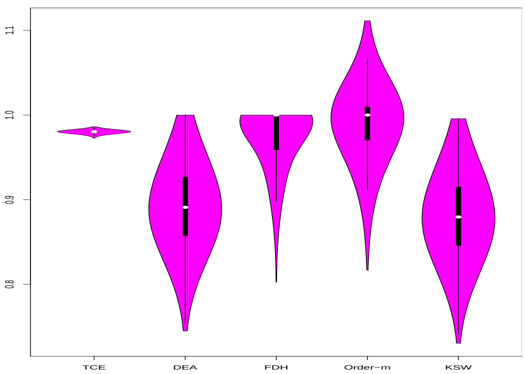


(e) S1, 95th percentile, n=100

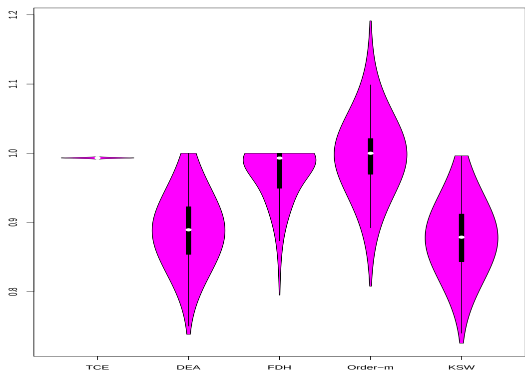


(f) S1, 95th percentile, n=200

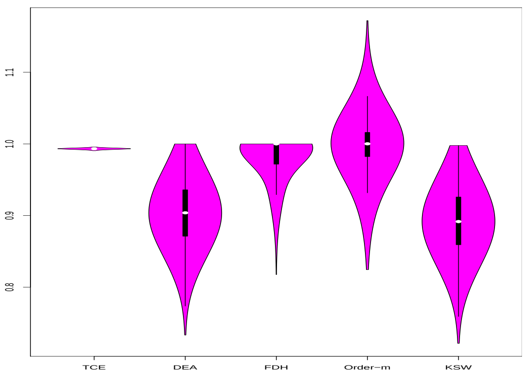
Figure 4.2: Distributions (violin plots) for scenario 2



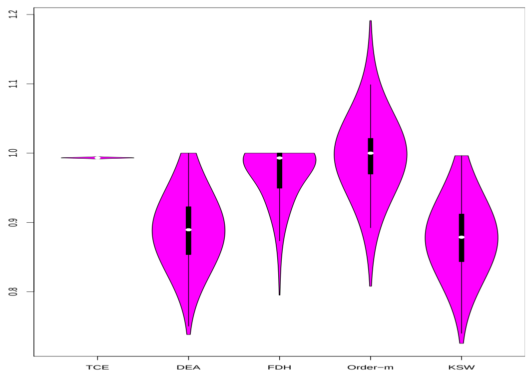
(a) S2, 5th percentile, n=100



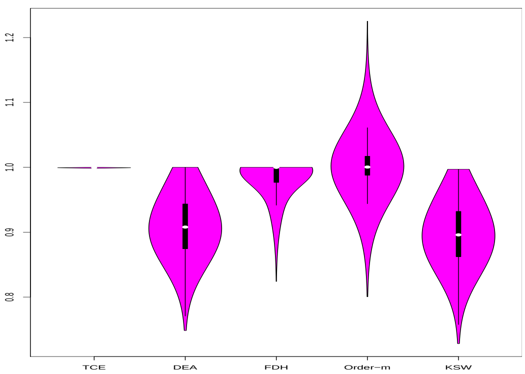
(b) S2, 50th percentile, n=200



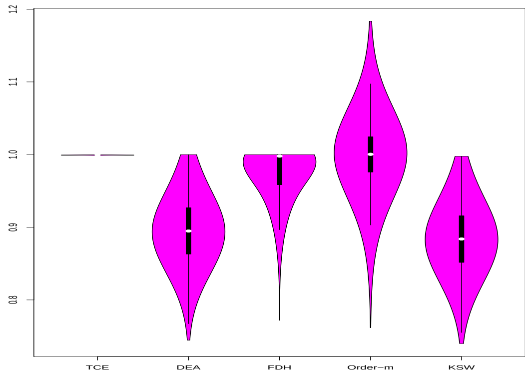
(c) S2, 50th percentile, n=100



(d) S2, 50th percentile, n=200

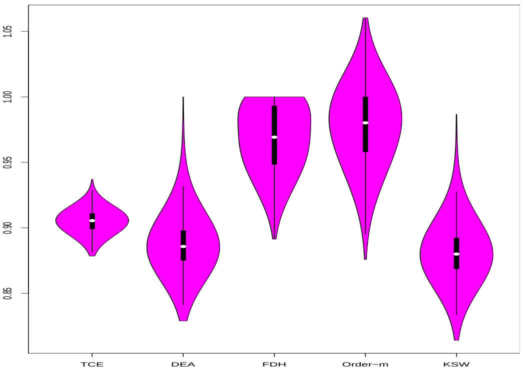


(e) S2, 95th percentile, n=100

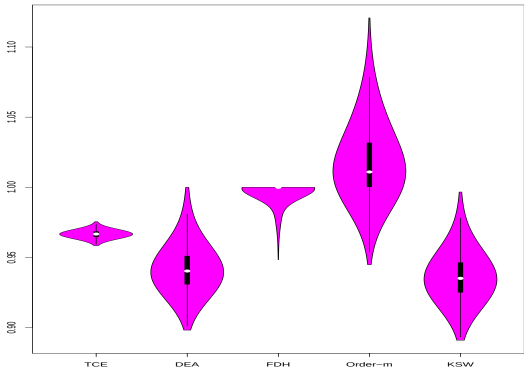


(f) S2, 95th percentile, n=200

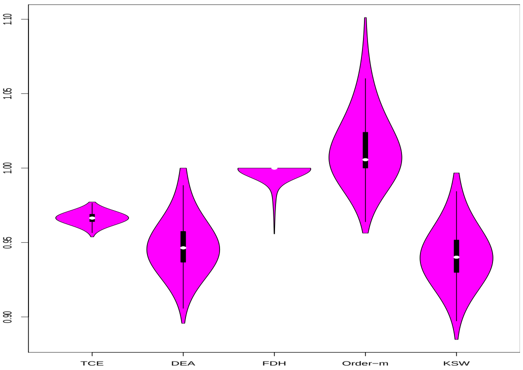
Figure 4.3: Distributions (violin plots) for scenario 3



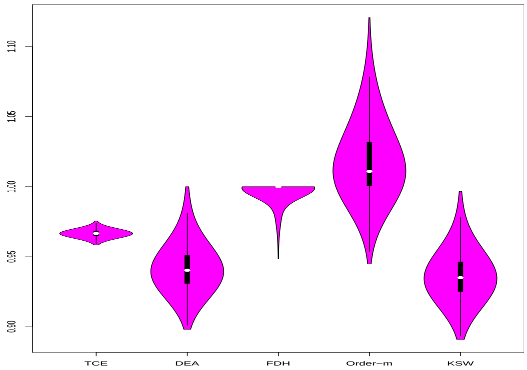
(a) S3, 5th percentile, n=100



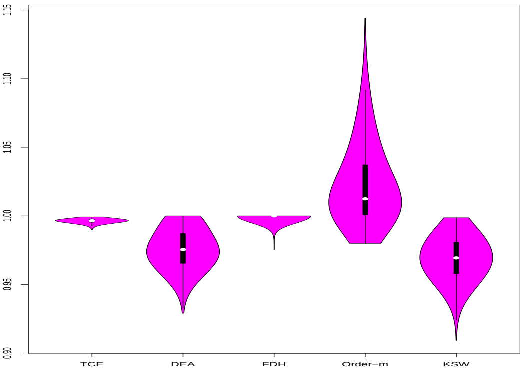
(b) S3, 50th percentile, n=200



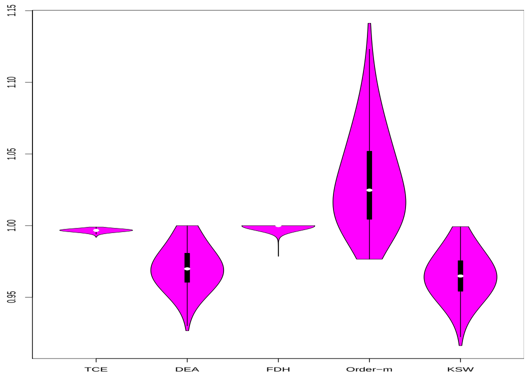
(c) S3, 50th percentile, n=100



(d) S3, 50th percentile, n=200

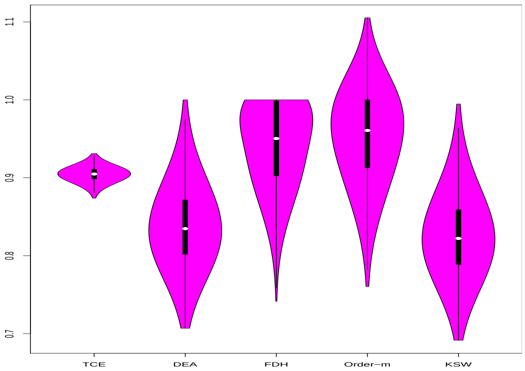


(e) S3, 95th percentile, n=100

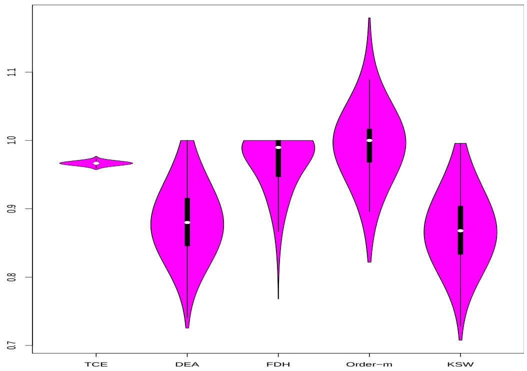


(f) S3, 95th percentile, n=200

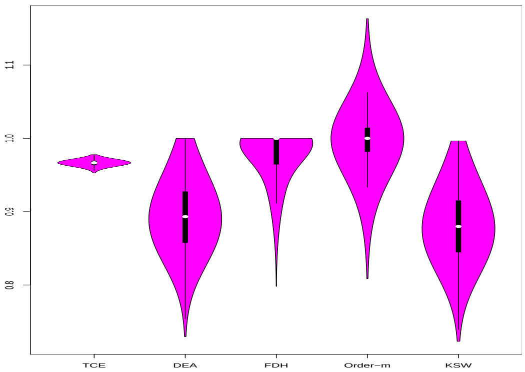
Figure 4.4: Distributions (violin plots) for scenario 4



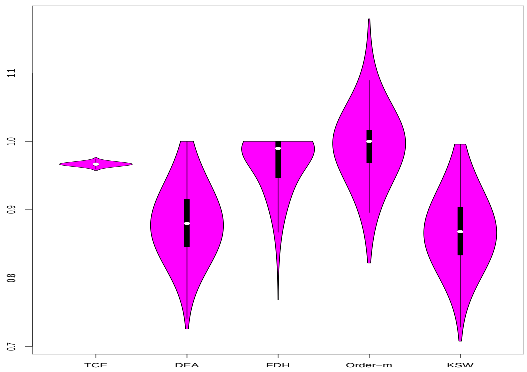
(a) S4, 5th percentile, n=100



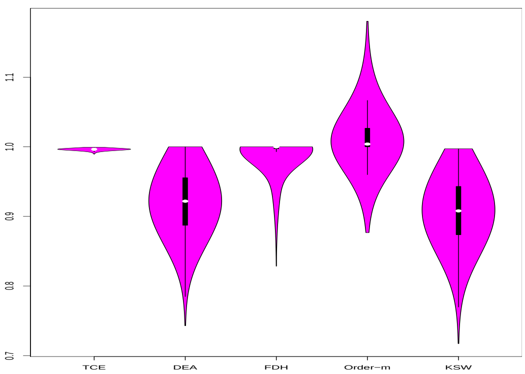
(b) S4, 50th percentile, n=200



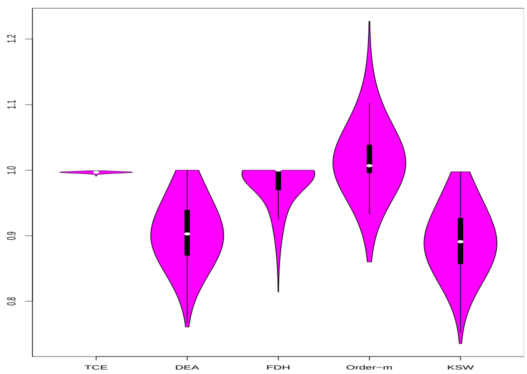
(c) S4, 50th percentile, n=100



(d) S4, 50th percentile, n=200

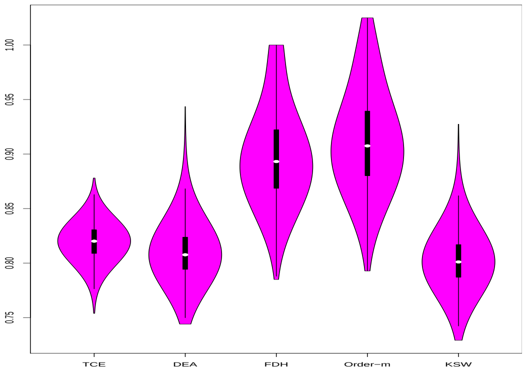


(e) S4, 95th percentile, n=100

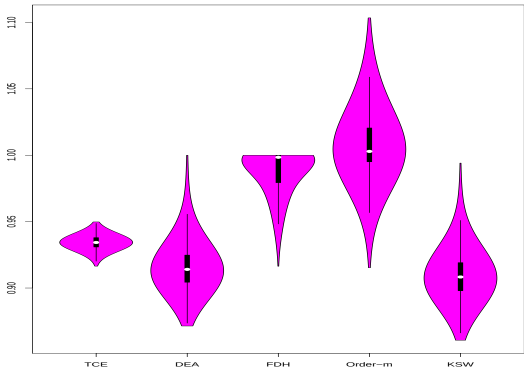


(f) S4, 95th percentile, n=200

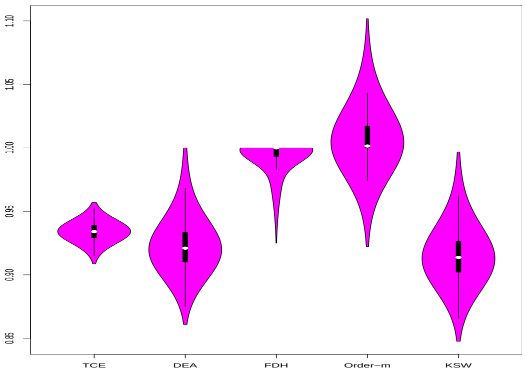
Figure 4.5: Distributions (violin plots) for scenario 5



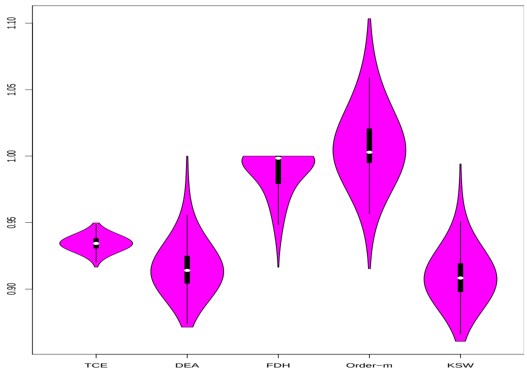
(a) S5, 5th percentile, n=100



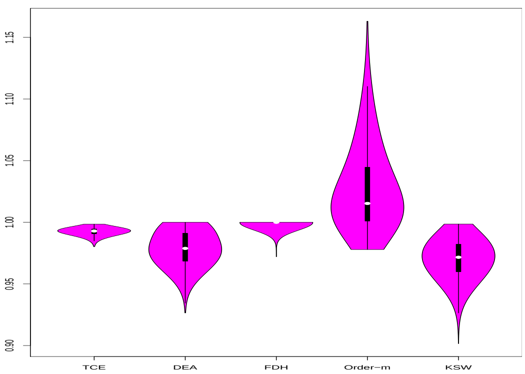
(b) S5, 50th percentile, n=200



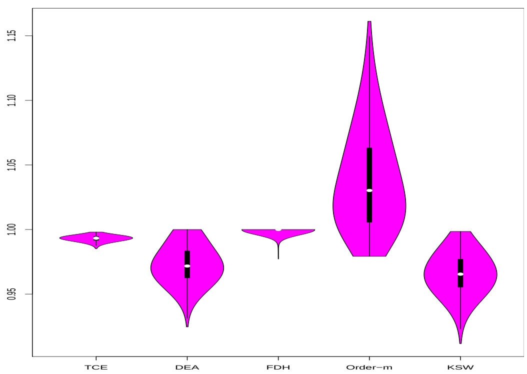
(c) S5, 50th percentile, n=100



(d) S5, 50th percentile, n=200

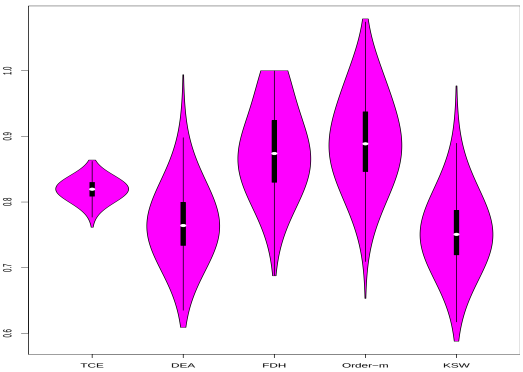


(e) S5, 95th percentile, n=100

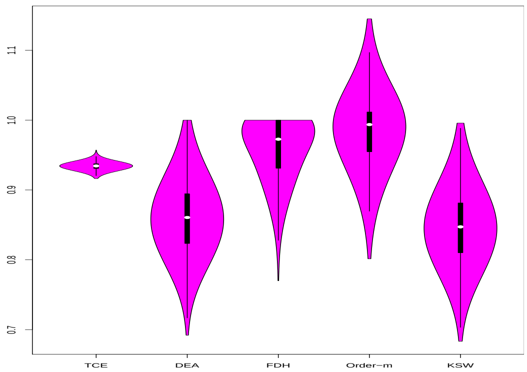


(f) S5, 95th percentile, n=200

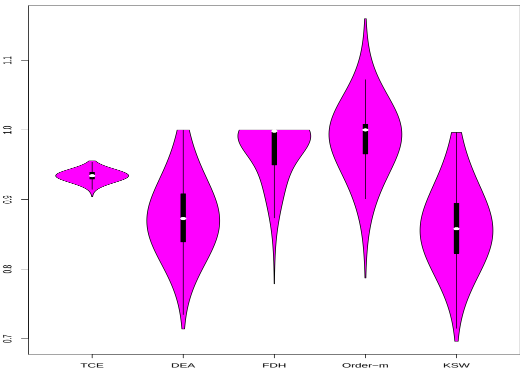
Figure 4.6: Distributions (violin plots) for scenario 6



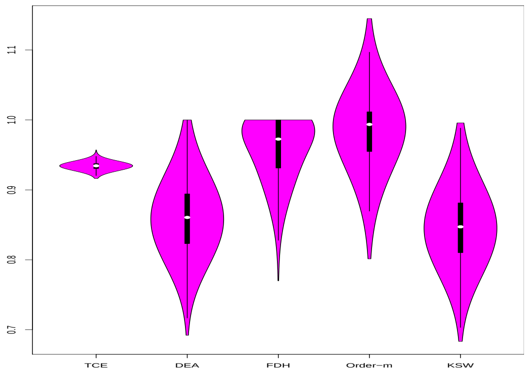
(a) S6, 5th percentile, n=100



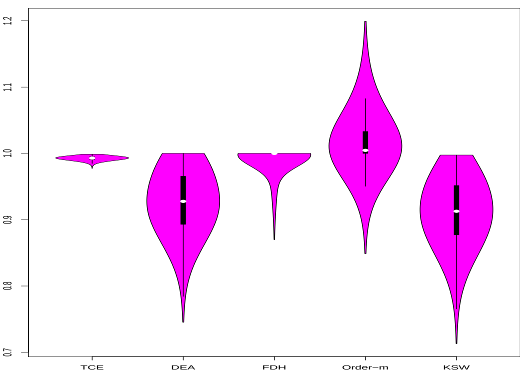
(b) S6, 50th percentile, n=200



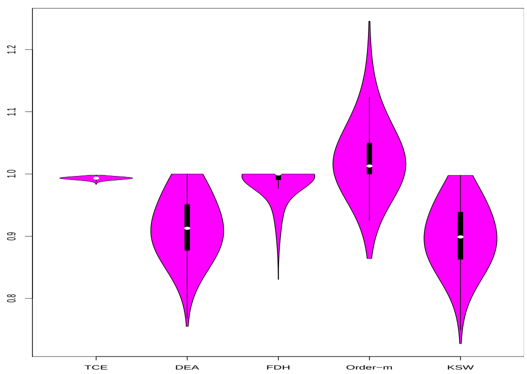
(c) S6, 50th percentile, n=100



(d) S6, 50th percentile, n=200



(e) S6, 95th percentile, n=100



(f) S6, 95th percentile, n=200

and KSW tend to underestimate the true efficiency scores, while FDH and order-*m* appear to be close to the TCE distribution (in terms of median values and mode). This scenario yields the poorest results as the dispersion of TCE is much more squeezed than the estimators' distributions. Therefore, when Λ is small, all four methodologies perform less well in predicting efficiency scores.

Scenario 3 (see Figures 4.3a, 4.3b, 4.3c, 4.3d, 4.3e and 4.3f), the error term is relatively small but the inefficiency term is relatively large. Because the Λ value has increased, all methodologies do better at predicting the efficiency scores. At the 5th and 50th percentiles, we observe that DEA and KSW underestimate efficiency, while order-*m* and FDH tend to overestimate it. However, if we consider the median and density modes, DEA (followed by KSW) is closer to the TCE distribution in both percentiles. At the 95th percentile FDH does better at estimating the efficient units, while DEA and KSW slightly underestimate efficiency and order-*m* slightly overestimates it.

In **scenario 5** (see Figures 4.3a, 4.3b, 4.3c, 4.3d, 4.3e and 4.3f), the error variation is relatively small but the inefficiency variation is very large. This scenario shows the most favourable results because the TCE distribution is highly dispersed and therefore better represents the estimators' performance. At the 5*th* and 50*th* percentiles DEA and KSW densities are very close to the true distribution of efficiency, while FDH and order-*m* overestimate it. In contrast, at the 95*th* percentile FDH seems to be closer to the TCE although it slightly overestimates it.

Finally, in **scenario 6** (see Figures 4.6a, 4.6b, 4.6c, 4.6d, 4.6f and 4.6e) the error term is relatively large and the inefficiency term is even larger. Again, we observe that when the variation of the inefficiency term increases (compared with scenarios 2 and 4), all the estimators perform better. At the 5*th* and 50*th* percentiles, DEA and KSW slightly underestimate efficiency and FDH and order-*m* slightly overestimate it (in terms of median values and density mode). However, despite all methods being quite close to the TCE distribution, DEA underestimates less than KSW, and FDH overestimates less than order-*m*. Finally, at the 95*th* percentile FDH (followed by order-*m*) is the best method to determine a higher number of efficient units because its mode and median values are closer to the true efficiency.

To sum up, in this subsection we have provided the baseline results for the relative performance of our four non-parametric methodologies. We have considered four median measures as well as other percentiles of the efficiency distribution. We found that the performance of the estimators vary greatly according to each particular scenario. However, we observe that both DEA and KSW consistently underestimate efficiency in nearlly all cases, while FDH and order-m tend to overestimate it. Moreover, we note that DEA and KSW perform best at identifying the ranks of the efficiency scores. In section 4.2.5 we will explain in greater detail which estimator to use in the various scenarios.

4.2.4. Robustness checks

We consider a number of robustness checks to verify that our baseline experiment represent the performance of our estimators. Tables with the results of the robustness checks are in Tables A.5 to A.9 of the appendix A.

