Explaining differences in efficiency: the case of local government literature

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Abstract One learns two main lessons from the efficiency literature on local governments. The first lesson regards the heterogeneity in the efficiency scores reported in primary papers. The second lesson is that there is no quantitative evidence on the role played by the features of each paper (i.e. estimation method, sample size, dimension, returns to scale) in explaining the differences in results. In order to fill this gap, we review the related empirical literature and perform a Meta Regression Analysis (MRA) by examining 360 efficiency scores retrieved from 54 papers published from 1993 to 2016. The meta-regression is based on a random effect model estimated with the Random Effects Maximum Likelihood (REML) technique, because it controls for within- and between-study heterogeneity. We also run a fixed effect unrestricted Weighted Least Squares (WLS) regression. Due to its main research focus, that is measuring the impact of potential sources of heterogeneity on local government efficiency, the paper contributes to the debate in two ways. One of this concerns the role of methodological choices made by researchers when performing an efficiency study. The second regards the role of deregulation in local government, which is a policy-issue in a number of countries. Results show that efficiency scores are highly heterogeneous. To be precise, significant differences in means are found when grouping efficiency by different criteria. The meta-regression estimates indicate that studies focusing on technical efficiency provide higher efficiency scores than works evaluating cost efficiency. Using panel data in primary studies allows researchers to obtain higher efficiency of local government than papers using cross-section data. Interestingly, FDH studies yield, on average, higher efficiency scores than DEA papers, thereby suggesting that in this literature the convexity hypothesis of the production set is a matter. Furthermore, we find that primary papers evaluating the efficiency of European municipalities provide lower efficiency scores than studies focusing on other countries (USA, Africa, Asia and Latina America). We also provide evidence that the estimated efficiency scores in primary papers focusing on the municipalities of a region are, one average, lower than those retrieved from studies addressing the efficiency of the national system of local government.

JEL classification: C13, C14, C80, D24, H11, H40, H50
Keywords: Efficiency, Municipalities, Frontier Models, Meta-analysis, Convexity

1. Introduction

Efficiency in local government has been a long-standing topic of discussion in economics and has received considerable attention over the last three decades. Two main forces have brought about the great interest in this subject.

First, even though theory clearly explains whether a decision unit is efficient or not (Farrell 1957), controversy has surrounded the empirics of much of the research. This is because the efficiency frontier is unknown and there is no consensus on the superiority of one estimation method over another, as argued by Berger and Humphrey (1997), Coelli and Perelman (1999) and Fethi and Pasourias (2010). The sensitivity of results to model specifications has been addressed in several individual studies which compare the results that different methods (i.e. parametric vs. nonparametric) yield from a fixed sample of municipalities (Athanassopoulos and Triantis 2016; De Borger and Kerstens 1996; Geys and

Moesen 2009; Worthington 2000). Furthermore, the reviews provided by da Cruz and Marques (2014) Narbò_Perpitna and De Witte (2017), Worthington and Dollery (2000) offer valuable arguments in terms of why results differ. However, no study has yet quantified the impact of methodological choices on the variability of efficiency scores in local government.

Second, the institutional architecture of many countries has changed rapidly since the 1990s due to extensive deregulation aimed at optimizing the use of public resources in offering services of general interest at local level. The institutional reforms accelerate over the last 15 years, thereby increasing the interest on economists and public administration to evaluate the efficiency level and the key-factors influencing the performance of the public sector (Lovell 2002). Importantly, the institutional framework on how municipalities work differ country-by-country and, therefore, it is reasonable to assume that the heterogeneity in national norms translates into heterogeneity in municipality efficiency.

This said, the main purpose of this paper is to measure the impact of methodological choices on efficiency score variability. To this end, we perform a meta-regression analysis (henceforth MRA), which is a statistical method that reveals more about a phenomenon which has been studied in a large set of empirical works. By investigating the relationship between the dependent variable (i.e. the efficiency scores of primary studies) and some features of each paper, MRA provides a systematic synthesis of a substantial number of studies and quantifies the role that specific aspects of original papers play in explaining the heterogeneity in results (Glass 1976; Glass et al. 1981; Stanley 2001; Stanley and Jarrell 1989). As Glass (1976: 3) states, MRA "connotes a rigorous alternative to the casual, narrative discussions of research studies which typify our attempt to make sense of the rapidly expanding research literature". Compared to standard qualitative literature surveys, MRA does not suffer from potential bias in selecting the studies to be reviewed because it can cover all the literature without restrictions accruing from the reviewer's judgments. As will become evident later, this study employs a very large sample of papers, thus ensuring ample coverage of the local government efficiency literature.

Given the increased interest in MRA in economics and the fact that the literature on local government efficiency lends itself well to being summarized through this approach, it is noteworthy that no exhaustive work has yet provided quantitative evidence about the link between the main features of primary papers and the heterogeneity in results.[1] In attempting to fill this gap, this paper uses different MRA specifications and refers to a meta-dataset which comprises 360 observations from 54 papers published between 1996 and 2016 (available in January 2017). In this respect, it is worth noticing that there are two streams of the literature of local government efficiency. Many papers focus on the efficiency of single services provided by local institutions, such as, for instance, public transports (Brons et al 2005), waste collection (Worthington and Dollery 2001), water (Byrnes et al 2010). An alternative approach is to evaluate the efficiency of municipality in providing any service, thereby addressing the issue from a global perspective (Afonso and Fernandes 2008; De Borger et al 1994; De Borger and Kerstens 1996; Lo Storto 2013). Our MRA considers of the literature on the global-services approach

[1] Poot (2012) counts 626 papers which applied MRA in the field of economics between 1980 and 2010, with an exponential growth in the 2000s. Some examples of recent MRA use in economics are Abreu et al. (2005), Bumann et al. (2013), Card et al. (2010), Chetty et al. (2011), Disdier and Head (2008), Gallet and Doucouliagos (2014), Doucouliagos and Paldam (2009), Ègert and Halpern (2006), Feld et al. (2013), Feld and Heckemeyer (2011) and Havránek et al. (2012). However, few MRA papers deal with efficiency. Bravo-Ureta et al. (2007) examine the efficiency scores of 167 farm-level studies published over the last four decades. Thiam et al. (2001) review 34 articles on agricultural efficiency in developing countries. Brons et al. (2005) focus on 45 urban transport studies and Odeck and Bråthen (2012) analyse the efficiency of seaports using 40 published papers. Nguyen and Coelli (2009) focus on hospital efficiency, referring to 95 studies published over the period 1987–2008. Finally, Aiello and Bonanno (2017) review 120 efficiency studies – with 1661 observations – on banking published over the period 2000–2014.

This paper stands in the second stream of literature

At this stage of the discussion, it is important to note how we address a specific issue, known as publication bias, which is result of two facts. On one side, journals tend to publish papers with robust evidence. On the other side, authors propose and publish results that satisfy their expectations. This is a relevant issue in empirical economics, suggesting to be cautious in interpreting the role of publication bias in any MRA paper. To control this issue, many scholars weight their observations by using appropriate measures for the variability of estimates (Bumann et al. 2013; Cipollina and Salvatici 2007; Doucouliagos and Stanley 2009; Feld et al. 2013; Gallet and Doucouliagos 2014; Stanley 2008). Following this literature and after controlling for publication bias, we proceed by using a random effects model estimated with the REML technique because it controls for within- and between-study heterogeneity. Due to its main research focus, i.e. measuring the impact of potential sources of heterogeneity on local government efficiency, this article contributes to the debate assessing the role of methodological choices made by researchers when specifying the frontier of municipalities (see Appendix A). Therefore, by applying MRA to a wide set of observations, the paper's contribution lies on the fact that we address the following relevant issues: whether parametric studies yield different results from nonparametric studies; whether DEA studies yield different results than FDH papers; whether the impact differs when considering cost instead of technical efficiency; whether the sample size of primary papers matters in influencing results; whether papers focusing on national municipality provide different efficiency score then papers focusing on restricted sub-national geographical area. As these issues refine the identification of the problem to be studied, they address the so-called "*apples and oranges"* MRA problem, which arises when bringing together studies which are different from one another (Glass et al. 1981).