- No noise (see table A.5): All our non-parametric estimators assume the absence of noise. However, in the baseline experiment we include noise in each scenario. In this situation, we consider the case where there is no noise in the data generating process. Results show that DEA and KSW perform better at predicting the efficiency scores, while FDH and order-m are slightly worse than the baseline experiment. All methods perform better at estimating the true ranks, except order-m in scenario 1. In short, we find that when noise is absent, DEA and KSW have a greater performance.

- Changes in sample size (see table A.6): The baseline experiment analyses two different sample sizes, n= 100 and 200. We also consider the case where the sample size is very large, that is, n= 500. There is a slight deterioration in the performance of DEA and KSW, while FDH and order-m vary depending on the scenario. However, the results only differed slightly. We find no qualitative changes from the baseline results.

- Returns to scale (see tables A.7 and A.8)): The baseline experiment assumes CRS technology. We also consider the case where the technology assumes decreasing and increasing returns to scale ($\gamma = 0.8$ and $\gamma = 1.2$). We find a slight deterioration in the performance of DEA and KSW estimators. Performance for order-m improves with decreasing returns to scale and deteriorates with increasing returns to scale, while FDH varies depending on the scenario. However, despite these minor quantitative differences, the qualitative results do not change.

- Different m values for order-m (see table A.9): Following Daraio and Simar's (2007a) suggestion, in order to choose the most reasonable value of m we considered different m sizes ($m = 20$, 30 and 40). In our application the baseline experiment sets $m = 30$. In general, compared with the other m values there are some quantitative changes (i.e., performance with $m = 20$ worsens, while with $m = 40$ it improves slightly); however, the qualitative results from the baseline case seem to hold.

In sort we find that after considering several robustness checks, we do not see any major differences from the baseline experiment. Therefore, despite the initial assumptions done, our simulations accurately depict the performance of our estimators.

4.2.5. Which estimator in each scenario

Based on the above comparative analysis of the four methodologies' performance, inspired by our results as well as Badunenko et al.'s (2012) proposal, we summarise which ones should be used in the various scenarios, assuming that the simulations remain true for different data generating processes. Table 4.3 suggests which estimators to use for each scenario when taking into account the efficiency scores. The first row in each scenario shows the relative magnitudes of the estimators compared with the True Cost Efficiency (TCE), while the rest of the rows suggest which estimators to use for each percentile (5th, 50th or 95th). In some cases the methodologies vary little in terms of identifying the efficiency scores.

Table 4.3: Relative performance of the efficiency scores at the 5*th*, 50*th* and 95*th* percentiles

	σ_u=**0.01**	σ_u=**0.05**	σ_u=**0.1**
σ_v=**0.01**	**scenario 1:** **KSW<DEA<TCE<FDH<order-*m*** 5: DEA or FDH 50: FDH 95: FDH	**scenario 3:** **KSW<DEA<TCE<FDH<order-*m*** 5: DEA 50: DEA 95: FDH	**scenario 5:** **KSW<DEA<TCE<FDH<order-*m*** 5: DEA 50: DEA 95: FDH
σ_v=**0.05**	**scenario 2:** **KSW<DEA<FDH<TCE<order-*m*** 5: order-*m* or FDH 50: order-*m* or FDH 95: order-*m* or FDH	**scenario 4:** **KSW<DEA<TCE<FDH<order-*m*** 5: DEA or FDH 50: order-*m* or FDH 95: order-*m* or FDH	**scenario 6:** **KSW<DEA<TCE<FDH<order-*m*** 5: DEA or FDH 50: DEA or FDH 95: order-*m* or FDH

Badunenko et al. (2012) conclude that if the Λ value is small, as in scenario 2 ($\Lambda = 0.2$), the efficiency scores and ranks will be poorly estimated.[10] This scenario yields the worst results, since the estimators are far from the "truth". Although Table 4.3 suggests scenario 2, we do not recommend efficiency analysis for this particular scenario, since it would be inaccurate.

Although scenarios 1 and 4 present better results than scenario 2 (when $\Lambda = 1$), estimators also perform poorly at predicting the true efficiency scores. In scenario 1, FDH seems to be the best method to estimate efficiency in all percentiles; however, DEA should also be considered at the 5*th* percentile (the TCE remains between DEA and FDH at this percentile). Similarly, in scenario 4 FDH predominates at the 5*th* percentile, although DEA should also be considered. On the other hand, both FDH and order-*m* perform better at the 50*th* and 95*th* percentiles. For efficiency rankings, DEA and KSW methodologies show a fairly good performance when ranking the observations in both scenarios.

Similarly, scenario 6 performs better than scenarios 1 and 4, since the variation of the inefficiency term increases and, as a consequence, the value of Λ also increases ($\Lambda = 2$). In this scenario the best methodologies for estimating the true efficiency scores seem to be DEA and FDH at the 5*th* and 50*th* percentiles, and FDH (followed by order-*m*) at the 95*th* percentile. In contrast, DEA and KSW methodologies are better at ranking the observations.

In scenario 3, the Λ value increases again ($\Lambda = 5$), and all the methodologies predict the efficiency scores more accurately. For the 5*th* and 50*th* percentiles, the closest estimator to the true efficiency seems to be DEA (followed by KSW). At the 95*th* percentile FDH is the best method. For the rankings, however, DEA and KSW provide more accurate estimations of the efficiency rankings.

Finally, scenario 5 has the largest Λ value ($\Lambda = 10$). Here, the estimators perform best at estimating efficiency and ranks. DEA (followed by KSW) performs better at the 5*th* and 50*th* percentiles and FDH at the 95*th* percentile. DEA and KSW excel at estimating the efficiency rankings.

[10] It is difficult to obtain the inefficiency from a relatively large noise component.

4.3. Results

Finally, in this section we identify the most appropriate methodologies to measure local government efficiency in Spain. First, we estimate Λ values for our particular dataset via Fan et al.'s (1996) non-parametric kernel estimator, hereafter FLW.[11] The estimated Λ value helps to determine in which scenario our data lies (see Table 4.1). Second, we refer to Table 4.3, check the recommendations for our scenario, and choose the appropriate estimators for our particular needs.

Table 4.4 reports results of the Λ parameters for our sample of 1,574 Spanish local governments for municipalities between 1,000 and 50,000 inhabitants for the 2008–2013 period (for further details, see output specification Model 1 from section 5.2.1 in chapter 3). The results of the Λ estimates range from 1.69 to 2.21, which are closer to 2 and correspond to scenario 6. Moreover, the goodness-of-fit measure (R^2) of our empirical data lies at around 0.8. The summary statistics for the overall cost-efficiency results averaged over all municipalities for each year are reported in Table 4.5. Figure 4.7 shows the violin plots of the estimated cost efficiencies for further interpretation of results.[12]

Table 4.4: Estimates to determine the scenario for Spanish local governments dataset

	2008	2009	2010	2011	2012	2013
Λ	2.0596	2.2143	1.7256	1.6953	1.8283	1.8371
R^2	0.7980	0.8331	0.8250	0.8244	0.8209	0.8478

In scenario 6, the DEA and FDH methods performed better than the others at the 5^{th} and 50^{th} percentiles of the distribution (the former slightly underestimates efficiency while the latter slightly overestimates it), and FDH (followed by order-*m*) performed better at the 95^{th} percentile. Therefore, the true efficiency would lie between the results of DEA and FDH both at the median and the lower percentiles, while FDH perform best at estimating the benchmark units. When using these results for performance decisions, local managers must be aware of which part of the observations are of particular interest and whether interest lies in the efficiency score or the ranking.

[11] In the appendix we describe how to obtain Λ measures via FLW derived from a cost function.
[12] For visual simplicity, we plot together years 2008–2013.

Table 4.5: Summary statistics for efficiency results in Spanish local governments

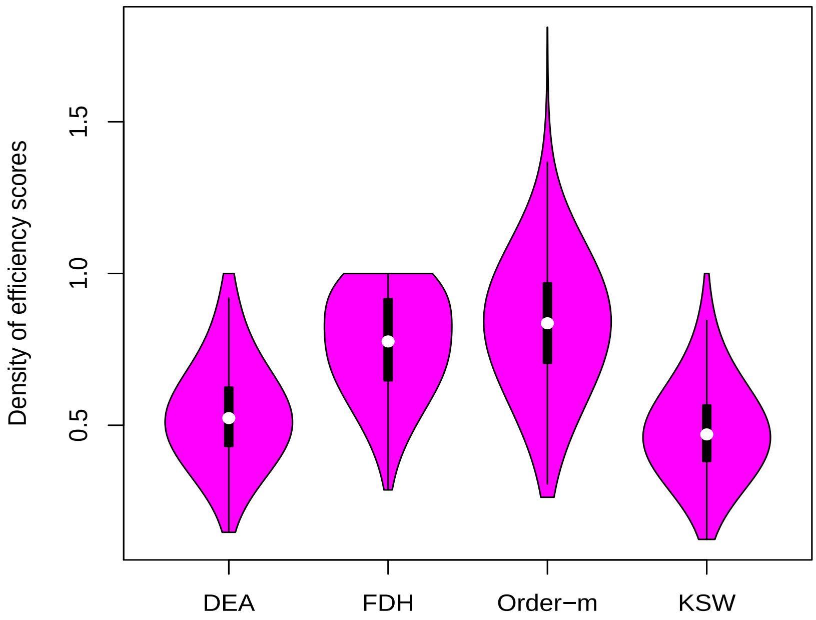
	DEA					
	Mean	**Median**	**Min**	**Max**	**Q1**	**Q3**
2008	0.4943	0.4689	0.0437	1.0000	0.3611	0.6038
2009	0.5843	0.5740	0.1257	1.0000	0.4633	0.6830
2010	0.5212	0.4953	0.1312	1.0000	0.4017	0.6135
2011	0.5314	0.5092	0.1359	1.0000	0.4104	0.6237
2012	0.5316	0.5128	0.1079	1.0000	0.4077	0.6429
2013	0.5712	0.5591	0.1138	1.0000	0.4458	0.6823
2008–2013	0.5390	0.5199	0.1097	1.0000	0.4150	0.6415

	FDH					
	Mean	**Median**	**Min**	**Max**	**Q1**	**Q3**
2008	0.7444	0.7678	0.0808	1.0000	0.5644	1.0000
2009	0.8186	0.8563	0.2045	1.0000	0.6821	1.0000
2010	0.7761	0.7848	0.1559	1.0000	0.6251	1.0000
2011	0.7453	0.7434	0.2037	1.0000	0.5808	0.9892
2012	0.7630	0.7737	0.1497	1.0000	0.6104	1.0000
2013	0.7619	0.7721	0.1497	1.0000	0.6104	0.9999
2008–2013	0.7682	0.7830	0.1574	1.0000	0.6122	0.9982

	Order-m					
	Mean	**Median**	**Min**	**Max**	**Q1**	**Q3**
2008	0.8089	0.8255	0.0834	1.9813	0.6312	1.0000
2009	0.8691	0.8926	0.2122	1.7369	0.7318	1.0013
2010	0.8385	0.8515	0.2172	1.8080	0.6938	1.0000
2011	0.8088	0.8100	0.2368	2.0281	0.6497	1.0000
2012	0.8222	0.8358	0.1797	1.8914	0.6644	1.0000
2013	0.8209	0.8328	0.1785	1.9204	0.6609	1.0000
2008–2013	0.8281	0.8414	0.1846	1.8944	0.6720	1.0002

	KSW					
	Mean	**Median**	**Min**	**Max**	**Q1**	**Q3**
2008	0.4421	0.4239	0.0400	1.0000	0.3183	0.5454
2009	0.5384	0.5297	0.1179	1.0000	0.4250	0.6370
2010	0.4541	0.4294	0.0563	1.0000	0.3420	0.5399
2011	0.4752	0.4558	0.1178	1.0000	0.3697	0.5558
2012	0.4677	0.4477	0.0134	1.0000	0.3503	0.5687
2013	0.4846	0.4711	0.0118	1.0000	0.3678	0.5848
2008–2013	0.4770	0.4596	0.0595	1.0000	0.3622	0.5719

Figure 4.7: Violin plots for the cost efficiency estimates in Spanish local governments (2008–2013)



In this context, DEA results indicate that the average cost efficiency during the period 2008–2013 at the central part of the distribution is 0.54, while the average in FDH is 0.77, so we expect the true cost efficiency scores to lie between 0.54 and 0.77. Moreover, average scores at the lowest quartile (Q1) are 0.42 in DEA and 0.61 in FDH, so we expect the true efficiency scores at the lower end of the distribution to lie between 0.42 and 0.61. Similarly, the average FDH scores at the upper quartile (Q3) are 0.99, so we expect these estimated efficiencies will be similar to the true ones.

The efficiency scores shown by KSW are smaller than those reported by DEA and FDH (the average efficiency scores in KSW for the period 2008–2013 are 0.36 for the lowest quantile (Q1), 0.48 for the mean and 0.57 for the upper quartile (Q3)). Based on our Monte Carlo simulations, we believe that KSW methodology consistently underestimates the true efficiency scores. In contrast, all the statistics estimated by order-m methodology are larger than those shown in DEA and FDH (the average efficiency scores in order-m for the period 2008–2013 are 0.67 for the lowest quantile (Q1), 0.83 for the mean and 1.00 for the upper quartile (Q3)). Therefore, the experiment leads us to understand that the order-m method overestimates the true efficiency scores.

As regards the rank estimates, note that in scenario 6, DEA and KSW methodologies performed best at identifying the ranks of the efficiency scores. Table 4.6 shows the rank correlation between the average cost efficiency estimates of the four methodologies for the period 2008–2013. As our Monte Carlo experiment showed, DEA and KSW have a high correlation between their rank estimates because of their similar distribution of the rankings. Accordindly, our results show a relatively high correlation between the rank estimates of these two estimators (0.90). Moreover, although there is a relatively high correlation between order-m and FDH rank estimates with DEA and KSW, the latter two outperform order-m and FDH. As a consequence, DEA and KSW estimators would be preferred to identify the efficiency rankings, but order-m and FDH will not necessarily produce poor efficiency rankings.

Table 4.6: Rank correlation Kendall coefficients between the average cost efficiency estimates of all methodologies for the period 2008–2013

	DEA	**FDH**	**Order-*m***	**KSW**
DEA	1.0000	0.6687	0.6463	0.9004
FDH	0.6687	1.0000	0.7755	0.6136
Order-*m*	0.6463	0.7755	1.0000	0.5801
KSW	0.9004	0.6136	0.5801	1.0000

4.4. Conclusion

Over the last years, many empirical research studies have set out to evaluate efficiency in local governments. However, despite this high academic interest there is still a lack of a clear, standard methodology to perform efficiency analysis. Since there is no obvious way to choose an estimator, the method chosen may affect the efficiency results, and could provide "unfair" or biased results. In this context, if local regulators take a decision based on an incorrect efficiency score, it could have relevant economic and political implications. Therefore, we note that each methodology leads to different cost efficiency results for each local government, but one method must provide efficiency scores that will be more reliable or closer to the *truth* (Badunenko et al., 2012).

In this setting, the current chapter has attempted to compare four different non-parametric estimators: DEA, FDH, order-m and KSW. All these approaches have been widely studied in the previous literature, but little is known about their performance in comparison with each other. Indeed, no study has compared these efficiency estimators. In contrast to previous literature, which has regularly compared techniques and made several proposals for alternative ones, we followed the method applied in Badunenko et al. (2012) to compare the different methods used via Montecarlo simulations and choose the ones which performed better with our particular dataset, in other words, the most appropriate methods to measure local government cost efficiency in Spain.

Our data included 1,574 Spanish local governments between 1,000 and 50,000 inhabitants for the period 2008–2013. Note that, as stated in chapters 1 and 3, the period considered is also important, since the economic and financial crisis that started in 2007 has had a huge impact on most Spanish local government revenues and finances in general. Under these circumstances, identifying a method for evaluating local governments' performance to obtain reliable efficiency scores and set benchmarks over time is even more important, if possible.

In general, we have observed that there is no approach suitable for all efficiency analysis. When using efficiency results for policy decisions, local regulators must be aware of which part of the efficiency distribution is of particular interest (for example, identifying benchmark local governments might be important to decide penalty decisions to poor performers) and if the interest lies in the efficiency scores or the rankings, i.e., it should be considered where and when to use a particular estimator. It is obvious that obtaining reliable efficiency scores might have some implications for local management decisions. Therefore, gaining deeper insights into the issue of local government inefficiency might help to further support effective policy measures, both those that might be appropriate as well as those that are not achieving the their objectives.

We learn that, for our sample of Spanish local governments, all methods showed some room for improvement in terms of possible cost efficiency gains, although some differences in the inefficiency levels obtained were also present. The methodologies which perform better with our sample of Spanish local governments are the DEA and FDH methods at the median and lower tail of the efficiency distribution (the former slightly underestimates efficiency while the latter slightly overestimates it), and FDH (followed by order-m) for local governments with higher performance, according to the findings in our simulations. Specifically, the results suggested that the average true cost efficiency would range between 0.54 and 0.77 during the period 2008–2013, suggesting that Spanish local governments could achieve the same level of local outputs with between 23% and 36% fewer resources. Similarly, the true efficiency scores at the lowest quantile would lie between 0.42 and 0.61, and at the upper quartile would be around 0.99. Further, DEA and KSW methodologies performed best at identifying the ranks of the efficiency scores.

The obtained results provide evidence as to how efficiency could certainly be assessed as close as possible in order to provide some additional guidance for policy makers. In addition, these results are particularly important given the overall financial constraints faced by Spanish local governments during the period under analysis, which have come under increasing pressure to meet strict budgetary and fiscal constraints without reducing their provision of local public services. Therefore, identifying accurately efficiency gains might help to limit the adverse impact of spending cuts on local governments' service provision.

We also note that the effects on the methodological choice identified in this paper might be valid only for our sample dataset. However, the analytical tools introduced in this study could have significant implications for researchers and policy makers which analyse efficiency using data from different countries. From a technical point of view, our results are obtained using a consistent method, which provides a significant contribution to previous literature in local governments efficiency. We emphasize that few studies from this literature have attempted to use two or more alternative approaches in a comparative way. Therefore, from a policy perspective one should take care when interpreting results and drawing conclusions from these research studies that have used only one particular methodology, since their results might be affected by the approach taken. We think that the implementation of our proposed method to compare different efficiency estimators would represent an interesting contribution that provides the opportunity for further research in this particular issue, given the lack of a clear and standard methodology to perform efficiency analysis.

Chapter 5

Explaining differences in local governments' cost efficiency: An instrumental variable quantile regression approach

5.1. Introduction

Efficiency analysis allows to assess whether local authorities are managing properly their available resources to provide the best possible local services and facilities. However, municipalities face different environmental conditions in terms of social, demographic, economic, political or financial, among others (Da Cruz and Marques, 2014). As efficiency may be affected not only by inadequate management but also by these external or environmental factors beyond the control of local managers, some municipalities may be unable to achieve the "best-practice" due to their relative harsh environment (Afonso and Fernandes, 2008). Therefore, performance analysis should control for this heterogeneity (Balaguer-Coll et al., 2007), otherwise policy-makers would lead to biased efficiency results which might carry wrong policy decisions. Accordingly, as stated by De Witte and Kortelainen (2013), efficiency estimations which do not account for the effect of the operational environment have only a limited value. The present chapter takes one step to address the latter question by analysing local governments' cost efficiency while explicitly accounting for external or environmental influences that might affect municipalities' performance.

Scholars have proposed different ways to incorporate external or environmental variables in non-parametric efficiency analysis. Following De Witte and Kortelainen (2008), we can consider different families of models, including methods based on the two-stage approach –such as Tobit censored regression model, OLS or the bootstrap approaches of Simar and Wilson, 2007–, the meta-frontier approach or the conditional efficiency models (Cazals et al., 2002).[1] All these procedures only estimate the mean of a response variable, conditional on the values of the explanatory variables (Abdelsalam et al., 2014), which means that they only provide information on the average impact of the determinants of local governments' efficiency. However, there is no reason why the impact should be the same over the entire efficiency distribution, since the effect of the environmental variables in local governments' efficiency could vary for the best to the worst performers. Under these circumstances, the use of different measures of central tendency and statistical dispersion to obtain a more comprehensive analysis of the relationship between variables might be more appropriate.

In this study we implement quantile regression models controlling for the likely existence of endogeneity among regressors, to date barely contemplated in the efficiency analysis setting.[2] In contrast to previous two-stage initiatives, this technique provides a more complete view as it considers the effect of the explanatory variables across different quantiles of the distribution of the response variable, that is, it provides information on the impact of the environmental variables on local governments' efficiency according to the differing levels of efficiency. In addition, this procedure allows to control for the possible endogeneity from "reverse causation" of some of

[1]The most popular techniques to include environmental variables in local governments' cost efficiency literature are Tobit censored regression model and OLS (see section 2.6 in chapter 2).

[2]The study of Abdelsalam et al. (2014) used quantile regression to analyse the relative performance of socially responsible investment and Islamic mutual funds. In this paper, we go one step forward since we also consider the presence of possible endogenous variables by using instrumental variable quantile regression.

our explanatory variables using instrumental variables.[3] Endogenous variables lead to inconsistencies in the model estimates since they are correlated with unobserved factors affecting the response variable. However, despite its relevance, the endogeneity problem has received little attention in local government efficiency literature, since past studies have interpreted their results in a causal way, neglecting the endogeneity issues in the data (this problem from previous literature has been earlier discussed in chapter 2).

In this setting, we contribute to the literature by combining several non-parametric methodologies in the first stage –namely DEA, FDH, the order-*m* partial frontier and KSW– with instrumental variable quantile regression in the second stage. We note that some previous researchers (Simar and Wilson, 2007, 2011) expressed their concern about using conventional models such as OLS or Tobit for the second stage regressions when analysing the determinants of efficiencies obtained in a first using techniques such as DEA or FDH.[4] However, our procedure offers a great advantage since it facilitates analyses of the impact of determinants of local governments' cost efficiency across different quantiles taking into account the presence of possible endogenous explanatory variables. Moreover, this method is more robust to departures from normality.

In addition, as regards of the efficiency estimator selection problem earlier considered in previous chapters, the present chapter also contributes to the literature by providing a comparative perspective using different methodologies to measure efficiency in the first stage. Comparing the results from different models gives a more complete view of the impact of the environmental variables over efficiency, while at the same time testing the robustness of our results. Accordingly, if the set of significant explanatory variables is robust across various methods, then the inefficiency analysis is not subject to manipulation and provides useful information to policy-makers (De Borger and Kerstens, 1996a).

[3]Note that endogeneity can arise as a result of different sources: measurement error, autoregression with autocorrelated errors, simultaneous or reversed causality and omitted variables. In this study we focus on simultaneous or reversed causality, which implies a loop of causality between the independent and dependent variables of a model.

[4]We will further discuss some theoretical limitations of the different methods to explain inefficiency.

We perform the analysis for a sample of 1,499 Spanish local governments between 1,000 and 50,000 inhabitants for the period 2009–2013. As stated in previous chapters, issues related to the study of Spanish public institutions, and particularly in Spanish local governments, have gained relevance since the beginning of the economic and financial crisis that started in 2007/2008. In addition, given how problematic it is to define the bundle of services and facilities that municipalities must provide, we consider two alternative output models in order to assess whether different choices might explain variations among local governments, and to determine how the number of outputs can affect efficiency scores. We use a comprehensive database, which includes measures of both quantity and quality of the services and facilities provided (for further details, see output specification Models 1 and 3 from section 5.2.1 in chapter 3).

Finally, another contribution of the study is related to our selection of determinants. In local governments' efficiency applications, the selection of the environmental variables is not an easy task, a common problem from previous literature earlier discussed in chapter 2. The inclusion of environmental factors in previous empirical efficiency studies often lacks structure (Da Cruz and Marques, 2014) and most studies do not explain the estimated inefficiencies in a systematic way, since there is no well-established theory as to which variables constitute the "environmental conditions" that might impact on each municipality's cost structure (Balaguer-Coll et al., 2013). In this chapter, we use a comprehensive dataset of environmental variables which includes different categories in order to facilitate the interpretation of the empirical results. Our selection is based on previous literature, the availability of data and the institutional framework of local governments in Spain.