The paper is structured into six sections. Section 2 describes the criteria adopted to create the meta-dataset, while Section 3 and highlights the heterogeneity in efficiency scores. Section 4 presents the MRA and the variables used in regressions. Section 5 presents and discusses the results and Section 6 concludes.

2. The local government efficiency meta-dataset

A delicate phase of MRA is the creation of the database. All authors searched, read and coded the research literature. The search was conducted in three phases.

First, we start from Google and we have the confirmation that the number of potential material is impressive: for instance, when searching through Google for "local government efficiency", one obtains more than 102,000 results. Similarly, the search for "local government studies" yields 195,000 results (as of 31 January 2017). Finally, searching together "municipalities efficiency" or "local governments efficiency" provides 4200 results. These results comprise a very large sample of documents, thereby making necessary the use of some selecting criteria to handle better the available information within the analytical framework of an MRA. In other words, to collect a representative sample of works, we employed some criteria to identify relevant academic studies from the large pool of papers on the efficiency of municipalities. The filter used browsing Google is "frontier": adding this to "local government studies" collapses the search results to 1400 (Figure 1).

Secondly, we referred to the EconBiz, Repec, ScienceDirect, IngentaConnect and Econlit archives. The key words used in the baseline search of titles, abstracts and key words were "municipalities", "local government", "efficiency" and "frontier". At the beginning, the search was not restricted and provided a sample of 630 published works and working papers encompassing a very broad set of hypotheses and empirical works. Before filtering this sample of works, we ensured that they (a) focused on the efficiency of municipalities when scholars aim at estimating the global rather than the specific-sector performance; (c) included sufficient information to perform the MRA (efficiency scores and standard deviations); (d) ran specific models to estimate the frontier (SFA, DEA, FDH); (e) were written in English; (f) were published in a journal or as working papers. We excluded papers with the same efficiency score results as reported in other papers by the same author(s) and papers that did not report efficiency estimates.

Thirdly, we (a) manually consulted the principal field journals (*Journal of Productivity Analysis*, *European Journal of Operational Research*, *Local Government Studies*, *Cities*, *Omega, Journal of Urban Economics*; (b) explored additional databases, such as Google Scholar, ResearchGate and the Social Science Research Network (SSRN); (c) verified that we had not overlooked efficiency studies by scanning the references of qualitative surveys dealing with issues strictly related to our research question that were published by da Cruz and Marques (2014), Narbò_Perpitna and De Witte (2017) and Worthington and Dollery (2000). The third round of the search yielded 20 additional studies. The compilation of the dataset was concluded on 31 January 2107 with a set of 54 papers and 360 observations (Figure 1).

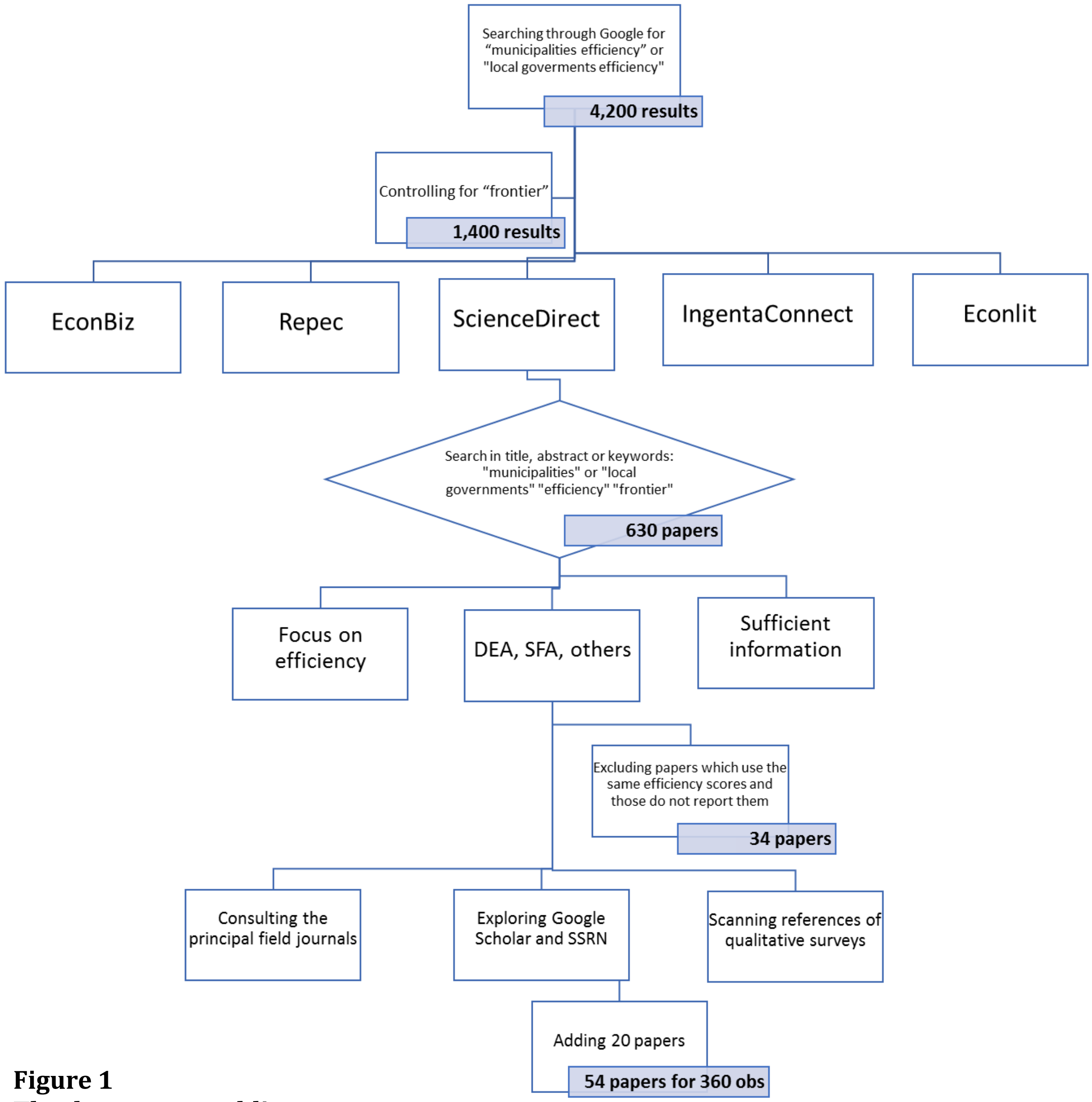

Figure 1
The dataset assembling process

3. Does heterogeneity exist in local efficiency literature?

A synthesis of the collected estimates that we retrieved from primary papers is reported in Table 1, in which different sub-samples of scores have been considered according to (a) the approach used in the estimations (parametric or nonparametric), (b) the approach (DEA or FDH) followed in estimating nonparametric frontiers, (c) the hypotheses regarding returns to scale (constant or variable),[2] (d) the structure of the data (panel or cross-sectional) and (e) the data aggregation used in primary papers (regional or national level). Finally, we summarize the efficiency scores retrieved from papers focusing on EU or extra-EU municipalities.

Overall, the sample of 360 observations yields an (un-weighted) average efficiency of 0.69. Some differences emerge by efficiency type: the average of the 50 cost-efficiency scores is 0.71, while it is 0.69 for the 310 observations of efficiency in production[3] The data also highlight that the overall mean of the 38 observations from parametric studies is higher than that of the 322 observations from nonparametric papers, although the difference in the mean is 0.036(=0.725-0.689) is low and not statistically significant. The sample-size impedes to compare nonparametric and parametric studies for technical efficiency, while the difference remains in favour of parametric methods for papers focusing on cost frontiers.