Our results show an asymmetry regarding the determinants of efficiency for the best and worst local governments. On the one hand, for the best local governments, performance is a result not only of their managers' skills but also other factors related to their environment, such as the unemployment rate, the citizens' disposable income, the tourist index and political concentration. On the other hand, for the worst local governments' performers their poor performance would be a consequence of the factors explaining their efficiency, such as tax revenues, the debt levels, transfers from higher levels of government, share of retired people or the electoral participation.

The chapter is organised as follows: section 5.2 presents the methodologies, the data employed in measuring efficiency, and results. Section 5.3 sets the environmental or explanatory variables for efficiency and the model to include the environmental variables in the second-stage analysis, together with the results. Finally, section 5.4 summarises the main conclusions.

5.2. Dependent variable: efficiency measures for Spanish municipalities

In a first stage, we compute the relative efficiency scores in Spanish local governments by implementing the four non-parametric estimation techniques previously explained in chapter 3 (see section 3.2.), namely DEA, FDH, the order-m partial frontier and KSW.

5.2.1. Sample, inputs and outputs

We carry out the analysis for a sample of Spanish local governments between 1,000 and 50,000 inhabitants for the 2009–2013 period. The final sample contains 1,499 municipalities for every year (representing 19.47%), after eliminating all the municipalities with unavailable data on inputs and outputs for the period 2009 to 2013. For further details about the sources used, particularities of the data and the selection of input and output variables, see section 5.2.1 in chapter 3. Table 5.1 shows the descriptive statistics for inputs and outputs for the period 2009–2013. We include the median rather than the mean to avoid distortion from outliers.

In addition, following the output specification models defined in section 3.3.3 in chapter 3, we consider different output models in order to assess whether the different choices might explain the differences between local governments, and to determine how the number of outputs can affect the efficiency scores. Specifically, we use output specification Model 1, which includes 6 output variables (i.e., the minimum services compulsory for all governments), and output specification Model 3, a more complete

Table 5.1: Descriptive statistics for inputs and outputs (2009–2013)

	Mean	S.d.
Inputs[a]		
Total costs (X_1)	6,883,465.89	8,039,103.09
Outputs		
Total population (Y_1)	7,582.21	8,501.24
Street infrastructure surface area[b](Y_2)	342,307.42	330,272.66
Number of lighting points (Y_3)	1,540.41	1,615.00
Tons of waste collected (Y_4)	3,803.01	12,373.95
Length of water distribution networks[b](Y_5)	50,596.02	90,175.24
Length of sewer networks[b](Y_6)	30,298.90	33,118.83
Public parks surface area[b](Y_7)	91,372.20	567,860.52
Public library surface area[b](Y_8)	373.48	1,807.78
Market surface area[b](Y_9)	93,238.14	526,126.86
Sport facilities surface area[b](Y_{10})	4,040.65	10,889.28

[a] In thousands of euros.
[b] In square metres.

model which includes 10 output variables taking into account quality measures (i.e., the minimum services compulsory for all governments and additional services which must provide larger municipalities with population of over 5,000 to 20,000 taking into account the quality of the services provided weighted by their quantity).

5.2.2. Efficiency results

We estimate cost efficiency of the provision of local services and facilities for 1,499 Spanish municipalities for the 2009–2013 period using the four non-parametric methodologies explained in the previous sections. Overall cost-efficiency results averaged over all municipalities for each year in output specification Models 1 and 3 are presented in table 5.2 and 5.3, respectively. They show summary statistics, including apart from the mean and the standard deviation, additional statistics which provide further insights on the different parts of the efficiency distributions. Note that we report results for two different output models in order to assess whether different choices might contribute to explain the variations between local governments, and to determine how the number of outputs can affect the efficiency scores.

Table 5.2: Summary statistics for efficiency results for the period 2009–2013, output specification Model 1[a]

DEA estimator						
Year	Mean	1st quantile	Median	3rd quantile	S.d.	% of efficient municipalities
2009	0.5841	0.4630	0.5743	0.6821	0.1679	2.6017
2010	0.5275	0.4039	0.5015	0.6188	0.1757	2.2682
2011	0.5353	0.4125	0.5140	0.6277	0.1754	2.5350
2012	0.5331	0.4094	0.5136	0.6433	0.1754	1.9346
2013	0.5727	0.4486	0.5602	0.6832	0.1819	2.8686
FDH estimator						
Year	Mean	1st quantile	Median	3rd quantile	S.d.	% of efficient municipalities
2009	0.8179	0.6815	0.8561	1.0000	0.1846	32.6217
2010	0.7821	0.6315	0.8001	1.0000	0.1942	26.8179
2011	0.7482	0.5839	0.7488	0.9988	0.2107	24.9500
2012	0.7650	0.6115	0.7763	1.0000	0.2080	26.0173
2013	0.7646	0.6126	0.7757	1.0000	0.2063	25.8839
Order-m estimator						
Year	Mean	1st quantile	Median	3rd quantile	S.d.	% of efficient municipalities
2009	0.8660	0.7282	0.8922	1.0011	0.1992	36.1574
2010	0.8394	0.6933	0.8611	1.0000	0.2014	30.2201
2011	0.8103	0.6546	0.8128	1.0000	0.2177	28.0187
2012	0.8218	0.6652	0.8365	1.0000	0.2159	29.5530
2013	0.8219	0.6624	0.8367	1.0000	0.2168	29.4863
KSW estimator						
Year	Mean	1st quantile	Median	3rd quantile	S.d.	% of efficient municipalities
2009	0.5374	0.4246	0.5296	0.6340	0.1579	0.0000
2010	0.4634	0.3448	0.4382	0.5513	0.1666	0.0000
2011	0.4774	0.3686	0.4557	0.5653	0.1592	0.0672
2012	0.4755	0.3581	0.4568	0.5792	0.1666	0.0000
2013	0.5306	0.4073	0.5239	0.6412	0.1740	0.0000

[a] This model includes minimum services compulsory for all governments (6 outputs variables from Y_1 to Y_6).

Table 5.3: Summary statistics for efficiency results for the period 2009–2013, output specification Model 3[a]

DEA estimator						
Year	Mean	1st quantile	Median	3rd quantile	S.d.	% of efficient municipalities
2009	0.5926	0.4672	0.5804	0.6935	0.1732	3.5357
2010	0.5448	0.4173	0.5166	0.6405	0.1833	3.6691
2011	0.5519	0.4232	0.5265	0.6525	0.1831	3.8025
2012	0.5580	0.4254	0.5396	0.6669	0.1859	3.4023
2013	0.5924	0.4607	0.5775	0.7106	0.1894	4.8699
FDH estimator						
Year	Mean	1st quantile	Median	3rd quantile	S.d.	% of efficient municipalities
2009	0.9159	0.8825	1.0000	1.0000	0.1513	65.5103
2010	0.9190	0.8956	1.0000	1.0000	0.1488	66.6444
2011	0.9182	0.8907	1.0000	1.0000	0.1499	66.4443
2012	0.9181	0.8909	1.0000	1.0000	0.1498	65.5771
2013	0.9175	0.8825	1.0000	1.0000	0.1476	64.9767
Order-*m* estimator						
Year	Mean	1st quantile	Median	3rd quantile	S.d.	% of efficient municipalities
2009	0.9484	0.9145	1.0000	1.0018	0.1617	66.7779
2010	0.9562	0.9267	1.0000	1.0039	0.1676	67.9787
2011	0.9576	0.9234	1.0000	1.0043	0.1710	67.8452
2012	0.9551	0.9216	1.0000	1.0033	0.1676	66.7779
2013	0.9555	0.9157	1.0000	1.0038	0.1669	66.4443
KSW estimator						
Year	Mean	1st quantile	Median	3rd quantile	S.d.	% of efficient municipalities
2009	0.4987	0.3630	0.4822	0.6194	0.1837	0.0000
2010	0.4928	0.3542	0.4762	0.6100	0.1852	0.0000
2011	0.4975	0.3634	0.4787	0.6062	0.1801	0.0000
2012	0.4825	0.3555	0.4611	0.5875	0.1774	0.0000
2013	0.5336	0.4037	0.5237	0.6483	0.1802	0.0000

[a] This model includes minimum services compulsory for all governments and additional services that must be provided by larger municipalities with populations of over 5,000 and 20,000 taking into account service quality (10 output variables from Y_1 to Y_{10} weighted by their quality).

DEA results in output specification Model 1 indicate that the mean cost efficiency during the period 2009–2013 ranges from 0.52 to 0.58. Similarly, the results for the first quartile (which include the worst performers) range from 0.40 to 0.46, while for the third quartile (which include the best performers) range from 0.61 to 0.68. We observe that, out of the 1,499 municipalities, only from 1.93% to 2.60% are found totally efficient (i.e., with efficiency scores of 1). When comparing FDH results with DEA, the number of efficient local governments in FDH increases (they range from 24% to 32%) due to the removal of the convexity assumption underlying DEA. As a consequence, the efficiency scores in all parts of the distribution are also higher. In addition, we note that the increase in the number of outputs from Model 1 to Model 3 implies higher efficiency scores for both DEA and FDH methodologies, since these estimators notoriously suffer from the "curse of dimensionality" (see Daraio and Simar (2007a), for further discussion). Also we observe that for the FDH case in output specification Model 3, from the median onwards all local governments are efficient, however, this trend is not surprising given the characteristics of FDH. This implies that, despite FDH method is more flexible than DEA, it has difficulties for both discriminating and ranking the observations (i.e., relative ordering of municipalities) according to their performance (Abdelsalam et al., 2014).

A comparison of DEA and KSW results shows that the cost efficiency scores using KSW are lower than those obtained with the DEA approach in all parts of the efficiency distribution and both output models. Moreover, under KSW most local governments are found to be inefficient (i.e., we observe 0% of efficient local governments in most of the years analysed). By construction, KSW methodology takes the standard DEA estimator to correct its bias and, as a consequence, municipalities considered as efficient when using DEA are considered inefficient in KSW because their bias has been corrected (i.e., the units could be very close to an efficiency score of 1, but they are no longer considered efficient). This means that KSW methodology is therefore useful for ranking municipalities but not for identifying the benchmark units.

Finally, the order-*m* approach yields higher efficiency scores and percentages of efficient units than all the other methods (the average cost efficiency ranges from 0.81 to 0.86 and the percentage of efficient units from 28% to 36%). This trend is actually expected if one takes into account that the results obtained by order-*m* are not bounded by 1, and a value greater than 1 indicates super-efficient units. Note that the order-*m* is more robust to extreme values and outliers, giving more prudent[5] results than DEA, FDH and KSW. Therefore, given these characteristics, the order-*m* approach partly overcome the difficulties from FDH and KSW for ranking the efficient local governments. In addition, we note that for the order-*m* case in output specification Model 3, from the median onwards all local governments are efficient or super-efficient. However, in contrast to FDH approach, the method allows to discriminate and ranking the units according to their performance due to the presence of super-efficient local governments whose efficiencies are leading to values above unity.

The descriptive analysis presented above, based on summary statistics, suggest that a quantile regression approach might add statistical robustness to these initial ideas. Moreover, despite some discrepancies are observed on comparing the results yielded by the different methods and models (output specifications), in general we observe that every combination shows some room for improvement. However, these efficiency estimations have not taken into account the effect of the environmental or exogenous factors that influence the observed efficiency and consequently they would have only a limited value. We address these issues in the following sections.

5.3. Explaining inefficiency

After the efficiency analysis yielded in the first-stage, we focus on analysing the effect of a set of environmental variables on efficiency. The four non-parametric models before only incorporate controllable inputs. However, municipalities face different external or environmental factors which can have a huge impact on the efficiency scores, so performance analysis should control for this heterogeneity. Accordingly, a second-stage analysis is called for, as efficiency results may be affected not only by

[5] The order-*m* estimator do not envelope all data points and consequently both the identification of the efficient units and the estimated efficiency scores are not affected by outliers or extreme values.

inadequate management but also by exogenous factors beyond the control of each local government (Balaguer-Coll et al., 2007). As we will see, two-stage procedures present some theoretical limitations, however, our procedure offers significant advantages given that it allows to control the possible endogeneity issues but, more important, it provides a specific analysis for each particular quantile of the performance distribution.

5.3.1. Environmental variables

Our selection of determinants is based on previous literature, the availability of data and the institutional framework of local governments in Spain. Specifically, we have chosen 12 variables to include in the analysis.[6] In line with the classification proposed in chapter 2 for the different type of determinants that may affect the local performance, we classify the observed variables in four main categories: social and demographic, economic, political, and financial.

In our search for environmental variables we considered the information provided by different institutions. Data on different financial variables, such as tax revenues, transfers or grants and outstanding debt, comes from the Spanish Ministry of the Treasury and Public Administrations (*Ministerio de Hacienda y Administraciones Públicas*) and correspond to the years from 2009 to 2013; while political variables, such as political sign, political concentration and voter turnout, were computed by the authors using data from the Spanish Home Office (*Ministerio del Interior*) and refer to the 2007 and 2011 municipal elections. We also considered information regarding the citizen's disposable income provided by the L.R. Klein Institute[7], and the variables unemployment and tourist index, which comes from the Economic Yearbook of La Caixa[8]. Finally, we included socio-demographic variables, such as population density, retired people and immigrants, which come from the Spanish Statistical Office (*Instituto Nacional de Estadística, INE*), years from 2009 to 2013.

[6]Note that initially we had 19 variables. However, after testing multicollinearity using the variance inflation factor (VIF), we found that dummies for population size (medium, large), population growth, deficit, economic activity index, and the commercial and industrial activity index were highly correlated.

[7]An Economic Institute called *Instituto de Predicción Económica "Lawrence R. Klein"* which depends on the Autonomous University of Madrid.

[8]An annual report called *Anuario Estadístico de La Caixa*, provided until September 2016 by the Spanish savings bank, *La Caixa*.

Summary statistics for the environmental variables are reported in Table 5.4. In addition, the particular definition of each variable considered and the possible impact on efficiency are commented on below (see section 2.7 in chapter 2 for an accurate summary for the impact that all these environmental variables had over efficiency in previous literature):

Social and demographic determinants

- Population density ($DENS$) is measured as the total population of each municipality divided by its extension (expressed in squared kilometres). A common intuition is that higher population density may entail economies of scale to provide public services and, as a consequence, it would increase efficiency. However, a higher population concentration also could increase the cost of providing public services given the problems of agglomeration and higher complexity (Kalb et al., 2012), so it would affect negatively to efficiency.
- Retired people (RET) represents the number of inhabitants over 65 years old in each municipality divided by the total population. This population group can exercise greater control over local governments performance because they take part in organizations of local nature (Bosch-Roca et al., 2012). However, the relation between this variable and efficiency could be also negative since retired people are less likely to use social and recreational services (such as, primary schools, public sports facilities, parks or playing fields) and could be less interested in local governments' performance.
- Immigrants ($IMMIG$) represents the share of foreign inhabitants over total population in a municipality. This variable is expected to decrease cost efficiency because this population group does not have the right to vote (Bosch-Roca et al., 2012) or are less interested in politics (Bruns and Himmler, 2011).

Table 5.4: Descriptive statistics for determinants of efficiency (2009–2013)

Variable name	Variable description	**Mean**	**S.d.**
Population density (*DENS*)	Total population/ Total extension (in squared kilometres)	279.30	1041.52
Retired people (*RET*)	% Population 65 years and above/Total population	0.21	0.07
Immigration share (*IMMIG*)	% Foreign inhabitants/Total population	0.09	0.10
Unemployment (*UNEMP*)	% Unemployed population/ Working population	13.27	4.48
Citizen's disposable income (*INC*)	Disposable income per capita	12.09	2.07
Tourist index (*TOUR*)	Index capturing importance of tourism	0.02	0.13
Political sign (*SIGN*)	Municipal government's ideological position	0.40	0.09
Political concentration (*CONCEN*)	Councillors from each party represented in each local council	0.51	0.50
Voter turnout (*VOTE*)	% participation of the citizens entitled to vote in local elections	76.54	8.42
Tax revenues (*TAX*)	Tax revenues/ Total population	451.41	254.94
Transfers or grants (*GRANTS*)	Grants received/ Total population	494.19	249.69
Outstanding debt (*DEBT*)	Financial liabilities at the financial year/ Total population	0.96	2.39

Economic determinants

- Unemployment ($UNEMP$) represents the share of unemployed people over the working population of each municipality. More unemployment could imply higher spending on social benefits ("cost effect"), so it would decrease efficiency (Kalb et al., 2012). Nevertheless, unemployment could entail a lower demand for high-cost or high-quality public services given the lower purchasing power of unemployed people ("preference effect"), so it will be expected to increase efficiency (Kalb, 2010).

- Citizen's disposable income (INC) is the economic level per capita measured for each municipality. Higher-income citizens might pay greater taxes and, as a consequence, they will exert a higher control on local performance (Balaguer-Coll et al., 2013), leading to higher efficiency levels. However, if local governments have higher financial resources (because they collect higher incomes), interest of the politicians in reaching efficiency in the provision of local services and facilities could be reduced. In addition, citizens from high income municipalities may be less motivated to monitor expenditures (Bosch-Roca et al., 2012). So, it could be negatively related to efficiency as well.

- Tourist index ($TOUR$) indicates the importance of the tourist activity of each municipality. Its value indicates each municipality's share (out of 100,000) of total national economic activities revenues related to tourism ("Impuesto de Actividades Económicas"). Seasonal population could have an impact on the provision of services because local governments must face higher investments during some periods of the year (Da Cruz and Marques, 2014). Moreover, tourists have a greater demand for higher quality public services that increase the costs (Kalb et al., 2012). Hence, we will expect a negative relation to efficiency. However, a higher tourist activity could entail a lower cost excess and thus higher levels of efficiency would be obtained.

Political determinants

- Political sign ($SIGN$) represents the municipal government's ideological position. It is a dummy variable which takes values 0 and 1 representing left-wing and right-wing parties, respectively. The basic hypothesis is that left-wing parties prefer a larger public sector which, in general, is associated with low efficiency levels (Ashworth et al., 2014).

- Political concentration ($CONCEN$) measures the number of councillors from each party represented in each local council. We use the Herfindahl index as indicator of political concentration which takes value between 0 and 1, with higher values indicating a higher degree of political concentration (or a lower degree of political fragmentation) and therefore a higher degree of political strength (or lower degree of competition). It is calculated as:

$$\sum_{i=1}^{n} c_i^2 / (\sum_{i=1}^{n} c_i)^2 \tag{5.1}$$

  where c_i is the number of city councillors of party i, and n is the number of parties in the local government.

  When the degree of political concentration and political strength are higher, there exist a lower political opposition and it is easier to implement policies and impose budget constraints (Borge et al., 2008), so it is expected to increase efficiency. Nevertheless, a low political competition makes more difficult to other parties to effectively control expenditures and therefore efficiency can be reduced (Ashworth et al., 2014).

- Voter turnout ($VOTE$) represents the political participation of the citizens entitled to vote in local elections. This variable affects the degree of control that inhabitants can exercise over politicians with their votes in local elections (Geys et al., 2010), so it is expected to increase local government efficiency. However, it could also have a negative correlation with efficiency given that lower levels of local governments' efficiency could also motivate more citizen participation

(Asatryan and De Witte, 2015).

Financial determinants

- Tax revenues (TAX) per capita are the total amount of taxes and fees collected by each local government divided by its number of inhabitants. We may hypothesize that local governments which are more able to generate revenues (by collecting higher taxes) are less motivated to manage them properly (Balaguer-Coll et al., 2007). In addition, these local governments will have good service provision even if they are not efficient. Therefore, we will expect a negative impact on efficiency. Nevertheless, higher taxes could increase citizen control on public management, so it will be expected to increase efficiency (De Borger and Kerstens, 1996a).
- Transfers or grants ($GRANTS$) per capita represents the municipal revenues which come from higher levels of government, divided by population. Local governments which have greater security in obtaining resources via grants may be less efficient because politicians will take less care in managing them adequately. Moreover, there will be less citizen control over public management because the cost of inefficient performance is shared by regional and national taxpayers (Balaguer-Coll et al., 2007). Hence, we will expect a negative association with efficiency. On the contrary, this variable could be positively related to efficiency, since obtaining transfers and grants could be linked to a more accurate control of expenditures by higher levels of government.
- Outstanding debt ($DEBT$) per capita is the value of the financial unresolved liabilities at the financial year end, divided by population. Local governments which need to take out loans are those with low fiscal revenue capacity and might be more concerned about cost saving due to their financial problems. Moreover, debt can be the result of past investments on equipment that enhance current efficiency (Benito et al., 2010). As a consequence, debt will be expected to be positively related to efficiency. However, if local government debt increase, there will be more resources employed to attend debt interests and amortization

payments and, as a consequence, less resources for the provision of local services (Geys and Moesen, 2009a; Ashworth et al., 2014), leading to a decrease in the efficiency levels.

5.3.2. The Model

In contrast to previous two-stage initiatives, we combine the cost efficiency measures for Spanish municipalities obtained via non-parametric techniques in a first stage with instrumental variable quantile regression in the second stage. We note that in efficiency analysis specialized literature, the study of Simar and Wilson (2007), also reviewed in Simar and Wilson (2011), expressed their concern about using a two-stage approach, where the efficiency scores obtained in a first stage via non-parametric frontier techniques (such as DEA or FDH), are regressed in a second stage including determinants of efficiency (using techniques such as OLS or Tobit). They outlined that these procedures could lead to "an unknown serial correlation" between the DEA efficiency scores and the explanatory variables, which may lead to biased inferences. However, in their extensive review, they did not mention the literature combining DEA with other types of regressions based on more flexible methods (Abdelsalam et al., 2014), such as non-parametric regression, conditional density estimation, quantile regression or, as we do here, instrumental variable quantile regression.[9]

Moreover, as stated by Bădin et al. (2014), we underline that Simar and Wilson (2007) did not advocate using the two-stage approach. Their goal was to define a statistical model where a second-stage regression would be meaningful, and to provide an approach that would allow for valid inference in the second-stage regression (the bootstrap method), although this approach also relied on the separability condition problem (also required by the two-stage approaches) between the input-output space and the external factors. An alternative to these methods would be the use of non-parametric conditional approach (Cazals et al., 2002; Daraio and Simar, 2005, 2007b),

[9]Some examples have already been published in the literature which combine DEA and their variants (such as FDH and order-*m*) with these more flexible methods, including Balaguer-Coll et al. (2007) and Nikolov and Hrovatin (2013) in the case of non-parametric regression, Illueca et al. (2009) in the case of conditional density estimation or Sampaio de Sousa et al. (2005) and Abdelsalam et al. (2014) in the case of quantile regression.

which avoids the separability condition. However, this technique also present some difficulties due to the bandwidth selection problem for the computation of conditional measures.

In this setting, taking into account that some intricate issues remain all the available methodologies to explain inefficiency, the great advantage of our procedure is that it allows to measure the impact of the environmental variables on local governments across different levels of efficiency or quantiles in presence of endogenous regressors. This methodology considers the entire efficiency distribution providing a more complete view of the effect of the different environmental variables affecting local governments performance. Moreover, quantile regression is more robust to departures from normality, given that it is characteristically robust to outliers on the dependent variable.

We consider different models corresponding to the different efficiency methods and output specifications described in the first stage. All models incorporate the environmental variables as well as fixed effects (time and geographic fixed effects). Regarding the geographic dummies we consider 13 Spanish regions: Andalusia, Aragon, Asturias, Balearic Islands, Canary Islands, Cantabria, Castile and Leon, Castile La Mancha, Extremadura, Galicia, La Rioja, Murcia and Valencian Community. In addition, the model includes time fixed effects given that we are dealing with longitudinal data (2009–2013 period).

Quantile-regression model: panel data and endogeneity issues

Classical procedures to analyse the determinants of efficiency only estimate the mean of a response variable, conditional on the values of the explanatory variables. However, we consider that the conditional impact of the covariates on the dependent variable might vary across quantiles (on the central and non-central location of the distribution), i.e., that the effects of the environmental variables may differ for different levels of efficiency. In this setting, Quantile regression model (QR model), introduced by Koenker and Bassett (1978), allows us to model the quantiles of the conditional distribution of the dependent variable expressed as functions of the independent variables. Given the quantile τ, the parameter estimates of the QR model are obtained by solving the following minimization problem,

$$min_{\beta} \sum_{i=1}^{n} \rho_{\tau}(y_i - x_i'\beta) \tag{5.2}$$

where $\rho_{\tau} = u(\tau - I(u_i \leq 0))$ is the quantile-regression loss function, y_i is dependent variable (local governments' cost efficiency), x_i is the vector of independent variables (determinants of efficiency) and β is the vector of parameters, which depends on τ. Given that we are dealing with longitudinal data, following we consider the extension of the QR model for panel data with the introduction of fixed effects. Let us consider the model:

$$y_{it} = x_{it}'\beta + \alpha_i + u_{it}, \qquad i = 1, ..., n, \qquad t = 1, ..., T \tag{5.3}$$

where y_{it} is the the efficiency level of a municipality i and year t, x_{it} is a vector of environmental variables, α_i is municipality i's fixed effect and u is the error term.

The minimizing problem to estimate Model 5.3 for several quantiles $(\tau_1, ..., \tau_q)$, under the Koenker and Bassett's approach is,

$$min_{\alpha\beta} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{i=t}^{T} \omega_k \rho_{\tau k}(y_{it} - \alpha_i - x_i'\beta(\tau_k)) \tag{5.4}$$

where the weights ω_k measure the relevance of quantile τ on the estimation of the α_i parameters.

Endogeneity is a common problem in cross-section or panel data regressions, leading to inconsistencies in OLS or QR model estimates since they are correlated with unobserved factors affecting the response variable. It can arise as a result of measurement error, autoregression with autocorrelated errors, simultaneous causality and omitted variables. In this setting, Chernozhukov and Hansen (2008) developed a model with instrumental variables in the presence of endogeneity along with a robust inference approach to partial or weak identification, and Harding and Lamarche (2009) extended the instrumental QR approach by Chernozhukov and Hansen (2008) by allowing for "fixed effects" as introduced in Koenker (2004).[10] Let us consider the following model,

$$y_{it} = d_{it}'\delta + x_{it}'\beta + \alpha_i + u_{it}, \qquad i = 1, ..., n, \qquad t = 1, ..., T \tag{5.5}$$

$$d_i = h(x_i, \omega_i, v_i) \tag{5.6}$$

where y_{it} is the dependent variable for a municipality i and year t, d_i is the municipality i's vector of endogenous variables, x_i is the vector of exogenous variables, α_i is municipality i's fixed effect and u is the error term. Equation 5.6 defines the endogenous variable d, related to a vector of instrumental variables ω_i which are independent of u. Given a quantile τ, the objective function for the conditional instrumental quantile is

$$R(\tau, \delta, \beta, \gamma, \alpha) = \sum_{t=1}^{T}\sum_{i=1}^{n} \rho_\tau(y_{it} - d_{it}'\delta - x_{it}'\beta - z_{it}'\alpha - \hat{\omega}_{it}'\gamma) \tag{5.7}$$

where $\hat{\omega}$ is the least square projection of the endogenous variables d on the instrument variables ω, the exogenous variables x and the vector of individual effects z.

The instrumental QR estimates are then obtained in two steps. In the first step the estimation of β, γ and α are obtained as a function of τ and δ, i.e.,

$$\hat{\beta}(\tau, \delta), \hat{\gamma}(\tau, \delta)\hat{\alpha}(\tau, \delta) \in arg \min_{\beta,\gamma,\alpha} R(\tau, \delta, \beta, \gamma, \alpha) \tag{5.8}$$

Following, the second step allows us estimate the coefficient of the endogenous variable by finding the value of δ as a function of τ, looking for the value of γ that minimize the instrumental variables' coefficients:

$$\hat{\delta}(\tau) \in arg \min_{\delta} \hat{\gamma}(\tau, \delta)' A \hat{\gamma}(\tau, \delta) \tag{5.9}$$

[10]Koenker (2004) noted that the introduction of a large number of fixed effects can increase the variability of the estimations of the covariates. The solution they propose consists of allowing the impact of the covariates be quantile-dependent, whereas the fixed effects are not.

where A is a positive-definite matrix. Then, the parameter estimates are $(\hat{\delta}(\tau), \hat{\beta}(\tau, \hat{\delta}))$.

5.3.3. Results

In this section we provide results of including the environmental variables in the local governments' cost efficiency analysis using quantile regression in presence of endogeneous variables, which allows to describe the impact of covariates not only on the average but also on the tails of the response variable distribution.

Before presenting the results, a number of methodological issues should be mentioned. First, the dependent variable (local government cost efficiency) is constrained between 0 and 1,[11] in which a number of efficiency scores will be concentrated at 1 (i.e., the efficient units). While this may not be severe as only a part of the municipalities are totally efficient during all the period, in the second stage we remove from our sample those municipalities that were efficient in at least 4 years during the full period. If one takes into account that we are studying the sources of inefficiency, dismissing part of the fully efficient observations seems to be reasonable in order to avoid possible problems related to the high concentration of efficient observations in some quantiles of the efficiency distribution. The remaining number of municipalities will depend on the model analysed.

Second, some environmental variables such as tax revenues (TAX) and outstanding debt ($DEBT$) might not be exogenous. Inefficient local governments might raise tax revenues or incur in a higher outstanding debt with the aim to increase municipal resources to provide the same level of public goods and services as efficient local governments do, i.e., inefficiency could affect tax collection and debt. In order to control for endogeneity issues (i.e., to mitigate the possibility of "simultaneity" or "reverse causality"), we will use instrumental variables for these two possible endogenous regressors following the methods presented in section 5.3.2. Since no instruments are directly available, we use the lagged values (one year) of the corresponding tax revenues and outstanding debt variables, a common strategy widely applied in social science studies.

[11] Note that the order-m approach also considers supper-efficient units above 1.

Results for the instrumental variable quantile regressions are reported in Tables 5.5 to 5.12. We consider 8 different models which vary according to the different efficiency methods and output specifications described in the first stage. Specifically, Models 1 to 4 (Tables 5.5, 5.6, 5.7 and 5.8) correspond to output specification 1 using DEA, FDH, order-m and KSW methodologies, respectively. Analogously, Models 5 to 8 (Tables 5.9, 5.10, 5.11 and 5.12) correspond to output specification 3. Comparing the results from different models gives a more complete view of the impact of the environmental variables over efficiency, while at the same time testing the robustness of our results. All models incorporate the financial, social and demographic, economic and political determinants as well as fixed effects (time and geographic fixed effects). The tables contain the coefficients for the estimated linear quantile regression for each of the selected quantiles (τ) and bootstrapped standard errors in parenthesis. Note that we are adopting input orientation efficiency models, so higher values of τ are associated with best performance, and vice versa.

In general, we observe that the results from the two different output specification models considered are fairly robust both in terms of sign and significance, however, some differences concerning the different estimation methodologies are found. When we focus on each particular environmental variable, several observations can be made.

First, regarding the financial variables, we find that the tax revenues (TAX), the grants or transfers from higher levels of government ($GRANTS$) and the debt levels ($DEBT$) are negative and significant at both the 5% and 1% significance levels. These results confirm the hypothesis that local governments which easily generate revenues (by collecting higher taxes or receiving grants from higher levels of government) are less motivated to manage them properly. Moreover, if the amount of local government debt is higher, there will be more resources employed to attend debt interests and amortization payments, and less resources could be employed in public service provision. The robustness of the results holds in most of the models and quantiles considered, except the variable outstanding debt ($DEBT$) in Model 6, which is found not significant (see Table 5.11). However, despite the general negative and significant results, we note that the impact of these three variables vary remarkably across

Table 5.5: Model 1, Instrumental Variable Quantile Regression with output specification 1[a] using DEA approach

	Dependent variable: cost efficiency				
	Quantile τ				
	Less efficient				More efficient
Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
(Intercept)	1.286694***	1.116032***	1.015715***	1.000203***	1.013589***
	(0.076183)	(0.013552)	(0.000982)	(0.000835)	(0.003162)
TAX	−0.001509***	−0.000746***	−0.000364***	−0.000248***	−0.000274***
	(0.000188)	(0.000073)	(0.000027)	(0.000027)	(0.000044)
DEBT	−0.013084***	−0.009068***	−0.007187***	−0.006482***	−0.006069***
	(0.003333)	(0.001557)	(0.000863)	(0.001375)	(0.001618)
GRANTS	−0.000549***	−0.000512***	−0.000452***	−0.000447***	−0.000408***
	(0.000032)	(0.000018)	(0.000012)	(0.000014)	(0.000018)
DENS	−0.000009*	−0.000002	0.000000	−0.000003	−0.000001
	(0.000004)	(0.000003)	(0.000001)	(0.000002)	(0.000003)
RET	−0.143883***	−0.025763***	0.001331	−0.026249***	−0.110311***
	(0.014354)	(0.005877)	(0.001011)	(0.001417)	(0.002812)
IMMIG	0.080089*	0.050153***	0.031949***	0.023180***	−0.022303***
	(0.032246)	(0.006899)	(0.001024)	(0.001280)	(0.003073)
UNEMP	0.002030	0.001980***	0.001739***	0.002244***	0.002655**
	(0.001637)	(0.000550)	(0.000360)	(0.000502)	(0.000849)
INC	0.002446	0.003201	0.002604**	0.006346***	0.009111***
	(0.005895)	(0.002546)	(0.000914)	(0.001165)	(0.001862)
TOUR	−0.009841	0.021899	0.033771***	0.064029***	0.055571***
	(0.007261)	(0.023470)	(0.002174)	(0.001171)	(0.005878)
CONCEN	0.046815	0.037348***	0.020186***	0.042357***	0.065342***
	(0.068692)	(0.011115)	(0.000922)	(0.000749)	(0.002027)
SIGN	−0.002609	−0.002968	−0.003469	−0.009420*	−0.015952*
	(0.009009)	(0.004132)	(0.003032)	(0.004463)	(0.007341)
VOTE	−0.001221	−0.001125**	−0.000903***	−0.000794***	−0.000590
	(0.001651)	(0.000420)	(0.000176)	(0.000228)	(0.000358)
Num. obs.	7415	7415	7415	7415	7415

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a] This specification includes minimum services compulsory for all governments (6 outputs variables from Y_1 to Y_6).

Table 5.6: Model 2, Instrumental Variable Quantile Regression with output specification 1[a] using FDH approach

	Dependent variable: cost efficiency				
	Quantile τ				
	Less efficient				More efficient
Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
(Intercept)	1.372924***	1.178472***	1.161491***	1.220561***	1.204983***
	(0.108671)	(0.008698)	(0.001681)	(0.000482)	(0.000866)
TAX	−0.001462***	−0.000641***	−0.000271***	−0.000242***	−0.000095**
	(0.000318)	(0.000102)	(0.000039)	(0.000028)	(0.000031)
DEBT	−0.008551**	−0.006476***	−0.005542***	−0.005598***	−0.004603***
	(0.003133)	(0.001700)	(0.001438)	(0.001190)	(0.001391)
GRANTS	−0.000534***	−0.000492***	−0.000483***	−0.000445***	−0.000323***
	(0.000034)	(0.000027)	(0.000014)	(0.000013)	(0.000019)
DENS	−0.000006	−0.000001	0.000000	−0.000003	−0.000002
	(0.000008)	(0.000004)	(0.000002)	(0.000002)	(0.000002)
RET	−0.121977**	−0.031167***	0.041562***	0.082626***	0.015100***
	(0.040165)	(0.002156)	(0.001606)	(0.000722)	(0.001290)
IMMIG	0.100416	0.064357***	0.048441***	0.012666***	0.023198***
	(0.062013)	(0.006682)	(0.002387)	(0.001368)	(0.000855)
UNEMP	0.001154	0.001390	0.000786	0.000384	0.000505
	(0.001591)	(0.000839)	(0.000681)	(0.000595)	(0.000542)
INC	0.003288	0.007432*	0.009950***	0.009045***	0.003806**
	(0.010603)	(0.002915)	(0.001441)	(0.001315)	(0.001381)
TOUR	−0.010323	0.017791	0.033660***	0.036921***	0.032379***
	(0.007178)	(0.020179)	(0.003395)	(0.003937)	(0.001999)
CONCEN	0.039570	0.038028***	0.004747*	−0.041937***	−0.011071***
	(0.134794)	(0.006601)	(0.001930)	(0.001001)	(0.001201)
SIGN	−0.000741	−0.000354	−0.009509	−0.006685	−0.007041
	(0.015890)	(0.006705)	(0.005541)	(0.005413)	(0.004306)
VOTE	−0.000925	−0.001199*	−0.000706*	−0.000351	0.000005
	(0.002569)	(0.000568)	(0.000277)	(0.000212)	(0.000207)
Num. obs.	6160	6160	6160	6160	6160

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a] This specification includes minimum services compulsory for all governments (6 outputs variables from Y_1 to Y_6).

Table 5.7: Model 3, Instrumental Variable Quantile Regression with output specification 1[a] using order-m approach

	Dependent variable: cost efficiency				
	Quantile τ				
	Less efficient				More efficient
Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
(Intercept)	1.480487***	1.122877***	1.150745***	1.212334***	1.232550***
	(0.075248)	(0.002371)	(0.000987)	(0.001240)	(0.000594)
TAX	−0.001957***	−0.000466***	−0.000209***	−0.000156**	−0.000290***
	(0.000255)	(0.000079)	(0.000050)	(0.000052)	(0.000033)
DEBT	−0.003330	0.002196*	0.000814	0.000570	0.002539
	(0.002331)	(0.000894)	(0.000931)	(0.001422)	(0.001948)
GRANTS	−0.000566***	−0.000449***	−0.000456***	−0.000443***	−0.000339***
	(0.000050)	(0.000021)	(0.000014)	(0.000017)	(0.000015)
DENS	−0.000005	0.000003	0.000001	−0.000001	−0.000005**
	(0.000005)	(0.000002)	(0.000002)	(0.000002)	(0.000002)
RET	−0.000833	−0.022504***	0.037926***	0.105274***	0.008291***
	(0.023973)	(0.002170)	(0.000868)	(0.001711)	(0.000853)
IMMIG	0.161222**	0.105232***	0.099229***	0.069353***	0.077377***
	(0.052715)	(0.001997)	(0.000708)	(0.001603)	(0.000682)
UNEMP	0.003450*	0.000364	0.001025	0.001010	0.002940***
	(0.001414)	(0.000670)	(0.000584)	(0.000710)	(0.000687)
INC	0.006384	0.003672	0.005956***	0.007410***	0.004975**
	(0.008357)	(0.002319)	(0.001608)	(0.001835)	(0.001781)
TOUR	0.000729	−0.004402	−0.016168***	0.016685	0.021800***
	(0.022107)	(0.010909)	(0.004264)	(0.010563)	(0.000609)
CONCEN	0.058498	0.042628***	0.008512***	−0.018207***	−0.008753***
	(0.075489)	(0.001845)	(0.001255)	(0.001486)	(0.000384)
SIGN	−0.011592	−0.007676	−0.010492*	−0.001305	−0.004597
	(0.015012)	(0.005583)	(0.005286)	(0.005832)	(0.005858)
VOTE	−0.000532	−0.000329	−0.000206	0.000057	0.000168
	(0.002164)	(0.000357)	(0.000276)	(0.000280)	(0.000221)
Num. obs.	5945	5945	5945	5945	5945

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a] This specification includes minimum services compulsory for all governments (6 outputs variables from Y_1 to Y_6).

Table 5.8: Model 4, Instrumental Variable Quantile Regression with output specification 1[a] using KSW approach

	Dependent variable: cost efficiency				
	Quantile τ				
	Less efficient				More efficient
Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
(Intercept)	1.244442***	1.092254***	0.966306***	1.003934***	0.971480***
	(0.042121)	(0.030576)	(0.000674)	(0.001412)	(0.000566)
TAX	−0.001492***	−0.000777***	−0.000251***	−0.000247***	−0.000271***
	(0.000212)	(0.000085)	(0.000018)	(0.000031)	(0.000053)
DEBT	−0.013594***	−0.010595***	−0.007157***	−0.007704***	−0.007428**
	(0.002996)	(0.001348)	(0.000905)	(0.001248)	(0.002567)
GRANTS	−0.000544***	−0.000503***	−0.000432***	−0.000433***	−0.000396***
	(0.000037)	(0.000016)	(0.000010)	(0.000014)	(0.000016)
DENS	−0.000010	−0.000004	0.000001	−0.000002	0.000000
	(0.000006)	(0.000003)	(0.000001)	(0.000002)	(0.000002)
RET	−0.129571***	−0.029854*	0.013151***	−0.043434***	−0.087198***
	(0.006742)	(0.014949)	(0.000986)	(0.001112)	(0.000517)
IMMIG	0.050727*	0.021956*	0.007889***	0.001055	−0.041774***
	(0.019838)	(0.009854)	(0.001097)	(0.001322)	(0.001026)
UNEMP	0.001253	0.001704**	0.001159**	0.001743***	0.001841
	(0.001582)	(0.000612)	(0.000353)	(0.000488)	(0.000966)
INC	0.004341	0.003425	0.001681*	0.004576***	0.010042***
	(0.005080)	(0.003909)	(0.000786)	(0.001149)	(0.002119)
TOUR	0.007502	0.042348**	0.037235***	0.069388***	0.061974***
	(0.004868)	(0.014963)	(0.001819)	(0.003880)	(0.000958)
CONCEN	0.055054	0.024699	0.021147***	0.040709***	0.044933***
	(0.035393)	(0.025343)	(0.000848)	(0.002030)	(0.000829)
SIGN	−0.005777	−0.004258	−0.001837	−0.007190	−0.006537
	(0.008197)	(0.004769)	(0.002942)	(0.004379)	(0.008717)
VOTE	−0.001201	−0.001052*	−0.000991***	−0.000953***	−0.000439
	(0.001382)	(0.000517)	(0.000152)	(0.000222)	(0.000426)
Num. obs.	7475	7475	7475	7475	7475

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a] This specification includes minimum services compulsory for all governments (6 outputs variables from Y_1 to Y_6).

Table 5.9: Model 5, Instrumental Variable Quantile Regression with output specification 3[a] using DEA approach

	Dependent variable: cost efficiency				
	Quantile τ				
	Less efficient				More efficient
Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
(Intercept)	1.316578***	1.071944***	1.018861***	1.055196***	1.092859***
	(0.063506)	(0.005936)	(0.000730)	(0.001200)	(0.001428)
TAX	−0.001703***	−0.000616***	−0.000275***	−0.000232***	−0.000253***
	(0.000215)	(0.000048)	(0.000022)	(0.000043)	(0.000053)
DEBT	−0.012788***	−0.008163***	−0.006869***	−0.005758***	−0.005393***
	(0.003405)	(0.001283)	(0.000963)	(0.001436)	(0.001207)
GRANTS	−0.000555***	−0.000482***	−0.000452***	−0.000454***	−0.000423***
	(0.000029)	(0.000015)	(0.000010)	(0.000016)	(0.000017)
DENS	−0.000008	0.000001	0.000000	−0.000003	−0.000001
	(0.000006)	(0.000002)	(0.000001)	(0.000002)	(0.000002)
RET	−0.154449***	−0.040140***	−0.022430***	−0.070261***	−0.122843***
	(0.032292)	(0.003019)	(0.000933)	(0.001719)	(0.001462)
IMMIG	0.087128**	0.041067***	0.004976***	0.004006**	−0.068589***
	(0.033320)	(0.004077)	(0.000666)	(0.001427)	(0.001996)
UNEMP	0.002332*	0.001761***	0.001825***	0.001825**	0.001532
	(0.001076)	(0.000474)	(0.000355)	(0.000631)	(0.000870)
INC	0.004344	0.002070	0.002133*	0.004539**	0.008460***
	(0.008488)	(0.001573)	(0.000879)	(0.001505)	(0.001679)
TOUR	0.029966	0.022314	0.033269***	0.049578***	0.071021***
	(0.045004)	(0.014783)	(0.002018)	(0.000910)	(0.001780)
CONCEN	0.063358	0.026163***	0.031739***	0.048624***	0.051569***
	(0.068069)	(0.005041)	(0.000852)	(0.001019)	(0.001508)
SIGN	−0.001620	−0.001652	−0.004411	−0.011198*	−0.013534
	(0.009535)	(0.003721)	(0.003180)	(0.005353)	(0.007205)
VOTE	−0.000820	−0.000863**	−0.001004***	−0.000841**	−0.001088**
	(0.001427)	(0.000288)	(0.000159)	(0.000275)	(0.000388)
Num. obs.	7350	7350	7350	7350	7350

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

[a] This specification includes minimum services compulsory for all governments and additional services which must provide larger municipalities with population of over 5,000 to 20,000 taking into account the quality of the services (10 outputs variables from Y_1 to Y_{10} weighted by their quality).

Table 5.10: Model 6, Instrumental Variable Quantile Regression with output specification 3[a] using FDH approach

	Dependent variable: cost efficiency			
	Quantile τ			
	Less efficient			More efficient
Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$[b]
(Intercept)	1.165473***	1.125483***	1.129694***	1.128181***
	(0.002701)	(0.004718)	(0.002552)	(0.007083)
TAX	−0.000893***	−0.000961***	−0.000499***	−0.000116
	(0.000251)	(0.000134)	(0.000090)	(0.000060)
DEBT	−0.013217***	−0.009253***	−0.004108	−0.000029
	(0.003084)	(0.002102)	(0.002132)	(0.001056)
GRANTS	−0.000291***	−0.000290***	−0.000230***	−0.000131***
	(0.000038)	(0.000031)	(0.000023)	(0.000027)
DENS	0.000004	−0.000001	−0.000004	−0.000001
	(0.000002)	(0.000003)	(0.000003)	(0.000002)
RET	−0.145022***	−0.235251***	−0.233678***	−0.074029***
	(0.002330)	(0.001359)	(0.002365)	(0.001254)
IMMIG	0.059818***	0.165842***	0.072312***	0.034254**
	(0.001170)	(0.003640)	(0.003325)	(0.011511)
UNEMP	0.007680***	0.005963***	0.000080	−0.000328
	(0.001245)	(0.000962)	(0.001084)	(0.000674)
INC	−0.000401	0.005396	0.001378	0.001289
	(0.007771)	(0.004442)	(0.003466)	(0.002293)
TOUR	0.070803***	0.032891***	0.019877	−0.009255
	(0.004439)	(0.009817)	(0.013639)	(0.008664)
CONCEN	0.223312***	0.291298***	0.173104***	0.090363***
	(0.001287)	(0.001956)	(0.002771)	(0.005815)
SIGN	−0.034051*	−0.009456	−0.005292	−0.005118
	(0.013658)	(0.010255)	(0.010095)	(0.005975)
VOTE	−0.003345***	−0.001156	−0.000538	−0.000544
	(0.000800)	(0.000598)	(0.000459)	(0.000387)
Num. obs.	2955	2955	2955	2955

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a] This specification includes minimum services compulsory for all governments and additional services which must provide larger municipalities with population of over 5,000 to 20,000 taking into account the quality of the services (10 outputs variables from Y_1 to Y_{10} weighted by their quality).
[b] Given the high concentration of observations at 1 (i.e., the efficient units) on account of FDH characteristics with a large number of output variables, we omit the estimation for the 90th percentile that brought problems with the quantile regression approach.