There are 285 observations referring to DEA studies (274 of which refer to technical efficiency), more than 76% of the entire sample, while the dataset includes 37 observations from studies using FDH approach. As for as the all sample is concerned, it emerges that FDH studies yield higher efficiency scores than DEA papers. The difference in means is high when considering the technical efficiency (unfortunately the meta data comprises only two observations of cost efficiency from FDH papers). With regard to the structure of the data used in primary studies, the analysis shows that about two-thirds of the observations come from estimations obtained from cross-sectional data and the other one-third from panel data. What clearly emerges is that the average of efficiency scores is 0.796 for papers using panel data, that is a value significantly higher than the average (0.638) associated to cross-sectional studies. The same applies for technical efficiency studies.

A pattern to be pointed out is observed when grouping the observations for the hypothesis of returns to scale in nonparametric studies. Overall, the use of variable returns to scale (VRS) translates to an average level of efficiency equal to 0.6861, which is slightly lower than that (0.698) associated with observations using the hypothesis of constant returns to scale (CRS). However, the difference is means is not statistically significant. This result is confirmed for the sub-sample of studies estimating the technical efficiency.

Furthermore, in the sample, another difference is that 215 observations refer to papers using data of municipalities belonging to one or more regions of a country and 145 refers to studies covering all the local entities of a country. In other words, there are more papers focusing on how municipalities work in a region than those looking at the country as a whole. The evidence shows that the un-weighted average of efficiency scores associated to "regional" studies is 0.66, that is lower than that (0.73) obtained from primary papers covering the national municipality organization. This outcome is found for both sub-sample of observations, that is technical or cost efficiency scores. Finally, we find that papers on European

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[2] The list of the studies which make up the meta-dataset is provided in the appendix table 1. This table includes the authors' name, the year of publication, the type of publication, the journal, the number of estimates, the average efficiency and some measures of variability (standard deviation, maximum and minimum values). We only display the average for the primary studies reporting different measures of efficiency (i.e. technical or cost efficiency). Nevertheless, the econometric analysis uses all the information from every paper.

[3] The average of efficiency by frontier (cost, production) is not intended to propose a ranking, but simply to summarize what emerges from papers, which differ from each other in a number of ways. The outcome ought to be viewed just as the result of the empirics surrounding any paper (see below).

municipalities yield lower efficiency scores than studies analysing the local government of other nations.

While table 1 reveals that there are differences in mean and a certain variability of efficiency scores, the figure 2 sheds some lights on the entire efficiency distribution. Indeed, it highlights significant differences in shapes and forms of efficiency score distributions when primary papers are grouped by the approach used in estimating the frontier (parametric vs nonparametric, panel a), the method set up in estimations (SFA, DEA and FDH, panel b), the efficiency-type (cost vs technical efficiency, panel c), the data used in the empirical analysis (panel data vs cross-section, panel d), the geographical focus (regional vs national, panel e) and, finally, by distinguishing papers addressing efficiency of European or non-European municipalities (panel f). What clearly emerges from these distributions is that any choice made by researchers may affect final estimations of efficiency. Phrased differently, a lesson learnt from this discussion is that the study design of primary papers plays an important role in determining differences in the means and distributions of local government efficiency scores.