Table 5.11: Model 7, Instrumental Variable Quantile Regression with output specification 3[a] using order-m approach

	Dependent variable: cost efficiency				
	Quantile τ				
	Less efficient				More efficient
Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
(Intercept)	0.979736***	1.029073***	1.124277***	1.082530***	0.983766***
	(0.001794)	(0.001521)	(0.001344)	(0.003726)	(0.002730)
TAX	−0.000449***	−0.000789***	−0.000505***	−0.000181*	0.000067
	(0.000109)	(0.000125)	(0.000088)	(0.000082)	(0.000051)
DEBT	−0.008074*	−0.008026**	−0.002879	0.000639	0.001561
	(0.003619)	(0.002532)	(0.002145)	(0.001257)	(0.001264)
GRANTS	−0.000212***	−0.000258***	−0.000225***	−0.000106***	0.000003
	(0.000025)	(0.000024)	(0.000022)	(0.000028)	(0.000016)
DENS	0.000004	−0.000002	−0.000002	−0.000002	−0.000002
	(0.000004)	(0.000003)	(0.000002)	(0.000002)	(0.000002)
RET	−0.245922***	−0.129432***	−0.138695***	−0.078877***	0.001132
	(0.002916)	(0.002566)	(0.002492)	(0.002514)	(0.001921)
IMMIG	0.060586***	0.211126***	0.076357***	0.075840***	0.003980
	(0.001145)	(0.001583)	(0.001882)	(0.004068)	(0.004073)
UNEMP	0.007561***	0.006274***	−0.000663	0.000031	−0.000073
	(0.001004)	(0.000836)	(0.000958)	(0.000708)	(0.000582)
INC	−0.002631	0.005069	−0.000086	0.002496	0.000931
	(0.003992)	(0.004027)	(0.003373)	(0.002743)	(0.001820)
TOUR	−0.114430***	−0.172802***	−0.010195***	−0.108292***	−0.128188***
	(0.002682)	(0.002590)	(0.001837)	(0.003037)	(0.002153)
CONCEN	0.234854***	0.221071***	0.152342***	0.118164***	0.038743***
	(0.002619)	(0.001820)	(0.002148)	(0.002901)	(0.002008)
SIGN	−0.016136	−0.010357	−0.004459	−0.006056	0.004262
	(0.010935)	(0.008963)	(0.009103)	(0.006292)	(0.004473)
VOTE	−0.001266*	−0.000462	−0.000068	−0.000238	−0.000235
	(0.000491)	(0.000489)	(0.000441)	(0.000416)	(0.000258)
Num. obs.	2840	2840	2840	2840	2840

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a] This specification includes minimum services compulsory for all governments and additional services which must provide larger municipalities with population of over 5,000 to 20,000 taking into account the quality of the services (10 outputs variables from Y_1 to Y_{10} weighted by their quality).

Table 5.12: Model 8, Instrumental Variable Quantile Regression with output specification 3[a] using KSW approach

	Dependent variable: cost efficiency				
	Quantile τ				
	Less efficient				More efficient
Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
(Intercept)	1.304280***	1.123110***	1.085752***	1.090677***	1.009879***
	(0.044139)	(0.017342)	(0.001460)	(0.001265)	(0.001010)
TAX	−0.001608***	−0.000947***	−0.000612***	−0.000321***	−0.000384***
	(0.000262)	(0.000104)	(0.000039)	(0.000044)	(0.000055)
DEBT	−0.017727***	−0.018927***	−0.015865***	−0.013499***	−0.009197***
	(0.002942)	(0.002337)	(0.001172)	(0.002011)	(0.001747)
GRANTS	−0.000522***	−0.000475***	−0.000433***	−0.000408***	−0.000357***
	(0.000043)	(0.000023)	(0.000014)	(0.000016)	(0.000013)
DENS	−0.000004	−0.000004	0.000002	−0.000001	0.000000
	(0.000007)	(0.000004)	(0.000002)	(0.000002)	(0.000002)
RET	−0.270821***	−0.141139***	−0.109076***	−0.159725***	−0.267979***
	(0.002417)	(0.013209)	(0.001150)	(0.001734)	(0.001565)
IMMIG	0.102157***	0.015161	−0.009291***	−0.044163***	−0.062172***
	(0.022258)	(0.009989)	(0.002115)	(0.001843)	(0.000939)
UNEMP	0.000783	0.002705***	0.002567***	0.001178	−0.000727
	(0.002038)	(0.000730)	(0.000476)	(0.000613)	(0.000738)
INC	0.000205	0.003874	0.003649**	0.005532***	0.009336***
	(0.005938)	(0.004330)	(0.001276)	(0.001507)	(0.001705)
TOUR	−0.018578***	0.075082***	0.050152***	0.035968***	0.056090***
	(0.004998)	(0.019497)	(0.004643)	(0.004109)	(0.001162)
CONCEN	0.042894	0.004323	0.059300***	0.032448***	0.069854***
	(0.038510)	(0.008794)	(0.001219)	(0.001275)	(0.002449)
SIGN	−0.005412	−0.004986	−0.006952	−0.006182	−0.006571
	(0.009579)	(0.005992)	(0.004091)	(0.005753)	(0.007074)
VOTE	−0.001861	−0.001637***	−0.001965***	−0.001534***	−0.000059
	(0.001540)	(0.000487)	(0.000220)	(0.000275)	(0.000359)
Num. obs.	7450	7450	7450	7450	7450

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[a] This specification includes minimum services compulsory for all governments and additional services which must provide larger municipalities with population of over 5,000 to 20,000 taking into account the quality of the services (10 outputs variables from Y_1 to Y_{10} weighted by their quality).

quantiles. For instance, the values of the quantile regression coefficients gradually decrease with the quantiles, being much stronger for the relatively less efficient performers. Therefore, these results suggest that although, on average, the impact of financial variables on efficiency is strong, it is particularly higher for the relatively less efficient municipalities in our sample.

Second, concerning the social and demographic variables, we observe that population density ($DENS$) is found not statistically significant. This result is obtained for most quantiles and models, which implies that local governments' efficiency is not significantly affected by the concentration of the population in a municipality. With reference to the share of immigrants ($IMMIG$), although its sign and significance varies somewhat for some models and quantiles, it is mostly positive and significant except for the highest quantile, which is found negative in Models 1, 4, 5 and 8 (Tables 5.5, 5.8, 5.9 and 5.12). One reasonable explanation for the unexpected positive association of the immigration share with local governments' efficiency is that foreign population could increase the number of inhabitants and the services of a municipality in a short term, while expenditures will not increase in the same proportion. Despite the divergences found across models, we observe a generally decreasing trend of the coefficients with the quantiles, to such an extent that it becomes negative in some models for the highest quantile. Hence, the impact of the share of immigrants over efficiency is relatively beneficial for the worst efficient municipalities, it decreases for the rest of the quantiles and even becomes adverse for the more efficient municipalities.

Moreover, the share of retired people (RET) is found negative and significant in most cases, although there are some discrepancies about its impact for some specific quantiles and models. A negative effect on efficiency could be explained since retired people could be less interested in local governments' performance given that they make less use of some social and recreational services (such as sports facilities, parks or playing fields). We find a negative and significant impact in Models 1, 4, 5 and 8 (Tables 5.5, 5.8, 5.9 and 5.12), which generally increase its magnitude in both tails of the efficiency distribution. Similarly, Models 6 and 7 (Tables 5.10 and 5.11) also show negative and significant results, however, its effect on efficiency is diminishing across quantiles, to the point that its significance is completely lost for the most efficient municipalities. Finally, the results for Models 2 and 3 (Tables 5.6 and 5.7) are found negative and significant for the lowest quantiles of the distribution, while they become positive for municipalities located at the median and highest quantiles. Despite all the differences found across models, we observe that the negative and significant results hold for the lowest quantiles of the distribution ($\tau = 0.10$ and $\tau = 0.25$), being stronger for the poorest performers. Therefore, the share of retired people is more detrimental for the least efficient municipalities in our sample.

Third, referring to the economic variables, we observe that the unemployment rate ($UNEMP$) is positive and significant in most models and quantiles. Only the Model 2 (Tables 5.6) find no statistical significance in any quantile. A higher unemployment rate could lead to a lower demand for high-cost or high-quality public services. In addition, we find that the magnitude of the coefficients also varies across quantiles but the trend holds for most of the models considered. Specifically, we observe that the impact increase in both tails of the efficiency distribution, suggesting that although the impact of the unemployment rate on efficiency is strong, it is less beneficial for the municipalities located at the central quantiles.

Moreover, we find that the variable citizens' disposable income (INC) is positive and significant, but only from the median onwards ($\tau = 0.50$, $\tau = 0.75$ and $\tau = 0.90$). This result holds most of the cases except for Models 6 and 7 (Tables 5.10 and 5.11), which find this variable not statistically significant in any quantile. A plausible explanation of a positive impact of the citizens' disposable income over efficiency previously examined is that richer local residents might pay greater taxes and, as a consequence, they put an increased pressure to provide efficient local services. Furthermore, we observe that the magnitude of the estimated coefficients increase strongly with τ, suggesting that, among the best performers, the higher-income citizens in a municipality will be more favourable for the most efficient municipalities.

As for the tourist index ($TOUR$), there are some differences across models, but the prevailing view is a positive and significant impact over efficiency, suggesting that the more tourism activity, the lower the cost excess. Models 1, 2 and 5 (Tables 5.5, 5.6 and

5.9) show positive and significant results only for the median and higher quantiles of the distribution ($\tau = 0.50$, $\tau = 0.75$ and $\tau = 0.90$), while Models 4 and 8 (Tables 5.8 and 5.12) also show a positive significance at the $\tau = 0.25$ quantile. The most surprising results are for Model 7 (Table 5.7) which shows negative and significant results in all quantiles, and Models 3 and 8 (Tables 5.7 and 5.12), which show negative results for some specific quantile. Despite these discrepancies, we find that the positive and significant results for the highest quantiles of the distribution hold most of the models, indicating that a higher tourist index increases efficiency of the municipalities with better performance.

Finally, regarding the political variables, we observe that the political concentration ($CONCEN$) is positive and significant in most models and quantiles. Accordingly, it confirms the hypothesis that when the degree of political concentration is higher, there exist a lower political opposition and it is easier to implement policies and impose budget constraints. Only the Models 1, 4, 5 and 8 (Tables 5.5, 5.8, 5.9 and 5.12) find not significant results for the less efficient municipalities, while Models 2 and 3 (Tables 5.6 and 5.7) find a negative impact for municipalities located at the highest quantiles ($\tau = 0.75$ and $\tau = 0.90$). As regards the trend of this variable across quantiles, the results are ambiguous. Models 1, 4, 5 and 8 (Tables 5.5, 5.8, 5.9 and 5.12), show an increasing tendency of the coefficients, suggesting that a higher political concentration is more beneficial for the most efficient municipalities, while Models 2, 3, 6 and 7 (Tables 5.6, 5.7, 5.10 and 5.12) show a decreasing tendency.

Otherwise, we observe that the political sign ($SIGN$) is found not statistically significant in most models and quantiles. Only some particular model find significant and negative results for some quantile at the 5% level of significance. Therefore, in general the results show that the local governments' efficiency is not significantly affected by the ideological position of the municipalities. The last variable is the voter turnout ($VOTE$), which has a negative impact on efficiency, supporting the idea that less efficient local governments motivate more citizen participation. However, this variable is found significant only for some quantiles of the efficiency distribution. The dominant view, explained by the Models 1, 2, 4 and 8 (Tables 5.5, 5.6, 5.8 and 5.12), is a negative and significant impact only for the central quantiles of the efficiency distribution ($\tau = 0.25$, $\tau = 0.50$ and $\tau = 0.75$), where the coefficients decrease with the quantiles. In addition, Model 5 (Tables 5.9) shows the same results, however, it also finds significance for the most efficient municipalities, while Models 6 and 7 (Tables 5.10 and 5.11) only find significance for the lowest quantile of the distribution.

5.4. Conclusion

The present chapter analyses local governments' cost efficiency in Spain while explicitly accounting for external or environmental influences that might affect municipalities' performance. We have considered an alternative methodology to analyse the impact of determinants of local governments' cost efficiency by combining a variety of non-parametric methods in the first stage (when the cost efficiency results are measured) and instrumental variable quantile regression in the second stage (when the factors causing inefficiency are included). In contrast to previous two-stage initiatives, this technique provides an alternative basis for considering the impact of the environmental variables on local governments' efficiency according to the differing levels of efficiency, while allowing to control for the possible endogeneity of some of our explanatory variables.

We performed the analysis for a sample of 1,499 Spanish local governments between 1,000 and 50,000 inhabitants for the period 2009–2013. Note that, as stated in previous chapters, the period considered is also important, since the economic and financial crisis that started in 2007 has had a huge impact on most Spanish local government revenues and finances in general. Under these circumstances, identifying the causes of inefficiency which come from both the inadequate management of the available resources and the external or environmental factors beyond the control of local managers is even more important, if possible. We employed a comprehensive dataset of environmental variables which includes different categories in order to facilitate the interpretation of the empirical results.

Our results suggest that, considering the various methodologies and output specification models in the first stage, we found large differences in the efficiency scores.

However, despite this variability, the explanatory analysis of inefficiency carried out in the second stage yielded, at least qualitatively, reasonably robust results. Although some differences were found in terms of sign and significance levels, it was reassuring to observe that with some exceptions the explanatory variables consistently had the same sign and trend across quantiles in most of the models. Therefore, our results are fairly robust and provide a complete view of the impact of the environmental variables over efficiency.

Focusing on each particular environmental variable, several observations can be made. In general, the three financial variables (tax revenues, the grants or transfers from higher levels of government, and the debt levels) had a negative and significant impact over efficiency. In addition, the quantile regressions indicated that their average impact concealed some interesting trends, since it was particularly higher for the relatively less efficient municipalities in our sample. Moreover, another two variables that robustly increased cost inefficiency were the share of retired people and the voter turnout. Results for these two variables also varied greatly according to each particular quantile. The former showed that, among the lowest quantiles, the impact was more detrimental for the least efficient municipalities, while the latter was only significant for the central quantiles of the distribution, where the coefficients decreased with the quantiles.

In contrast, the variables share of immigrants, unemployment rate, citizens' disposable income, tourist index and political concentration were found to decrease inefficiency. Therefore, for the best local governments, performance is a result not only of their managers' skills but also these external factors related to their environment. Quantile regression revealed that both the citizens' disposable income and tourist index showed that, among the best performers, their impact was more favourable for the most efficient municipalities. Moreover, a higher unemployment rate was less beneficial for the municipalities located at the central quantiles. The most surprising results were for the share of immigrants, since its impact over efficiency was relatively beneficial for the worst efficient municipalities, it decreased for the rest of the quantiles and even became adverse for the more efficient municipalities. Finally, we found that local governments' efficiency was not significantly affected by either the ideological position or the population concentration in a municipality.

In sum, we find an asymmetry regarding the determinants of efficiency for the best and worst local governments, a benefit from using quantile regression. Our results yield a significant contribution to the previous literature which only provide information on the average impact of the environmental variables in local governments' efficiency. The application of our proposed method could help to explain inefficiency in some circumstances, particularly in those cases in which the literature has been inconclusive about the direction of the determinants on local governments' cost efficiency. Indeed, for the worst local governments' performers, since a large share of their efficiency is explained by several determinants, their poor performance would be a consequence of the factors explaining their efficiency. Therefore, for a given level of efficiency, it is easy to assume that the environmental factors will be more decisive than the local managers' decisions. So the policies to be applied would not have to be universal, since the environmental conditions could be more decisive in some municipalities allowing to perform better. These results are particularly interesting for both scholars and policy makers interested in understanding the causes of local governments inefficiency in search for performance benchmarks.

In addition, another relevant contribution to the literature that analyse local governments' efficiency along with its determinants is that we considered the presence of the possible endogeneity caused from "reverse causation" of some of our explanatory variables using instrumental variables. The large majority of studies tended to interpret their results in a causal way, neglecting the endogeneity issues in the data. Therefore, our results represent and interesting contribution that afford opportunities in this particular issue.

Chapter 6

General conclusions, contributions and ways for further research

In recent years the study of local government efficiency has attracted much scholarly interest in the field of public administration partly due to the macroeconomic crisis scenario which has highlighted improving efficiency and reducing the costs of local public services as prime area of concern. In the particular case of Spanish local governments, on which we focus, the economic and financial situation that started in 2007 had a huge impact on most local revenues and finances in general, provoking an increase on their deficits. In addition, the huge budgetary limitations became stricter with the law on budgetary stability *(Ley General Presupuestaria)*, which set up more control on public debt and public spending. Under these circumstances, during these last years Spanish local governments have come under increasing pressure to accommodate severe economic restrictions while maintaining (or even increasing) their provision of local public services and facilities.

In effect, public sector efficiency is an issue that not only concerns scholars but also policy makers and citizens. On the one hand, the policy makers' interest lies in the principle of doing more with less in order to comply with current legislation, since more efficient public entities will incur lower costs per unit of output and, therefore, they will provide more and better services and facilities. On the other hand, citizens' interests in public sector efficiency are based on their desire to pay lower taxes for the public services and facilities they receive, as well as to obtain higher quality services. Therefore, these objectives are possible to be achieved when local governments are more efficient.

The present thesis has considered a multidimensional evaluation of the cost efficiency of local governments in Spain, using non-parametric frontier analysis methods. In doing so, the economic crisis scenario that seriously affected Spanish local government revenues and finances in general has been taken into account. The thesis contributes to the development of robust tools to evaluate and promote the improvement of the efficiency of local governments in Spain. The empirical results provide evidence for a better definition of public policies through the evaluation and identification of benchmark local governments and, therefore, minimize (cost) inefficiencies which might help to further support effective policy measures and reduce public expenditures. The questions that have been tried to answer in the preceding pages refer to both theoretical and analytical aspects, as well as to the interpretation of the economic reality under study.

Despite each chapter of the thesis includes a specific section detailing their conclusions, in this section we summarize the main conclusions and contributions in view of the results obtained. First, in the introductory chapter (**chapter 1**), we presented a brief overview on the Spanish economy during the economic crisis, with a special focus on how local governments finances were affected. Moreover, in order to clarify the context of local governments in Spain, this chapter also provided an introduction to the institutional framework.

In **chapter 2**, we have presented an extensive and comprehensive systematic review of the existing empirical literature on local governments' efficiency from a global point of view, covering all articles from 1990 up to the year 2016. To the best of our knowledge, it is heretofore the most complete source of references on local government efficiency analysis. The chapter showed a detailed overview of the studies on local governments' efficiency across various countries, comparing the data and samples employed, and the main results obtained. Moreover, it summarised the inputs, outputs and the environmental variables used, as well as the methodologies applied to measure efficiency in the context of local governments. This chapter provides a good basis for researchers in the field of local governments' efficiency since it shows a complete view of the current status of this research topic. In addition, this literature review has allowed us to identify some operative directions and considerations to take into account in the remaining chapters of the thesis.

The chapter led us to several conclusions and ways for further research. Following, we sum up some of the most important points of debate which have helped to guide the research line of this thesis:

- First, we found that a minority of studies had an underlying panel data structure and most of them have not exploited the intertemporal variation as they have used cross-sectional efficiency techniques. In this line, we suggested that more research is needed in dynamic efficiency analysis in order to investigate the evolution of local government efficiency over time, since time period analysis could provide interesting managerial and policy-making insights into the efficiency effect of long-term decision. Bearing in mind this consideration for future research, in chapter 3, although we have not set out to analyse the dynamics of efficiency, we have observed some tendencies and tested whether significant differences in efficiency levels took place between the initial and the final period of the analysis. In appendix B we have also included a commonly non-parametric approach used in previous literature to analyse the evolution of efficiency changes over time. Moreover, in chapter 5 we have used a panel data regression model which includes time fixed effects.

- Second, we observed that the accurate definition of local governments' inputs and outputs is usually highly complex, due to the difficulties found in data collection, the measurement of the costs of public activities and the accurate definition of local services and facilities. In general, there is a lack of consensus on the selection and number of variables to include in the analysis, which depends on the availability of data and the specific services and facilities that local governments must provide in each country. We suggested to consider alternative input-output models, in order to assess whether the different choices might explain the heterogeneity among local governments, and to determine how the number of outputs can affect the efficiency scores. In addition, we found interesting and informative to include indicators to measure the quality of the services, since performance decisions may have an impact on their quality and not in their quantity. Following these ideas, in chapters 3 and 5 we have considered alternative output models, including quantity and quality variables.

- Third, we noticed that the large majority of the previous studies have focused only on one frontier technique to analyse efficiency. Despite the high academic and policy interest in efficiency measurement, widely applied in local governments and other public and private organizations, there is no commonly accepted methodology to perform efficiency analysis. In this context, we must be cautious when interpreting results from research studies using one particular method, since their results might be affected by the approach taken. In light of the efficiency estimator selection problem, we found interesting to provide in chapters 3, 4 and 5 a comparative perspective using several methods to estimate efficiency. In addition, we have dedicated chapter 4 exclusively to further compare methodologies by using a consistent method to choose an efficiency estimator which might be more appropriate to measure local governments performance in Spain.

- Fourth, we concluded that is necessary to consider the influence of environmental variables on municipal performance. If local governments are affected by factors beyond their control, performance analysis should control for this heterogeneity. Moreover, we found that the inclusion of environmental variables in empirical efficiency analysis often lacks structure and most studies have not explained the estimated inefficiencies in a systematic way. Given these considerations, in chapter 5 we have analysed the impact of a comprehensive set of external or environmental factors that affect local governments' cost efficiency, including different categories in order to facilitate the interpretation of the empirical results.

- Finally, we also identified that past studies interpreted their results in a causal way, and the problem of endogenous data in local government efficiency literature (arising from selection bias, unobserved heterogeneity or reversed causality) has received little attention. Taking this premise into account, in chapter 5 we have considered possible endogeneity issues in data by introducing fixed effects as well as instrumental variables estimation techniques to allow to control both the unobserved heterogeneity in panel data regression models and the possible reversed causality bias.

Therefore, given all these considerations and conclusions drawn from chapter 2, here we have summarised some common problems and limitations found in previous literature which we have addressed in the remaining chapters from this thesis.

In **chapter 3** we have investigated different aspects of the cost efficiency in Spanish local governments during the period of the economic crisis (2008–2013). Specifically, we have attempted to learn whether Spanish local governments' efficiency has improved in times of crisis. To this end, we used a sample of 1,574 Spanish local governments with population between 1,000 and 50,000 for the period 2008–2013. Our results suggested that Spanish local governments became more efficient over the crisis period 2008–2013 since they have succeeded in reducing their budget expenditures (inputs or costs) while at the same time they managed to maintain (or even increase) local public services and facilities (outputs). These results are reasonable given that Spanish local governments have been under pressure to vastly accommodate severe economic restrictions and indiscriminate budgets cuts while paying attention to citizen needs. Benchmarking techniques could help to support the implementation of future economic measures in order to reallocate the available resources and reduce public expenditures.

Moreover, regardless of the context of the analysis, this chapter has also attempted to address some common problems from previous literature earlier discussed, such as the accurate definition of output variables as well as the selection of methodologies to measure efficiency. For this, in order to assess whether the different choices might explain the differences between local governments, we have considered several output models (including both quantity and quality variables) and different non-parametric methodologies (namely, DEA, FDH, order-m frontier and KSW) to assess the robustness of the efficiency results. Our results confirmed the importance of considering both alternative input-output models and the quality of the services when measuring local governments cost efficiency. The inclusion of quality variables is particularly interesting and informative for policy-makers, suggesting that some performance decisions may have an impact in the quality of public services offered to citizens (service effectiveness) and not in the quantity. Therefore, a properly managed municipality should operate efficiently but not to the detriment of the quality of the services.

Finally, this chapter has also investigated the existence of structural differences in the efficiency scores between municipalities located in different Spanish regions and provinces as well as the variation of the efficiency scores according to the size of the municipalities. We found that municipalities which presented higher efficiency scores were concentrated in the north area of the country, while La Rioja or some eastern provinces such as Murcia or Aragon showed the lower efficiency values. These results indicate that the design of public policies and fiscal adjustments that attempt to control local governments' budget expenditures should take into account these interregional differences, which could affect the equal access to local public services. This is an important contribution to previous literature given that it the first time that the local governments' location in a given territory has been investigated. In addition, we observed that our results also varied according to the size of the municipalities, indicating that larger municipalities performed better. This result could be attributable to the economies of scale and the quality of public management given that larger municipalities use more innovative management tools (such as financial budgetary control, highly prepared technical staff, contracting out of services, etc.) than smaller municipalities.

In **chapter 4** we have compared the four non-parametric estimation techniques previously explained in chapter 3 using an extension of the experiment developed in the study of Badunenko et al. (2012). Since the method chosen to perform efficiency analysis may affect the efficiency results, this chapter aimed to uncover which techniques were more appropriate to assess cost efficiency in Spanish local governments. In contrast to previous literature, which has regularly compared techniques and made several proposals for alternative ones, we carried out an experiment via Monte Carlo simulations and we have discussed the relative performance of the efficiency estimators under various scenarios. Then, from the simulation results, we have determined in which scenario our data lies in, and we have followed the suggestions related to the performance of the estimators for this scenario. Bearing in mind the economic crisis situation, the results from this chapter contributes to identify a method for evaluating local governments' performance to obtain reliable efficiency gains which might help to limit the adverse impact of spending cuts on local governments' service provision.

The findings showed that, in general, there was no one approach suitable for all efficiency analysis. When using these results for policy decisions, local regulators must be aware of which part of the distribution is of particular interest and if the interest lies in the efficiency scores or the rankings estimates. Both DEA and FDH methodologies showed the most reliable efficiency results, according to the findings of our simulations. Therefore, our results indicated that the average cost efficiency would have been between 0.54 and 0.77 during the period 2008–2013, suggesting that Spanish local governments could have achieved the same level of local outputs with about 23% to 36% fewer resources. From a technical point of view, the analytical tools introduced in this chapter represent an interesting contribution that has examined the possibility of using a consistent method to choose an efficiency estimator, and the obtained results have given evidence on how efficiency could certainly be assessed as close as possible in order to provide some additional guidance for policy makers. Indeed, the implications of these results are particularly important when using efficiency analysis to take economic performance decisions in real contexts given the important economic consequences of employing the results of a particular method for efficiency measurement.

In **chapter 5** we have analysed local governments' cost efficiency in Spain while explicitly accounting for external or environmental influences that might affect municipalities' performance. To this end, we performed the analysis for a sample of 1,499 Spanish local governments between 1,000 and 50,000 inhabitants for the period 2009–2013. Based on the classification provided for the different types of determinants of local governments' efficiency in chapter 2, we have identified a comprehensive set of environmental variables which includes different categories in order to explain the estimated inefficiencies in a structured and systematic way. Afterwards, the relationship between these environmental variables and the efficiency scores has been assessed in a two-stage analysis. In a first stage, cost efficiency results have been measured via the non-parametric methods developed in chapter 3. In the second stage, when the factors causing inefficiency are included in the analysis, a instrumental variable quantile regression has been considered.

In contrast to previous two-stage initiatives, this technique provides an alternative basis for considering the impact of the environmental variables on local governments' efficiency according to the differing levels of efficiency, while allowing to control for the possible endogeneity of some of our explanatory variables. Our results showed an asymmetry regarding the determinants of efficiency for the best and worst local governments. Indeed, for the worst local governments, performance was a result not only of their managers' decisions but also other factors related to their environment, such as such as tax revenues, the debt levels, transfers from higher levels of government, share of retired people or the electoral participation. Therefore, for a given level of efficiency, it is easy to assume that the environmental factors will be more decisive than the local managers' decisions.

These results are particularly interesting for scholars and policy makers which interested in understanding the causes of local governments inefficiency in search for performance benchmarks, and yield a significant contribution to the previous literature which only provide information on the average impact of the environmental variables in local governments' efficiency. Therefore, the results obtained advance our understanding of how to determine the most efficient local governments, taking into account the particular characteristics of the municipality, and thus facilitate decision making by public managers. So the policies to be applied would not have to be universal, since the environmental conditions could be more decisive in some municipalities allowing to perform better. The application of our proposed method could help to explain inefficiency in some circumstances, particularly in those cases in which the literature has been inconclusive about the direction of the determinants on local governments' cost efficiency.

It should be noted that the current thesis, despite their virtues, also suffers some limitations. Here we propose some ways for further research. First, taking into account the availability of data, the sample of the municipalities analysed covers several years from the economic crisis period. However, in future research it would be interesting to expand the sample to analyse and compare different economic cycles, which might be affected by the different policies and performance decisions adopted by the economic agents (related to events such as the political elections in 2011 or 2015, laws concerning budgetary targets like the Law on Budgetary Stability in 2012 with its subsequent reforms in 2016, or the Law on transparency, access to public information and good governance in 2013) and, as a consequence, results might vary according to the period in which they are analysed.

Second, despite we have analysed some intertemporal variation in chapters 3 and 5, it is necessary more research to further investigate the evolution of local government efficiency over time. New advanced robust non-parametric techniques are being developed in order to analyse the dynamics of efficiency, such as the DEA data panel method proposed by Surroca et al. (2016). These methods allow to estimate a global coefficient of efficiency for the period of analysis, taking into account the data panel structure.

Third, despite the method employed to analyse the determinants of efficiency in chapter 5 allowed to assess the impact of the environmental variables across different quantiles and to control endogeneity issues in the data, it was based on the traditional two-stage analysis. In general, it is necessary further research on more advanced techniques to measure the incorporation of environmental variables which avoid the separability condition required by two-stage analysis, but taking into account the possible endogeneity issues on data. An alternative solution would be to validate the two-stage approach by using non-parametric test such as the proposed by Daraio et al. (2010) to test separability condition that is required for the second-stage regression to be meaningful (Bădin et al., 2014).

Finally, given the structural differences in the efficiency scores between municipalities located in different Spanish regions and provinces found in chapter 3, it would be an interesting and promising future line of research to perform a multi-level decomposition of the efficiency to provide useful information about local governments' location in a given territory. In a decentralised country such as Spain, these analysis could help to design public policies and fiscal adjustments taking into account the interregional differences which could affect the equal access to local public services.

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Appendix A

Additional tables

Table A.1: Studies on efficiency in local governments in several countries

Country	Author(s)	Sample	Period studied	Main results
Australia	Worthington and Dollery (2000b)	177 New South Wales local governments	1993	Mean efficiency differs from 0.69 to 0.86.
	Fogarty and Mugera (2013)	98 Western Australian local councils	2009 and 2010	Mean efficiency differs from 0.40 to 0.72.
	Marques et al. (2015)	29 Tasmanian local councils	From 1999 to 2008	Mean efficiency differs from 0.70 to 0.80.
Belgium	Eeckaut et al. (1993)	235 Walloon municipalities	1985	–
	De Borger et al. (1994)	589 municipalities in Belgium	1985	Mean efficiency differs from 0.86 to 0.99. They applied different input specifications.
	De Borger and Kerstens (1996a)	589 municipalities in Belgium	1985	Mean efficiency differs from 0.57 to 0.93.
	De Borger and Kerstens (1996b)	589 municipalities in Belgium	1985	Mean efficiency differs from 0.81 to 0.97 depending on the specification used.

Table A.1 – continued from previous page

Country	Author(s)	Sample	Period studied	Main results
	Coffé and Geys (2005)	305 Flemish municipalities	2000	Mean efficiency is 0.70. They study the relationship between social capital and institutional performance in Flemish municipalities.
	Geys (2006)	304 Flemish municipalities	2000	Mean efficiency is 0.84. They analyse the existence of spatial interdependence in local government policies.
	Geys and Moesen (2009b)	304 Flemish municipalities	2000	Mean efficiency differs from 0.49 to 0.95.
	Geys and Moesen (2009a)	300 Flemish municipalities	2000	Mean efficiency is 0.86.
	Ashworth et al. (2014)	308 Flemish municipalities	2000	Mean efficiency is 0.58. They analyse whether different aspects of the extent of competition in the political arena within the municipality affect local government performance.
Brazil	Sampaio de Sousa and Ramos (1999)	3,756 Brazilian municipalities	1991	–
	Sampaio de Sousa and Stošić (2005)	4,796 Brazilian municipalities	1991	Mean efficiency differs from 0.52 to 0.92. Smaller cities in Brazil tend to be less efficient than the larger ones.
	Sampaio de Sousa et al. (2005)	4,796 Brazilian municipalities	2000	Mean efficiency is 0.52. Smaller cities in Brazil tend to be less efficient than the larger ones.
Chile	Pacheco et al. (2014)	309 Chilean municipalities	From 2008 to 2010	Mean efficiency is 0.70.
Czech Republic	Štastná and Gregor (2011)	202 local governments in Czech Republic	From 2003 to 2008	Mean efficiency differs from 0.3 to 0.79.
	Štastná and Gregor (2015)	202 local governments in Czech Republic	From 1995 to 1998 and 2003 to 2008	Comparison of public sector efficiency in and beyond transition. Mean efficiency scores increase from 0.62 in 1995-1998 to 0.69 in 2005-2008.

Table A.1 – continued from previous page

Country	Author(s)	Sample	Period studied	Main results
Finland	Loikkanen and Susiluoto (2005)	353 Finnish municipalities	From 1994 to 2002	Mean efficiency differs from 0.85 to 0.89. They applied different output specifications.
	Loikkanen et al. (2011)	353 Finnish municipalities	From 1994 to 1996	Mean efficiency differs from 0.75 in 1994 to 0.82 in 1996. They examined whether Finnish city managers' characteristics and work environment, in addition to external factors, explain differences in cost efficiency.
Germany	Geys et al. (2010)	987 German municipalities	1998, 2002 and 2004	They analyse whether voter involvement in the political sphere is related local government performance.
	Kalb (2010)	1,111 German municipalities	From 1990 to 2004	They analyse the impact of intergovernmental grants on local cost efficiency.
	Bönisch et al. (2011)	46 independent municipalities and 157 administrative collectivities in Saxony-Anhalt	2004	On average cost should be reduced by 7% to 18%. They study the relevance of population size in local governments' efficiency.
	Kalb et al. (2012)	1,015 German municipalities	2004	Local governments should reduce inputs by 17% to 20%.
	Bischoff et al. (2013)	46 independent municipalities and 157 municipal associations in Saxony-Anhalt	2004	On average cost should be reduced by 18%. They study the impact of intergovernmental and vertical grants on cost efficiency.
	Geys et al. (2013)	1,021 German municipalities	2001	On average cost should be reduced by 12% to 14%. They study the relevance of population size in local governments' efficiency.
	Asatryan and De Witte (2015)	2,000 Bavarian municipalities	2011	On average cost should be reduced by 1% to 3%. They study the role of direct democracy in explaining efficiency.
	Lampe et al. (2015)	396 German municipalities	From 2006 to 2008	They analys the effect of new accounting and budgeting regimes on local government efficiency.

Table A.1 – continued from previous page

Country	Author(s)	Sample	Period studied	Main results
Greece	Athanassopoulos and Triantis (1998)	172 Greek municipalities	1986	Mean efficiency differs from 0.5 to 0.85.
	Doumpos and Cohen (2014)	2,017 Greek municipalities	From 2002 to 2009	Mean efficiency differs from 0.65 to 0.75.
Indonesia	Yusfany (2015)	491 municipalities in Indonesia	2010	Mean efficiency is 0.50.
Italy	Barone and Mocetti (2011)	1,115 Italian municipalities	From 2001 to 2004	On average cost should be reduced by 81%. They analyse links between public spending inefficiency and tax morale.
	Boetti et al. (2012)	262 Italian municipalities from Turin province	2005	Mean efficiency differs from 0.74 to 0.80. They assessed whether efficiency of local governments is affected by the degree of vertical fiscal imbalance.
	Lo Storto (2013)	103 Italian municipalities	2011	Mean efficiency differs from 0.85 to 0.88.
	D'Inverno et al. (2017)	282 Tuscan municipalities	2011	Mean efficiency is 0.44.
	Agasisti et al. (2015)	331 Italian municipalities	From 2010 to 2012	Mean efficiency differs from 0.66 to 0.67.
	Lo Storto (2016)	108 Italian municipalities	2013	Mean efficiency differs from 0.69 to 0.82.
Japan	Nijkamp and Suzuki (2009)	34 cities in Hokkaido prefecture in Japan	2005	Mean efficiency differs from 0.75 to 0.82.
	Haneda et al. (2012)	92 municipalities from Ibaraki prefecture	From 1979 to 2004	Mean efficiency differs from 0.80 to 0.89.
	Nakazawa (2013)	479 Japanese municipalities	2005	On average cost should be reduced by 10% to 14%. They examine the cost inefficiency of municipalities after amalgamation (municipalities that were amalgamated from 2000 to 2005).

Table A.1 – continued from previous page

Country	Author(s)	Sample	Period studied	Main results
	Nakazawa (2014)	479 Japanese municipalities	2005	On average cost should be reduced by 15% to 16%. They examine the effect of differences in facility distribution methods on municipal cost inefficiency after amalgamation.
Korea	Seol et al. (2008)	106 Korean local governments	2003	Mean efficiency is 0.77. They examine the impact of information technology on organizational efficiency in public services.
	Sung (2007)	222 Korean local governments	From 1999 to 2001	Mean efficiency differs from 0.57 to 0.97. They examine the impact of information technology on local government performance.
Macedonia	Nikolov and Hrovatin (2013)	74 municipalities in Macedonia	–	Mean efficiency is 0.59. They take into account the ethnic fragmentation of municipalities as a determinant of efficiency.
Malaysia	Ibrahim and Karim (2004)	46 local governments in Malaysia	2000	Mean efficiency is 0.76.
	Ibrahim and Salleh (2006)	46 local governments in Malaysia	2000	Mean efficiency is 0.59.
Morocco	El Mehdi and Hafner (2014)	91 rural districts in the oriental region of Morocco	1998/1999	Mean efficiency differs from 0.38 to 0.50.
Norway	Kalseth and Rattsø (1995)	407 Norwegian local authorities	1988	Mean efficiency differs from 0.74 to 0.84.
	Revelli and Tovmo (2007)	205 local governments in the 12 southern counties of Norway	–	Mean efficiency is 100. They investigates whether the production efficiency of Norwegian local governments exhibits a spatial pattern that is compatible with the hypothesis of yardstick competition.

Table A.1 – continued from previous page

Country	Author(s)	Sample	Period studied	Main results
	Borge et al. (2008)	362-384 Norwegian municipalities	From 2001 to 2005	Median values differ from 100.9 to 104.8. They investigate whether efficiency is affected by political and budgetary institutions, fiscal capacity, and democratic participation.
	Bruns and Himmler (2011)	362-384 Norwegian municipalities	From 2001 to 2005	Mean efficiency efficiency is 103.73. They examine the role of the newspaper market for the efficient use of public funds by elected politicians.
	Sørensen (2014)	430 Norwegian local authorities	From 2001 to 2010	Mean efficiency is 100. They study whether political competition and party polarization affect government performance.
	Helland and Sørensen (2015)	430 Norwegian local authorities	From 2001 to 2010	Mean efficiency is 1.04. They study whether partisan bias and electoral volatility affect government performance.
Portugal	Afonso and Fernandes (2003)	51 Portuguese municipalities Region of Lisboa e Vale do Tejo	2001	Mean efficiency differs from 0.41 to 0.61.
	Afonso and Fernandes (2006)	51 Portuguese municipalities Region of Lisboa e Vale do Tejo	2001	Mean efficiency differs from 0.32 to 0.73.
	Afonso and Fernandes (2008)	278 Portuguese municipalities	2001	Mean efficiency differs from 0.22 to 0.68.
	Da Cruz and Marques (2014)	308 Portuguese municipalities	2009	Mean efficiency differs from 0.73 to 0.84.
	Cordero et al. (2017)	278 Portuguese mainland municipalities	From 2009 to 2014	Mean efficiency differs from 0.67 to 0.76.
Serbia	Radulovic and Dragutinović (2015)	143 Serbian local governments	2012	On average cost should be reduced by 15% to 33%.

Table A.1 – continued from previous page

Country	Author(s)	Sample	Period studied	Main results
Slovenia	Pevcin (2014a)	200 Slovenian municipalities	2011	Mean efficiency differs from 0.75 to 0.78.
	Pevcin (2014b)	200 Slovenian municipalities	2011	Mean efficiency differs from 0.75 to 0.88.
Spain	Prieto and Zofio (2001)	209 municipalities in Castile and Leon Region	1994	–
	Balaguer-Coll et al. (2007)	414 municipalities Valencian Region	1995	Mean efficiency differs from 0.53 to 0.90.
	Giménez and Prior (2007)	258 municipalities in Catalonia Region	1996	The mean cost excess of inefficient municipalities is 25%. They decompose the total cost efficiency into short and long term.
	Balaguer-Coll and Prior (2009)	258 municipalities Valencian Region	From 1992 to 1995	Mean efficiency differs from 0.69 to 0.75. They tested the temporal evolution of efficiency and applied different output specifications.
	Balaguer-Coll et al. (2010a)	1,221 Spanish municipalities	1995 and 2000	Mean efficiency differs from 0.85 to 0.91. They analyse links between overall cost efficiency and the decentralization power in Spain.
	Bosch-Roca et al. (2012)	102 Catalonian municipalities	2005	Mean efficiency is 0.71. They connect efficiency with citizen's control in a decentralized context.
	Balaguer-Coll et al. (2010b)	1,164 Spanish municipalities	1995, 2000 and 2005	Mean efficiency change differs from 0.96 in 1995-2000 to 0.89 in 2000-2005. They analysed the links between devolution and efficiency of Spanish municipalities from a dynamic perspective.
	Benito et al. (2010)	31 municipalities in Murcia Region	2002	Mean efficiency differs from 0.53 to 0.90.
	Zafra-Gómez and Muñiz-Pérez (2010)	923 Spanish municipalities	2005 and 2010	Mean efficiency is 0.71 in 2000 and 0.69 in 2005. They evaluation the cost efficiency joint the financial condition.

Table A.1 – continued from previous page

Country	Author(s)	Sample	Period studied	Main results
	Balaguer-Coll et al. (2013)	1,198 Spanish municipalities	2000	Mean efficiency is 0.91. They analyse efficiency after splinting municipalities into clusters according to various criteria (output mix, environmental conditions, level of powers).
	Cuadrado-Ballesteros et al. (2013)	129 Spanish municipalities	From 1999 to 2007	Mean efficiency differs from 0.92 to 0.97. They analyse the effect of functional decentralisation and externalisation processes on the efficiency of Spanish municipalities.
	Arcelus et al. (2015)	260 municipalities from Navarre Region	2005	Mean cost-inefficiency is 1.264.
	Pérez-López et al. (2015)	1,058 Spanish municipalities	From 2001 to 2010	Mean efficiency is 0.85. They analysed the long term effects of the new delivery forms over efficiency.
South Africa	Dollery and van der Westhuizen (2009)	231 local municipalities and 46 district municipalities in South Africa	2006/2007	Mean efficiency differs from 0.30 to 0.64.
	Mahabir (2014)	129 municipalities in South Africa	From 2005 to 2010	Mean efficiency differs from 0.42 to 0.46.
	Monkam (2014)	231 local municipalities in South Africa	2007	Mean efficiency is 0.17.
Taiwan	Liu et al. (2011)	22 Local Governments in Taiwan	2007	Mean efficiency differs from 0.38 to 0.82.
Turkey	Kutlar and Bakirci (2012)	27 municipalities in Turkey	From 2006 to 2008	Mean efficiency differs from 0.53 to 0.86.
United Kingdom	Revelli (2010)	148 local authorities in England	From 2002 to 2007	–
	Andrews and Entwistle (2015)	386 local authorities in England	2007	Mean efficiency is 1.05. They examine the relationship between a commitment to public-private partnership, management capacity and the productive efficiency of English local authorities.

Table A.1 – continued from previous page

Country	Author(s)	Sample	Period studied	Main results
United States	Hayes and Chang (1990)	191 US municipalities	1982	Mean efficiency is 0.81. They study whether or not the Council Management form is more efficient than the Mayor Council form of government in formulating and implementing public policies.
	Grossman et al. (1999)	49 US central cities	1967, 1973, 1977 and 1982	Mean efficiency differs from 0.81 to 0.84. They measure technical inefficiency in the local public sector based upon a comparison of local property values.
	Moore et al. (2005)	46 largest cities in US	From 1993 to 1996	–

Table A.2: Overview of inputs

Variables	Studies
1. Financial expenditures	
Total expenditures	Kalseth and Rattsø (1995); De Borger and Kerstens (1996a,b); Prieto and Zofio (2001); Afonso and Fernandes (2003); Coffé and Geys (2005); Afonso and Fernandes (2006); Sung (2007); Afonso and Fernandes (2008); Seol et al. (2008); Nijkamp and Suzuki (2009); Balaguer-Coll et al. (2010b); Kutlar and Bakirci (2012); Nakazawa (2013, 2014); Ashworth et al. (2014); Pevcin (2014a,b); Mahabir (2014); Yusfany (2015); Andrews and Entwistle (2015); Asatryan and De Witte (2015); Lampe et al. (2015); Cordero et al. (2017)
Current expenditures	Hayes and Chang (1990); Eeckaut et al. (1993); Athanassopoulos and Triantis (1998); Sampaio de Sousa and Ramos (1999); Ibrahim and Karim (2004); Loikkanen and Susiluoto (2005); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Moore et al. (2005); Geys (2006); Ibrahim and Salleh (2006); Balaguer-Coll et al. (2007); Geys and Moesen (2009a,b); Balaguer-Coll and Prior (2009); Geys et al. (2010); Kalb (2010); Balaguer-Coll et al. (2010a); Zafra-Gómez and Muñiz-Pérez (2010); Bosch-Roca et al. (2012); Benito et al. (2010); Revelli (2010); Štastná and Gregor (2011); Barone and Mocetti (2011); Loikkanen et al. (2011); Kutlar and Bakirci (2012); Kalb et al. (2012); Boetti et al. (2012); Lo Storto (2013); Geys et al. (2013); Nikolov and Hrovatin (2013); Balaguer-Coll et al. (2013); Cuadrado-Ballesteros et al. (2013); Pacheco et al. (2014); D'Inverno et al. (2017); Monkam (2014); Pacheco et al. (2014); Marques et al. (2015); Štastná and Gregor (2015); Radulovic and Dragutinović (2015); Arcelus et al. (2015); Pérez-López et al. (2015); Nakazawa (2014); Lampe et al. (2015); Agasisti et al. (2015); Lo Storto (2016)
Personnel expenditures	Hayes and Chang (1990); De Borger et al. (1994); Worthington (2000); Moore et al. (2005); Sampaio de Sousa and Stošić (2005); Sampaio de Sousa et al. (2005); Sung (2007); Balaguer-Coll et al. (2007); Giménez and Prior (2007); Seol et al. (2008); Nijkamp and Suzuki (2009); Balaguer-Coll and Prior (2009); Dollery and van der Westhuizen (2009); Benito et al. (2010); Balaguer-Coll et al. (2010a); Zafra-Gómez and Muñiz-Pérez (2010); Bönisch et al. (2011); Liu et al. (2011); Kutlar and Bakirci (2012); Haneda et al. (2012); Fogarty and Mugera (2013); Bischoff et al. (2013); Nakazawa (2013); Balaguer-Coll et al. (2013); Da Cruz and Marques (2014); Cordero et al. (2017)
Capital and financial expenditures	Hayes and Chang (1990); De Borger et al. (1994); Worthington (2000); Balaguer-Coll et al. (2007); Balaguer-Coll and Prior (2009); Nijkamp and Suzuki (2009); Balaguer-Coll et al. (2010a); Bosch-Roca et al. (2012); Zafra-Gómez and Muñiz-Pérez (2010); Bönisch et al. (2011); Liu et al. (2011); Kutlar and Bakirci (2012); Balaguer-Coll et al. (2013); Fogarty and Mugera (2013); Bischoff et al. (2013); Cuadrado-Ballesteros et al. (2013); Da Cruz and Marques (2014)