Figure 2 Heterogeneity in Local Governments' Efficiency Literature

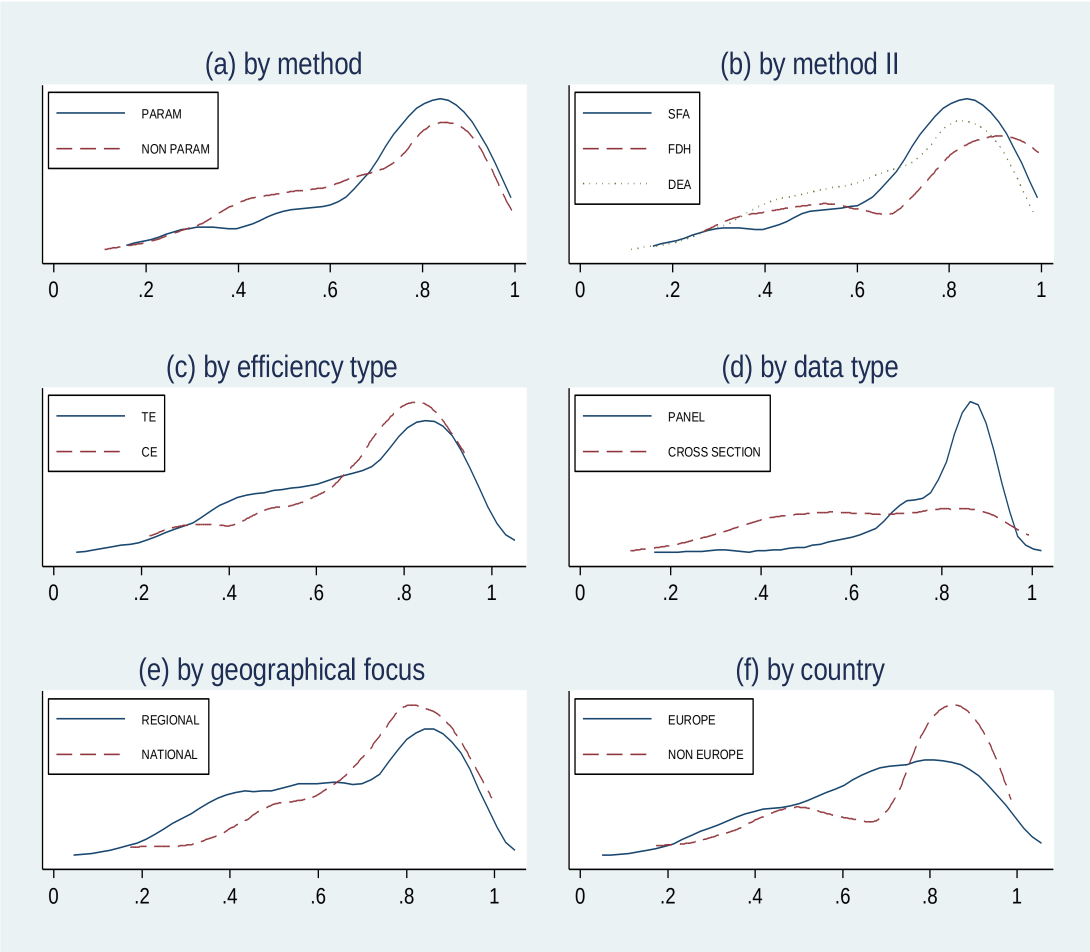

Table 1 Average, standard deviation and number of observations in local government literature, by group (averages are un-weighted)

		All sample	Technical Efficiency	Cost Efficiency
ALL	Mean	0.694	0.690	0.713
	SD	0.204	0.205	0.194
	Obs	*360*	*310*	*50*
Estimation approach				
PARAMETRIC	Mean	0.725	0.857	0.721
	SD	0.190	0	0.191
	Obs	*38*	*1*	*37*
NON PARAMETRIC	Mean	0.690	0.690	0.688
	SD	0.205	0.205	0.210
	Obs	*322*	*309*	*13*
Convexity of production set for nonparametric studies				
DEA	Mean	0.682	0.683	0.648
	SD	0.201	0.201	0.202
	Obs	*285*	*274*	*11*
FDH	Mean	0.754	0.745	0.913
	SD	0.227	0.230	0.033
	Obs	*37*	*35*	*2*
Returns to scale in nonparametric studies				
CRS	Mean	0.698	0.693	0.798
	SD	0.195	0.198	0.107
	Obs	*103*	*98*	*5*
VRS	Mean	0.686	0.689	0.620
	SD	0.210	0.209	0.234
	Obs	*219*	*211*	*8*
Data type				
PANEL	Mean	0.796	0.795	0.891
	SD	0.133	0.134	0.025
	Obs	*126*	*124*	*2*
CROSS SECTION	Mean	0.638	0.622	0.705
	SD	0.214	0.215	0.195
	Obs	*234*	*186*	*48*
Geographical focus				
REGION	Mean	0.665	0.664	0.678
	SD	0.211	0.209	0.257
	Obs	*215*	*202*	*13*
NATIONAL	Mean	0.737	0.741	0.725
	SD	0.185	0.190	0.169
	Obs	*145*	*108*	*37*
Country				
EUROPE	Mean	0.677	0.662	0.786
	SD	0.202	0.203	0.164
	Obs	*236*	*207*	*29*
NON-EUROPE	Mean	0.724	0.747	0.612
	SD	0.203	0.199	0.190
	Obs	*124*	*103*	*21*