Table A.2 – continued from previous page

Variables	Studies
Other financial expenditures	Worthington (2000); Giménez and Prior (2007); Bönisch et al. (2011); Bischoff et al. (2013); Fogarty and Mugera (2013); Da Cruz and Marques (2014)
2. Financial resources	
Local revenues	Revelli and Tovmo (2007); Borge et al. (2008); Bruns and Himmler (2011); Sørensen (2014); Doumpos and Cohen (2014); El Mehdi and Hafner (2014); Helland and Sørensen (2015)
Current transfers	Balaguer-Coll et al. (2007); Giménez and Prior (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010a, 2013); Benito et al. (2010); Kutlar and Bakirci (2012); Zafra-Gómez and Muñiz-Pérez (2010)
3. Non-financial inputs	
Public health services	Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005)
Area	Haneda et al. (2012)

Table A.3: Overview of outputs

Variables	Studies
1. Total output indicator	
	Afonso and Fernandes (2003, 2006); Revelli and Tovmo (2007); Afonso and Fernandes (2008); Borge et al. (2008); Bosch-Roca et al. (2012); Revelli (2010); Bruns and Himmler (2011); Nakazawa (2013); Nijkamp and Suzuki (2009); Sørensen (2014); Nakazawa (2014); Yusfany (2015); Andrews and Entwistle (2015); Helland and Sørensen (2015)
2. Population	
	Eeckaut et al. (1993); De Borger et al. (1994); De Borger and Kerstens (1996a,b); Athanassopoulos and Triantis (1998); Sampaio de Sousa and Ramos (1999); Worthington (2000); Ibrahim and Karim (2004); Coffé and Geys (2005); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Ibrahim and Salleh (2006); Balaguer-Coll et al. (2007); Giménez and Prior (2007); Balaguer-Coll and Prior (2009); Geys et al. (2010); Kalb (2010); Zafra-Gómez and Muñiz-Pérez (2010); Balaguer-Coll et al. (2010a,b); Bönisch et al. (2011); Štastná and Gregor (2011); Haneda et al. (2012); Kalb et al. (2012); Kutlar and Bakirci (2012); Boetti et al. (2012); Fogarty and Mugera (2013); Cuadrado-Ballesteros et al. (2013); Nikolov and Hrovatin (2013); Bischoff et al. (2013); Geys et al. (2013); Nikolov and Hrovatin (2013); Balaguer-Coll et al. (2013); Lo Storto (2013); Pevcin (2014a,b); Pacheco et al. (2014); D'Inverno et al. (2017); Monkam (2014); Da Cruz and Marques (2014); Lampe et al. (2015); Radulovic and Dragutinović (2015); Agasisti et al. (2015); Pérez-López et al. (2015); Cordero et al. (2017); Lo Storto (2016)
3. Area of municipality and built area	
	Athanassopoulos and Triantis (1998); Giménez and Prior (2007); Štastná and Gregor (2011); Lo Storto (2013); Cuadrado-Ballesteros et al. (2013); Fogarty and Mugera (2013); Štastná and Gregor (2015); Arcelus et al. (2015); Pérez-López et al. (2015); Lo Storto (2016)
4. Administrative services	
	Kalseth and Rattsø (1995); Moore et al. (2005); Sung (2007); Seol et al. (2008); Barone and Mocetti (2011); Cuadrado-Ballesteros et al. (2013); Arcelus et al. (2015); Marques et al. (2015); Cordero et al. (2017)
5. Infrastructures	
Street lighting	Prieto and Zofio (2001); Balaguer-Coll et al. (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010a,b); Zafra-Gómez and Muñiz-Pérez (2010); Barone and Mocetti (2011); Balaguer-Coll et al. (2013); Doumpos and Cohen (2014); Arcelus et al. (2015); Pérez-López et al. (2015)

Table A.3 – continued from previous page

Variables	Studies
Municipal roads	Eeckaut et al. (1993); De Borger et al. (1994); De Borger and Kerstens (1996b); Worthington (2000); Prieto and Zofio (2001); Ibrahim and Karim (2004); Moore et al. (2005); Ibrahim and Salleh (2006); Geys (2006); Balaguer-Coll et al. (2007); Sung (2007); Giménez and Prior (2007); Geys and Moesen (2009a,b); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010a,b); Zafra-Gómez and Muñiz-Pérez (2010); Barone and Mocetti (2011); Štastná and Gregor (2011); Boetti et al. (2012); Lo Storto (2013); Fogarty and Mugera (2013); Nikolov and Hrovatin (2013); Balaguer-Coll et al. (2013); Doumpos and Cohen (2014); D'Inverno et al. (2017); Da Cruz and Marques (2014); Ashworth et al. (2014); Štastná and Gregor (2015); Marques et al. (2015); Agasisti et al. (2015); Radulovic and Dragutinović (2015); Arcelus et al. (2015)
6. Communal services	
Waste collection	Hayes and Chang (1990); Sampaio de Sousa and Ramos (1999); Worthington (2000); Ibrahim and Karim (2004); Moore et al. (2005); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Ibrahim and Salleh (2006); Balaguer-Coll et al. (2007); Giménez and Prior (2007); Geys and Moesen (2009a,b); Balaguer-Coll and Prior (2009); Benito et al. (2010); Balaguer-Coll et al. (2010a,b); Zafra-Gómez and Muñiz-Pérez (2010); Benito et al. (2010); Štastná and Gregor (2011); Barone and Mocetti (2011); Boetti et al. (2012); Balaguer-Coll et al. (2013); Pacheco et al. (2014); Mahabir (2014); Monkam (2014); Da Cruz and Marques (2014); Ashworth et al. (2014); Pérez-López et al. (2015); Štastná and Gregor (2015); Agasisti et al. (2015); Cordero et al. (2017).
Sewerage system	Worthington (2000); Prieto and Zofio (2001); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Sung (2007); Liu et al. (2011); Pacheco et al. (2014); Monkam (2014); Mahabir (2014); Da Cruz and Marques (2014); Marques et al. (2015)
Water supply	Sampaio de Sousa and Ramos (1999); Worthington (2000); Prieto and Zofio (2001); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Moore et al. (2005); Sung (2007); Benito et al. (2010); Mahabir (2014); Monkam (2014); Da Cruz and Marques (2014); Marques et al. (2015); Pérez-López et al. (2015); Arcelus et al. (2015); Radulovic and Dragutinović (2015); Cordero et al. (2017)
Electricity	(Dollery and van der Westhuizen, 2009; Monkam, 2014; Mahabir, 2014)
7. Parks, sports, culture and recreational facilities	
Sport facilities	Prieto and Zofio (2001); Benito et al. (2010); Štastná and Gregor (2011, 2015)
Cultural facilities	Prieto and Zofio (2001); Benito et al. (2010); Štastná and Gregor (2011, 2015)
Libraries	Benito et al. (2010); Loikkanen and Susiluoto (2005); Moore et al. (2005); Loikkanen et al. (2011)

Table A.3 – continued from previous page

Variables	Studies
Parks and green areas	Prieto and Zofio (2001); Ibrahim and Karim (2004); Moore et al. (2005); Ibrahim and Salleh (2006); Balaguer-Coll et al. (2007); Sung (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010a,b); Benito et al. (2010); Zafra-Gómez and Muñiz-Pérez (2010); Štastná and Gregor (2011); Balaguer-Coll et al. (2013); Pacheco et al. (2014); Štastná and Gregor (2015); Pérez-López et al. (2015)
Recreational facilities	De Borger et al. (1994); De Borger and Kerstens (1996a,b); Coffé and Geys (2005); Geys (2006); Geys and Moesen (2009a,b); Geys et al. (2010); Balaguer-Coll et al. (2010a,b); Bönisch et al. (2011); Kalb et al. (2012); Geys et al. (2013); Balaguer-Coll et al. (2013); Bischoff et al. (2013); Doumpos and Cohen (2014); Ashworth et al. (2014); Da Cruz and Marques (2014); Lampe et al. (2015); Asatryan and De Witte (2015)
8. Health	
	Loikkanen and Susiluoto (2005); Moore et al. (2005); Loikkanen et al. (2011); Kutlar and Bakirci (2012); Pacheco et al. (2014); Marques et al. (2015)
9. Education	
Kindergardens or nursery places	Geys et al. (2010); Revelli (2010); Barone and Mocetti (2011); Boetti et al. (2012); Štastná and Gregor (2011); Kalb et al. (2012); Lo Storto (2013); Nikolov and Hrovatin (2013); Geys et al. (2013); D'Inverno et al. (2017); Lampe et al. (2015); Štastná and Gregor (2015); Radulovic and Dragutinović (2015); Asatryan and De Witte (2015)
Primary and secondary education	Eeckaut et al. (1993); De Borger et al. (1994); De Borger and Kerstens (1996a,b); Sampaio de Sousa and Ramos (1999); Coffé and Geys (2005); Sampaio de Sousa et al. (2005); Loikkanen and Susiluoto (2005); Sampaio de Sousa and Stošić (2005); Geys (2006); Geys and Moesen (2009a,b); Geys et al. (2010); Kalb (2010); Revelli (2010); Štastná and Gregor (2011); Loikkanen et al. (2011); Bönisch et al. (2011); Boetti et al. (2012); Kalb et al. (2012); Kutlar and Bakirci (2012); Bischoff et al. (2013); Nikolov and Hrovatin (2013); Geys et al. (2013); D'Inverno et al. (2017); Ashworth et al. (2014); Pacheco et al. (2014); Pevcin (2014a,b); Radulovic and Dragutinović (2015); Štastná and Gregor (2015); Asatryan and De Witte (2015); Lampe et al. (2015)
10. Social services	
Grants beneficiaries	Eeckaut et al. (1993); De Borger et al. (1994); De Borger and Kerstens (1996a,b); Coffé and Geys (2005); Sampaio de Sousa et al. (2005); Sampaio de Sousa and Stošić (2005); Geys (2006); Geys and Moesen (2009a,b); Loikkanen et al. (2011); Ashworth et al. (2014)

Table A.3 – continued from previous page

Variables	Studies
Care for elderly	Eeckaut et al. (1993); De Borger and Kerstens (1996a,b); Loikkanen and Susiluoto (2005); Coffé and Geys (2005); Kalb (2010); Geys et al. (2010); Šťastná and Gregor (2011); Kutlar and Bakirci (2012); Boetti et al. (2012); Kalb et al. (2012); Nikolov and Hrovatin (2013); Geys et al. (2013); Pevcin (2014a,b); D'Inverno et al. (2017); Ashworth et al. (2014); Lampe et al. (2015); Šťastná and Gregor (2015); Asatryan and De Witte (2015); Arcelus et al. (2015)
Care for children	Loikkanen and Susiluoto (2005); Loikkanen et al. (2011); Bönisch et al. (2011); Bischoff et al. (2013)
Social services and organizations	Loikkanen and Susiluoto (2005); Sung (2007); Loikkanen et al. (2011); Balaguer-Coll et al. (2010a,b); Radulovic and Dragutinović (2015); Šťastná and Gregor (2011); Balaguer-Coll et al. (2013); Cuadrado-Ballesteros et al. (2013); D'Inverno et al. (2017); Šťastná and Gregor (2015)
11. Public safety	
	Eeckaut et al. (1993); Hayes and Chang (1990); Moore et al. (2005); Benito et al. (2010); Šťastná and Gregor (2011); Barone and Mocetti (2011); Cuadrado-Ballesteros et al. (2013); Šťastná and Gregor (2015); Agasisti et al. (2015)
12. Markets	
	Ibrahim and Karim (2004); Ibrahim and Salleh (2006); Balaguer-Coll et al. (2010a,b, 2013)
13. Public transport	
	Šťastná and Gregor (2011, 2015)
14. Environmental protection	
	Athanassopoulos and Triantis (1998); Šťastná and Gregor (2011); Liu et al. (2011); Lo Storto (2013); Cuadrado-Ballesteros et al. (2013)
15. Business development	
	Geys et al. (2010); Kalb (2010); Bönisch et al. (2011); Liu et al. (2011); Kalb et al. (2012); Bischoff et al. (2013); Geys et al. (2013); Pevcin (2014a,b); Asatryan and De Witte (2015); Lampe et al. (2015); Arcelus et al. (2015)
16. Quality index	
	Balaguer-Coll et al. (2007); Balaguer-Coll and Prior (2009); Balaguer-Coll et al. (2010b); Zafra-Gómez and Muñiz-Pérez (2010); Haneda et al. (2012)
17. Others	

Table A.3 – continued from previous page

Variables	Studies
	Athanassopoulos and Triantis (1998); Grossman et al. (1999); Nijkamp and Suzuki (2009); El Mehdi and Hafner (2014); Doumpos and Cohen (2014); Pérez-López et al. (2015)

Table A.4: Overview of determinants of efficiency in local governments

Variables	Studies
1. Social determinants	
Population density	Kalseth and Rattsø (1995); De Borger and Kerstens (1996a); Athanassopoulos and Triantis (1998); Loikkanen and Susiluoto (2005); Sampaio de Sousa et al. (2005); Geys (2006); Sung (2007); Giménez and Prior (2007); Revelli and Tovmo (2007); Afonso and Fernandes (2008); Geys and Moesen (2009a); Geys et al. (2010); Kalb (2010); Revelli (2010); Bönisch et al. (2011); Loikkanen et al. (2011); Bruns and Himmler (2011); Kalb et al. (2012); Boetti et al. (2012); Fogarty and Mugera (2013); Bischoff et al. (2013); Geys et al. (2013); Balaguer-Coll et al. (2013); Doumpos and Cohen (2014); Da Cruz and Marques (2014); D'Inverno et al. (2017); Ashworth et al. (2014); Pevcin (2014a,b); Arcelus et al. (2015); Yusfany (2015); Agasisti et al. (2015); Radulovic and Dragutinović (2015); Lampe et al. (2015); Andrews and Entwistle (2015); Lo Storto (2016); Cordero et al. (2017)
Population growth	Kalseth and Rattsø (1995); Afonso and Fernandes (2008); Bönisch et al. (2011); Bischoff et al. (2013); Balaguer-Coll et al. (2013); Monkam (2014)
Population size	De Borger et al. (1994); Kalseth and Rattsø (1995); Grossman et al. (1999); Loikkanen and Susiluoto (2005); Sung (2007); Balaguer-Coll et al. (2007); Giménez and Prior (2007); Geys and Moesen (2009a); Benito et al. (2010); Revelli (2010); Štastná and Gregor (2011); Loikkanen et al. (2011); Bruns and Himmler (2011); Boetti et al. (2012); Nakazawa (2013, 2014); D'Inverno et al. (2017); Doumpos and Cohen (2014); Sørensen (2014); Ashworth et al. (2014); Štastná and Gregor (2015); Pérez-López et al. (2015); Andrews and Entwistle (2015); Asatryan and De Witte (2015)
Age distribution of the population	Bönisch et al. (2011); Bruns and Himmler (2011); Bosch-Roca et al. (2012); Nakazawa (2013); Bischoff et al. (2013); Nakazawa (2014); Da Cruz and Marques (2014); Agasisti et al. (2015); Radulovic and Dragutinović (2015); Andrews and Entwistle (2015)
Education level	De Borger et al. (1994); De Borger and Kerstens (1996a,b); Ibrahim and Karim (2004); Loikkanen and Susiluoto (2005); Afonso and Fernandes (2008); Geys and Moesen (2009a); Revelli (2010); Kalb (2010); Bruns and Himmler (2011); Štastná and Gregor (2011); Loikkanen et al. (2011); Bosch-Roca et al. (2012); Da Cruz and Marques (2014); Monkam (2014); Radulovic and Dragutinović (2015); Štastná and Gregor (2015)
Immigration share and ethnic diversity	Hayes and Chang (1990); Revelli (2010); Bruns and Himmler (2011); Bosch-Roca et al. (2012); Nikolov and Hrovatin (2013); Andrews and Entwistle (2015); Lampe et al. (2015)
Share of homeowners	Hayes and Chang (1990); Geys (2006); Geys and Moesen (2009a)

Table A.4 – continued from previous page

Variables	Studies
Other related social and demographic characteristics	Revelli (2010); Bruns and Himmler (2011); Nakazawa (2013); Da Cruz and Marques (2014); Agasisti et al. (2015); Andrews and Entwistle (2015); Lo Storto (2016)
2. Economic determinants	
Unemployment	Loikkanen and Susiluoto (2005); Geys and Moesen (2009a); Balaguer-Coll and Prior (2009); Revelli (2010); Kalb (2010); Loikkanen et al. (2011); Bönisch et al. (2011); Kalb et al. (2012); Geys et al. (2013); Pevcin (2014a,b); Radulovic and Dragutinović (2015); Pérez-López et al. (2015); Lampe et al. (2015); Cordero et al. (2017)
Citizen's income or purchasing power	De Borger et al. (1994); De Borger and Kerstens (1996a,b); Ibrahim and Karim (2004); Loikkanen and Susiluoto (2005); Sampaio de Sousa et al. (2005); Geys (2006); Giménez and Prior (2007); Afonso and Fernandes (2008); Geys and Moesen (2009a); Balaguer-Coll and Prior (2009); Benito et al. (2010); Afonso et al. (2010); Bruns and Himmler (2011); Bosch-Roca et al. (2012); Boetti et al. (2012); Nikolov and Hrovatin (2013); Balaguer-Coll et al. (2013); Cuadrado-Ballesteros et al. (2013); Monkam (2014); Ashworth et al. (2014); Da Cruz and Marques (2014); Asatryan and De Witte (2015); Agasisti et al. (2015); Yusfany (2015); Cordero et al. (2017)
Municipal economic situation	Sampaio de Sousa et al. (2005); Revelli (2010); Fogarty and Mugera (2013); Balaguer-Coll et al. (2013); Andrews and Entwistle (2015); Lo Storto (2016)
Tourism	Sampaio de Sousa et al. (2005); Giménez and Prior (2007); Geys and Moesen (2009a); Balaguer-Coll and Prior (2009); Kalb (2010); Benito et al. (2010); Bosch-Roca et al. (2012); Kalb et al. (2012); Cuadrado-Ballesteros et al. (2013); Da Cruz and Marques (2014); D'Inverno et al. (2017); Pérez-López et al. (2015); Lampe et al. (2015)
Commercial activity	Giménez and Prior (2007); Sung (2007); Balaguer-Coll and Prior (2009); Bosch-Roca et al. (2012)
Industrial activity	Giménez and Prior (2007); Geys and Moesen (2009a)
Other related economic characteristics	Sampaio de Sousa et al. (2005); Geys and Moesen (2009a); Revelli (2010); Balaguer-Coll et al. (2013); Da Cruz and Marques (2014)
3. Political determinants	
Ideological position	De Borger et al. (1994); De Borger and Kerstens (1996a,b); Geys (2006); Geys and Moesen (2009a); Borge et al. (2008); Geys et al. (2010); Kalb (2010); Revelli (2010); Benito et al. (2010); Bruns and Himmler (2011); Šťastná and Gregor (2011); Loikkanen et al. (2011); Kalb et al. (2012); Boetti et al. (2012); Sørensen (2014); Doumpos and Cohen (2014); Da Cruz and Marques (2014); Ashworth et al. (2014); Šťastná and Gregor (2015); Agasisti et al. (2015); Asatryan and De Witte (2015); Pérez-López et al. (2015); Helland and Sørensen (2015); Andrews and Entwistle (2015); Cordero et al. (2017)

Table A.4 – continued from previous page

Variables	Studies
Political concentration/ fragmentation and strentgh	Eeckaut et al. (1993); De Borger et al. (1994); Athanassopoulos and Triantis (1998); Geys (2006); Balaguer-Coll et al. (2007); Revelli and Tovmo (2007); Borge et al. (2008); Geys et al. (2010); Revelli (2010); Kalb (2010); Loikkanen et al. (2011); Bruns and Himmler (2011); Štastná and Gregor (2011); Kalb et al. (2012); Geys et al. (2013); Cuadrado-Ballesteros et al. (2013); Nikolov and Hrovatin (2013); Doumpos and Cohen (2014); Ashworth et al. (2014); Monkam (2014); Pacheco et al. (2014); Sørensen (2014); Yusfany (2015); Pérez-López et al. (2015); Helland and Sørensen (2015)
Voter turnout and democratic participation	Revelli and Tovmo (2007); Borge et al. (2008); Geys et al. (2010); Loikkanen et al. (2011); Štastná and Gregor (2011); Bosch-Roca et al. (2012); Da Cruz and Marques (2014); Asatryan and De Witte (2015); Štastná and Gregor (2015)
Re-election and number of years for elections	Boetti et al. (2012); D'Inverno et al. (2017); Doumpos and Cohen (2014); Da Cruz and Marques (2014); Agasisti et al. (2015)
Other related politic characteristics	Grossman et al. (1999); Bruns and Himmler (2011)
4. Financial determinants	
Self-generated revenues	De Borger and Kerstens (1996a,b); Athanassopoulos and Triantis (1998); Moore et al. (2005); Balaguer-Coll et al. (2007); Revelli and Tovmo (2007); Sung (2007); Borge et al. (2008); Balaguer-Coll and Prior (2009); Benito et al. (2010); Štastná and Gregor (2011); Bosch-Roca et al. (2012); Boetti et al. (2012); Nikolov and Hrovatin (2013); Fogarty and Mugera (2013); Ashworth et al. (2014); Doumpos and Cohen (2014); Da Cruz and Marques (2014); Monkam (2014); D'Inverno et al. (2017); Yusfany (2015); Arcelus et al. (2015); Pérez-López et al. (2015); Štastná and Gregor (2015); Agasisti et al. (2015)
Transfers or grants	De Borger and Kerstens (1996a,b); Athanassopoulos and Triantis (1998); Grossman et al. (1999); Worthington (2000); Loikkanen and Susiluoto (2005); Geys (2006); Balaguer-Coll et al. (2007); Borge et al. (2008); Geys and Moesen (2009a); Balaguer-Coll and Prior (2009); Geys et al. (2010); Kalb (2010); Bönisch et al. (2011); Štastná and Gregor (2011); Bosch-Roca et al. (2012); Boetti et al. (2012); Bischoff et al. (2013); Pacheco et al. (2014); Doumpos and Cohen (2014); Da Cruz and Marques (2014); Ashworth et al. (2014); Pérez-López et al. (2015); Yusfany (2015); Štastná and Gregor (2015); Agasisti et al. (2015)
Debt or financial liabilities	Worthington (2000); Geys (2006); Balaguer-Coll et al. (2007); Revelli and Tovmo (2007); Geys and Moesen (2009a); Balaguer-Coll and Prior (2009); Benito et al. (2010); Štastná and Gregor (2011); Bönisch et al. (2011); Bischoff et al. (2013); Ashworth et al. (2014); Da Cruz and Marques (2014); Pérez-López et al. (2015); Cordero et al. (2017)

Table A.4 – continued from previous page

Variables	Studies
Fiscal surplus	Geys (2006); Geys and Moesen (2009a); Ashworth et al. (2014); Agasisti et al. (2015); Yusfany (2015); Pérez-López et al. (2015)
Infrastructure investments	Athanassopoulos and Triantis (1998); Štastná and Gregor (2011); Doumpos and Cohen (2014); Pacheco et al. (2014); Arcelus et al. (2015); Štastná and Gregor (2015); Agasisti et al. (2015)
Other related financial characteristics	Worthington (2000); Borge et al. (2008); Revelli (2010); Kalb (2010); Benito et al. (2010); Boetti et al. (2012); Doumpos and Cohen (2014); Da Cruz and Marques (2014); Agasisti et al. (2015); Pérez-López et al. (2015); Andrews and Entwistle (2015)
5. Geographical or natural determinants	
Distance from centre and localization effects	Grossman et al. (1999); Loikkanen and Susiluoto (2005); Sampaio de Sousa et al. (2005); Afonso and Fernandes (2008); Loikkanen et al. (2011); Štastná and Gregor (2011); Boetti et al. (2012); Pacheco et al. (2014); Štastná and Gregor (2015); Radulovic and Dragutinović (2015); Andrews and Entwistle (2015)
Area	Ibrahim and Karim (2004); Moore et al. (2005); Sung (2007); Nakazawa (2013); Da Cruz and Marques (2014)
Type of municipality (Sea, Mountain)	D'Inverno et al. (2017); Da Cruz and Marques (2014); Boetti et al. (2012); Agasisti et al. (2015); Cordero et al. (2017)
Other related to geographical or natural characteristics	Sampaio de Sousa et al. (2005); Moore et al. (2005); Agasisti et al. (2015); Arcelus et al. (2015)
6. Institutional and management determinants	
Informatization or level of computer usage	Ibrahim and Karim (2004); Sampaio de Sousa et al. (2005); Sung (2007); Seol et al. (2008)
Mayor and local government employees	Grossman et al. (1999); Worthington (2000); Ibrahim and Karim (2004); Sampaio de Sousa et al. (2005); Loikkanen and Susiluoto (2005); Revelli (2010); Loikkanen et al. (2011); Boetti et al. (2012); Fogarty and Mugera (2013); Agasisti et al. (2015)
Amalgamation	Geys (2006); Geys and Moesen (2009a); Nakazawa (2013, 2014); Da Cruz and Marques (2014)
Managerial forms	Sampaio de Sousa et al. (2005); Loikkanen and Susiluoto (2005); Benito et al. (2010); Bönisch et al. (2011); Boetti et al. (2012); Cuadrado-Ballesteros et al. (2013); Bischoff et al. (2013); Arcelus et al. (2015); Pérez-López et al. (2015); Agasisti et al. (2015); Andrews and Entwistle (2015)

Table A.4 – continued from previous page

Variables	Studies
Other related to institutional and characteristics	Hayes and Chang (1990); Sampaio de Sousa et al. (2005); Moore et al. (2005); Andrews and Entwistle (2015); Arcelus et al. (2015); Agasisti et al. (2015)

Table A.5: Finite sample performance with no noise under a Cobb-Douglas cost function, $\upsilon = 0.00$

In the baseline experiment we include noise in each scenario. However, non-parametric methodologies assume the absence of noise. This table provides the results for the performance of the methodologies in the Monte Carlo experiment with the absence of noise ($\upsilon = 0.00$). We simulate three scenarios, which represent different inefficiency (σ_u) terms.

	Bias[a]				RMSE[b]				Upward Bias[c]				Kendall's τ[d]			
	DEA	FDH	Order-m	KSW	DEA	FDH	Order-m	KSW	DEA	FDH	Order-m	KSW	DEA	FDH	Order-m	KSW
s1: $\sigma_\upsilon = 0.00$, $\sigma_u = 0.01$																
n=100	-0.0249	0.0078	0.0237	-0.0293	0.0270	0.0098	0.0309	0.0308	0.0400	1.0000	1.0000	0.0000	0.4243	0.1590	0.0507	0.4276
n=200	-0.0286	0.0078	0.0298	-0.0320	0.0303	0.0097	0.0373	0.0334	0.0250	1.0000	1.0000	0.0050	0.4242	0.1870	0.0747	0.4240
s3: $\sigma_\upsilon = 0.00$, $\sigma_u = 0.05$																
n=100	-0.0140	0.0331	0.0485	-0.0199	0.0181	0.0398	0.0552	0.0224	0.1100	1.0000	1.0000	0.0500	0.7771	0.4650	0.3217	0.7935
n=200	-0.0192	0.0303	0.0524	-0.0240	0.0221	0.0360	0.0588	0.0260	0.0650	1.0000	1.0000	0.0300	0.7855	0.5512	0.3892	0.7925
s5: $\sigma_\upsilon = 0.00$, $\sigma_u = 0.1$																
n=100	-0.0069	0.0533	0.0692	-0.0139	0.0158	0.0628	0.0771	0.0188	0.1900	1.0000	1.0000	0.0800	0.8648	0.6058	0.5218	0.8832
n=200	-0.0132	0.0464	0.0698	-0.0192	0.0178	0.0542	0.0768	0.0219	0.1100	1.0000	1.0000	0.0500	0.8764	0.6773	0.5821	0.8852

[a] The bias reports the difference between the estimated and true efficiency scores. When it is negative (positive), the estimators are underestimating (overestimating) the true efficiency.
[b] The *RMSE* (root mean squared error) measures the standard deviation or error from the true efficiency.
[c] The upward bias is the proportion of estimated efficiencies larger than the true efficiencies (returning a value of 1). The desired value is 0.5. The values less (greater) than 0.5 indicate underestimation (overestimation) of cost efficiencies.
[d] Kendall's τ shows the correlation coefficient for the efficiency ranks between true and estimated efficiency scores.

Table A.6: Finite sample performance with a bigger sample size under a Cobb-Douglas cost function, $n = 500$

The baseline experiment analyses two different sample sizes, $n = 100$ and 200. This table provides the results for the performance of the methodologies in the Monte Carlo experiment with a bigger sample size ($n = 500$). We simulate six scenarios, which represent different combinations for the error (σ_v) and inefficiency (σ_u) terms.

	Bias[a]				RMSE[b]				Upward Bias[c]				Kendall's τ[d]			
	DEA	FDH	Order-m	KSW	DEA	FDH	Order-m	KSW	DEA	FDH	Order-m	KSW	DEA	FDH	Order-m	KSW
s1: $\sigma_v = 0.01$, $\sigma_u = 0.01$ n=500	-0.0403	0.0058	0.0338	-0.0439	0.0427	0.0090	0.0420	0.0460	0.0120	0.9080	0.9760	0.0040	0.2537	0.2056	0.1051	0.2537
s2: $\sigma_v = 0.01$, $\sigma_u = 0.05$ n=500	-0.1187	-0.0351	0.0028	-0.1281	0.1275	0.0556	0.0527	0.1361	0.0100	0.3300	0.5540	0.0020	0.0694	0.0610	0.0576	0.0694
s3: $\sigma_v = 0.05$, $\sigma_u = 0.01$ n=500	-0.0308	0.0238	0.0540	-0.0353	0.0340	0.0291	0.0608	0.0380	0.0320	0.9740	0.9960	0.0160	0.6914	0.5996	0.4365	0.6934
s4: $\sigma_v = 0.05$, $\sigma_u = 0.05$ n=500	-0.1023	-0.0146	0.0256	-0.1126	0.1122	0.0482	0.0599	0.1216	0.0220	0.4560	0.7000	0.0100	0.3131	0.2803	0.2698	0.3127
s5: $\sigma_v = 0.01$, $\sigma_u = 0.1$ n=500	-0.0247	0.0355	0.0689	-0.0298	0.0286	0.0423	0.0759	0.0328	0.0560	0.9860	0.9980	0.0300	0.8262	0.7263	0.6195	0.8300
s6: $\sigma_v = 0.05$, $\sigma_u = 0.1$ n=500	-0.0887	0.0019	0.0443	-0.0999	0.1000	0.0493	0.0713	0.1098	0.0340	0.5600	0.7960	0.0200	0.5129	0.4624	0.4522	0.5119

[a] The bias reports the difference between the estimated and true efficiency scores. When it is negative (positive), the estimators are underestimating (overestimating) the true efficiency.
[b] The *RMSE* (root mean squared error) measures the standard deviation or error from the true efficiency.
[c] The upward bias is the proportion of estimated efficiencies larger than the true efficiencies (returning a value of 1). The desired value is 0.5. The values less (greater) than 0.5 indicate underestimation (overestimation) of cost efficiencies.
[d] Kendall's τ shows the correlation coefficient for the efficiency ranks between true and estimated efficiency scores.

Table A.7: Finite sample performance with decreasing returns to scale under a Cobb-Douglas cost function, $\gamma = 0.8$

The baseline experiment assumes CRS technology. This table provides the results for the performance of the methodologies in the Monte Carlo experiment with decreasing returns to scale ($\gamma = 0.8$). We simulate six scenarios, which represent different combinations for the error (σ_v) and inefficiency (σ_u) terms.

	Bias[a]				RMSE[b]				Upward Bias[c]				Kendall's τ[d]			
	DEA	**FDH**	**Order-m**	**KSW**	**DEA**	**FDH**	**Order-m**	**KSW**	**DEA**	**FDH**	**Order-m**	**KSW**	**DEA**	**FDH**	**Order-m**	**KSW**
s1: $\sigma_v = 0.01$, $\sigma_u = 0.01$																
n=100	-0.0397	0.0072	0.0201	-0.0444	0.0499	0.0095	0.0265	0.0534	0.0800	0.9700	0.9800	0.0300	0.1140	0.1429	0.0762	0.1158
n=200	-0.0439	0.0066	0.0246	-0.0477	0.0531	0.0093	0.0317	0.0562	0.0450	0.9450	0.9750	0.0150	0.1225	0.1793	0.0957	0.1233
s2: $\sigma_v = 0.05$, $\sigma_u = 0.01$																
n=100	-0.0967	-0.0148	-0.0012	-0.1088	0.1107	0.0376	0.0395	0.1213	0.0500	0.5800	0.6300	0.0100	0.0606	0.0588	0.0536	0.0610
n=200	-0.1100	-0.0252	-0.0034	-0.1208	0.1224	0.0470	0.0458	0.1321	0.0250	0.4400	0.5550	0.0050	0.0614	0.0615	0.0570	0.0614
s3: $\sigma_v = 0.01$, $\sigma_u = 0.05$																
n=100	-0.0283	0.0308	0.0436	-0.0348	0.0418	0.0374	0.0499	0.0459	0.1900	0.9900	1.0000	0.1000	0.4474	0.4825	0.3673	0.4537
n=200	-0.0340	0.0271	0.0458	-0.0392	0.0455	0.0330	0.0519	0.0491	0.1150	0.9850	0.9950	0.0650	0.4561	0.5481	0.4301	0.4594
s4: $\sigma_v = 0.05$, $\sigma_u = 0.05$																
n=100	-0.0769	0.0088	0.0234	-0.0902	0.0943	0.0412	0.0490	0.1048	0.0900	0.7000	0.7700	0.0500	0.2729	0.2608	0.2561	0.2719
n=200	-0.0917	-0.0030	0.0195	-0.1035	0.1061	0.0436	0.0519	0.1164	0.0500	0.5750	0.7000	0.0250	0.2810	0.2730	0.2669	0.2792
s5: $\sigma_v = 0.01$, $\sigma_u = 0.1$																
n=100	-0.0206	0.0492	0.0626	-0.0287	0.0373	0.0586	0.0702	0.0416	0.2800	1.0000	1.0000	0.1600	0.6393	0.6202	0.5605	0.6461
n=200	-0.0274	0.0418	0.0619	-0.0338	0.0408	0.0498	0.0686	0.0448	0.1800	0.9950	1.0000	0.1050	0.6505	0.6816	0.6144	0.6557
s6: $\sigma_v = 0.05$, $\sigma_u = 0.1$																
n=100	-0.0631	0.0287	0.0439	-0.0777	0.0831	0.0563	0.0660	0.0946	0.1300	0.7800	0.8400	0.0800	0.4600	0.4247	0.4206	0.4582
n=200	-0.0786	0.0144	0.0391	-0.0916	0.0949	0.0514	0.0645	0.1056	0.0800	0.6650	0.7950	0.0450	0.4681	0.4448	0.4478	0.4659

[a] The bias reports the difference between the estimated and true efficiency scores. When it is negative (positive), the estimators are underestimating (overestimating) the true efficiency.

[b] The *RMSE* (root mean squared error) measures the standard deviation or error from the true efficiency.

[c] The upward bias is the proportion of estimated efficiencies larger than the true efficiencies (returning a value of 1). The desired value is 0.5. The values less (greater) than 0.5 indicate underestimation (overestimation) of cost efficiencies.

[d] Kendall's τ shows the correlation coefficient for the efficiency ranks between true and estimated efficiency scores.

Table A.8: Finite sample performance with increasing returns to scale under a Cobb-Douglas cost function, $\gamma = 1.2$

The baseline experiment assumes CRS technology. This table provides the results for the performance of the methodologies in the Monte Carlo experiment with decreasing returns to scale ($\gamma = 1.2$). We simulate six scenarios, which represent different combinations for the error (σ_v) and inefficiency (σ_u) terms.

	Bias[a]				RMSE[b]				Upward Bias[c]				Kendall's τ[d]			
	DEA	**FDH**	**Order-m**	**KSW**	**DEA**	**FDH**	**Order-m**	**KSW**	**DEA**	**FDH**	**Order-m**	**KSW**	**DEA**	**FDH**	**Order-m**	**KSW**
s1: $\sigma_v = 0.01$, $\sigma_u = 0.01$																
n=100	-0.0486	0.0075	0.0256	-0.0540	0.0586	0.0097	0.0343	0.0628	0.0700	0.9900	0.9900	0.0200	0.1029	0.1139	0.0534	0.1035
n=200	-0.0530	0.0072	0.0321	-0.0572	0.0621	0.0095	0.0416	0.0656	0.0450	0.9700	0.9900	0.0150	0.1010	0.1447	0.0683	0.1019
s2: $\sigma_v = 0.05$, $\sigma_u = 0.01$																
n=100	-0.1012	-0.0084	0.0097	-0.1135	0.1153	0.0312	0.0412	0.1260	0.0500	0.6800	0.7400	0.0000	0.0592	0.0541	0.0478	0.0586
n=200	-0.1149	-0.0172	0.0104	-0.1262	0.1272	0.0398	0.0486	0.1374	0.0250	0.5450	0.6700	0.0050	0.0569	0.0594	0.0513	0.0569
s3: $\sigma_v = 0.01$, $\sigma_u = 0.05$																
n=100	-0.0363	0.0332	0.0510	-0.0434	0.0489	0.0406	0.0588	0.0539	0.1600	1.0000	1.0000	0.0900	0.4182	0.4152	0.2808	0.4232
n=200	-0.0423	0.0302	0.0556	-0.0479	0.0533	0.0367	0.0634	0.0575	0.1050	0.9900	1.0000	0.0600	0.4209	0.4932	0.3453	0.4236
s4: $\sigma_v = 0.05$, $\sigma_u = 0.05$																
n=100	-0.0818	0.0166	0.0356	-0.0953	0.0987	0.0411	0.0565	0.1098	0.0800	0.7900	0.8400	0.0400	0.2706	0.2488	0.2277	0.2699
n=200	-0.0963	0.0062	0.0346	-0.1082	0.1103	0.0414	0.0610	0.1209	0.0500	0.6750	0.7950	0.0250	0.2737	0.2663	0.2458	0.2733
s5: $\sigma_v = 0.01$, $\sigma_u = 0.1$																
n=100	-0.0277	0.0549	0.0731	-0.0364	0.0432	0.0654	0.0822	0.0487	0.2300	1.0000	1.0000	0.1300	0.6171	0.5696	0.4783	0.6230
n=200	-0.0347	0.0479	0.0746	-0.0418	0.0474	0.0568	0.0827	0.0522	0.1550	0.9950	1.0000	0.0950	0.6239	0.6385	0.5410	0.6289
s6: $\sigma_v = 0.05$, $\sigma_u = 0.1$																
n=100	-0.0685	0.0390	0.0583	-0.0833	0.0878	0.0615	0.0776	0.0995	0.1200	0.8500	0.9000	0.0700	0.4569	0.4111	0.3864	0.4554
n=200	-0.0829	0.0255	0.0561	-0.0961	0.0987	0.0546	0.0779	0.1096	0.0750	0.7600	0.8700	0.0400	0.4638	0.4359	0.4195	0.4626

[a] The bias reports the difference between the estimated and true efficiency scores. When it is negative (positive), the estimators are underestimating (overestimating) the true efficiency.

[b] The *RMSE* (root mean squared error) measures the standard deviation or error from the true efficiency.

[c] The upward bias is the proportion of estimated efficiencies larger than the true efficiencies (returning a value of 1). The desired value is 0.5. The values less (greater) than 0.5 indicate underestimation (overestimation) of cost efficiencies.

[d] Kendall's τ shows the correlation coefficient for the efficiency ranks between true and estimated efficiency scores.

Table A.9: Finite sample performance of order-m approach with different m values under a Cobb-Douglas cost function, $m = 20$, $m = 40$

The baseline experiment sets $m = 30$. This table provides the results for the performance of order-m methodology in the Monte Carlo experiment with different m values ($m = 20$, $m = 40$). We simulate six scenarios, which represent different combinations for the error (σ_v) and inefficiency (σ_u) terms.

	Bias		**RMSE**		**Upward Bias**		**Kendall's τ**	
	$m = 20$	$m = 40$	$m = 20$	$m = 40$	$m = 20$	$m = 40$	$m = 20$	$m = 40$
s1: $\sigma_v = 0.01$, $\sigma_u = 0.01$								
n=100	0.0310	0.0185	0.0408	0.0247	0.9900	0.9900	0.0591	0.0608
n=200	0.0372	0.0237	0.0471	0.0310	0.9900	0.9800	0.0742	0.0801
s2: $\sigma_v = 0.05$, $\sigma_u = 0.01$								
n=100	0.0135	0.0002	0.0464	0.0370	0.7300	0.6700	0.0476	0.0500
n=200	0.0143	-0.0017	0.0527	0.0441	0.6700	0.5900	0.0562	0.0585
s3: $\sigma_v = 0.01$, $\sigma_u = 0.05$								
n=100	0.0560	0.0433	0.0642	0.0500	1.0000	1.0000	0.3087	0.3295
n=200	0.0600	0.0459	0.0680	0.0523	1.0000	0.9950	0.3587	0.3938
s4: $\sigma_v = 0.05$, $\sigma_u = 0.05$								
n=100	0.0390	0.0250	0.0613	0.0485	0.8400	0.7900	0.2363	0.2436
n=200	0.0387	0.0220	0.0655	0.0518	0.8000	0.7300	0.2497	0.2577
s5: $\sigma_v = 0.01$, $\sigma_u = 0.1$								
n=100	0.0772	0.0640	0.0861	0.0724	1.0000	1.0000	0.5037	0.5233
n=200	0.0784	0.0632	0.0866	0.0705	1.0000	1.0000	0.5522	0.5856
s6: $\sigma_v = 0.05$, $\sigma_u = 0.1$								
n=100	0.0614	0.0467	0.0814	0.0678	0.9000	0.8600	0.3984	0.4028
n=200	0.0596	0.0416	0.0817	0.0660	0.8700	0.8150	0.4245	0.4329

[a] The bias reports the difference between the estimated and true efficiency scores. When it is negative (positive), the estimators are underestimating (overestimating) the true efficiency.
[b] The *RMSE* (root mean squared error) measures the standard deviation or error from the true efficiency.
[c] The upward bias is the proportion of estimated efficiencies larger than the true efficiencies (returning a value of 1). The desired value is 0.5. The values less (greater) than 0.5 indicate underestimation (overestimation) of cost efficiencies.
[d] Kendall's τ shows the correlation coefficient for the efficiency ranks between true and estimated efficiency scores.

Appendix B

Efficiency over time: Malmquist productivity index

When panel data is available, a commonly non-parametric approach used in previous literature to analyse the efficiency changes over time is the Malmquist productivity index (MPI) (Caves et al., 1982; Färe et al., 1992, 1994). This method, based on the non-parametric DEA approach, allows to measure the productivity changes between two time periods as the distance between a DMU and the frontier for each period. The MPI in its input-oriented version is defined as follows:

$$MPI_i(t, t+1) = \frac{\theta_i^{t+1}(x_i^{t+1}, y_i^{t+1})}{\theta_i^t(x_i^t, y_i^t)} \cdot \sqrt{\frac{\theta_i^t(x_i^{t+1}, y_i^{t+1})}{\theta_i^{t+1}(x_i^{t+1}, y_i^{t+1})} \cdot \frac{\theta_i^t(x_i^t, y_i^t)}{\theta_i^{t+1}(x_i^t, y_i^t)}} \tag{B.1}$$

where (x_i^t, y_i^t) and (x_i^{t+1}, y_i^{t+1}) are the input and output data for the municipality i over periods t and $t+1$, and $\theta_i^r(x_i^j, y_i^j)$ indicate the distance of the DMUi from the efficiency frontier defined by a input-oriented algorithm at period r, with $r = t$ or $t+1$, given its inputs x and output y at period j, with $j = t$ or $t+1$.

MPI values higher than one indicate productivity improvements from period t to period $t+1$, low values correspond to a decline in productivity and values equal to 1 indicate no productivity changes. The first element in B.1 indicates the efficiency change, which captures the efficiency improvements, while the second element (the one within the square root) represents the technological change, i.e., the shift of the efficiency frontier between periods t and $t+1$. Moreover, the efficiency change factor can be further decomposed into into changes involving the pure technical efficiency and the scale efficiency.

In order to assess whether there are some important changes in the efficiency levels or some technological progress over time, we carry out the MPI with our panel data of Spanish local governments. Results are reported in Table B.1, computed for the full period 2008–2013. The table contains the Malmquist productivity index together with all its components.

Table B.1: Efficiency variation over time: Malmquist index

	Years	MPI	Efficiency change	Technological change	Pure Technical Efficiency	Scale Efficiency
Model 1	2008–2013	1.1958	1.2735	0.9532	1.2514	1.0247
Model 2	2008–2013	1.2059	1.2678	0.9645	1.2490	1.0222
Model 3	2008–2013	1.1940	1.2072	0.9959	1.0556	1.1640

The results indicate that the mean MPI is higher than 1 in all Models, so the total productivity factor has increased from 2008 to 2013 in Spanish municipalities. On the one hand, the efficiency change show levels above unity, i.e., the Spanish local governments have improved their efficiency levels in times of crisis. These results confirm that Spanish local governments have reduced their costs between 2008 and 2013, while maintaining (or even increasing) the level of services and facilities (outputs). These findings are consistent with the results found in section 3.4.3. The improvement in the efficiency factor where driven from both the pure technical efficiency and scale efficiency. On the other hand, the efficiency change factor has decreased during the period 2008–2013, which could be explained by the lower public investments during the period.

Appendix C

Estimation of Λ

We use the following semi-parametric stochastic cost frontier model:

$$C_i = g(y_i) + \varepsilon_i, \qquad i = 1, ..., n, \tag{C.1}$$

where y_i is a $p \times 1$ vector of random regressors (outputs), $g(.)$ is the unknown smooth function and ε_i is a composed error term, which has two components: (1) v_i, the two-sided random error term which is assumed to be normally distributed N(0, σ_v^2), and (2) u_i, the cost efficiency term which is half-normally distributed ($u_i \geq 0$). These two error components are assumed to be independent.

We use available data on cost (municipal budgets) due to the difficulty of using market prices to measure public services. Hence the assumption allows us to omit the factor prices from the model.

We derive the concentrated log-likelihood function $\ln l(\Lambda)$ and maximise it over the single parameter Λ:

$$\max_{\Lambda} \ln l(\Lambda) = \max_{\Lambda} \left\{ -n \ln \hat{\sigma} + \sum_{i=1}^{n} \ln \left[1 + \Phi\left(\frac{\hat{\epsilon}_i}{\hat{\sigma}} \Lambda \right) \right] - \frac{1}{2\hat{\sigma}^2} \sum_{i=1}^{n} \hat{\epsilon}_i{}^2 \right\}, \tag{C.2}$$

with $\hat{\epsilon}_i = C_i - \hat{E}(C_i|y_i) + \mu(\hat{\sigma}^2, \Lambda)$ and

$$\sigma^2 = \left\{ \frac{1}{n} \sum_{i=1}^{n} [C_i - \hat{E}(C_i|y_i)]^2 \Bigg/ \left[1 - \frac{2\Lambda^2}{\pi(1+\Lambda^2)} \right] \right\}^{1/2}, \tag{C.3}$$

where $\hat{E}(C_i|y_i)$ is the kernel estimator of the conditional expectation $E(C_i|y_i)$ and it is given as:

$$\hat{E}(C_i|y_i) = \sum_{j=1}^{n} C_j \cdot K\left(\frac{y_i - y_j}{h}\right) \Bigg/ \sum_{j=1}^{n} K\left(\frac{y_i - y_j}{h}\right), \tag{C.4}$$

where $K(.)$ is the kernel function and $h = h_n$ is the smoothing parameter. For further details about the estimation procedure see Fan et al. (1996).