4. Meta-analysis of local government efficiency

4.1 Methodological issues

The previous section highlights that heterogeneity is relevant when grouping observations by different criteria. Given this, providing a systematic explanation of the variability in efficiency becomes an important issue to be addressed on econometric grounds. This section focuses on the MRA carried out to explain the heterogeneity in efficiency scores of municipalities.

There are two main issues to be addressed in this kind of empirical analyses. The first concerns heteroscedasticity, while the second relates to publication bias.

The dependent variable of the MRA is the efficiency score of municipalities retrieved from the primary literature. As we have seen above, in creating the meta-dataset we have collected all the information from each paper and many papers provide more than one estimate of efficiency. From an econometric perspective, this means that the unit of observation is the individual value of the estimated efficiency, with the result that there is within-study heterogeneity to control for. As for publication bias, the success of a paper depends greatly on the study results in that the probability of a paper being published increases the more conclusive its conclusions. A simple method for detecting publication bias is to regress the key variable of the meta-analysis – municipalities efficiency in our case – against its precision in primary estimations (Egger et al. 1997). If this regression yields significant results, there is evidence of publication bias in the meta-dataset which must be controlled for in the MRA.

This said, to provide answers to the research questions raised throughout the paper, we refer to the following equation:

$$\mathrm{E_i} = \beta_1 + \beta_0 S_i + \sum_{\mathrm{j}} \beta_{\mathrm{j}} \mathrm{X_j} + \varepsilon_i \qquad [1]$$

where the dependent variable E_i is the i-*th* efficiency score. Eq. [1] is known as the funnel asymmetry test–precision effect test (FAT-PET) MRA (Stanley 2005, 2008). X_j comprises the explanatory variables that summarize various model characteristics of the primary studies. Furthermore, S_i is a measure of the variability of E_i, which is the standard deviation of the efficiency scores as estimated in primary papers. It enters into the meta-regression to control for publication bias as proposed by Egger et al. (1997) and applied by Bumann et al. (2013), Cipollina and Salvatici (2007), Feld et al. (2013), Stanley (2008) and Aiello and Bonanno (2017). ε is the error of the model, which is clearly heteroscedastic because the variance in individual estimates changes in the sample and the estimates are not independent within the same study. This issue is addressed by weighting the observation through a measure S of the variability of each observation:

$$\begin{aligned} \frac{\mathrm{E_i}}{S_i} &= \beta_0 + \beta_1 \frac{1}{S_i} + \sum_{\mathrm{j}} \beta_{\mathrm{j}} \frac{\mathrm{X_j}}{S_i} + e_i \\ E_i^* &= \beta_0 + \beta_1 S_i^* + \sum_{\mathrm{j}} \beta_{\mathrm{j}} X_i^* + e_i \end{aligned} \qquad [2]$$

where the disturbance $e = \varepsilon / S$ is corrected for heteroscedasticity. The test for publication bias is carried out on the constant β_0, as in Cipollina and Salvatici (2007), Doucouliagos and Stanley (2009), Feld et al. (2013) and Stanley (2008).

The method used in estimating eq. [2] may be a fixed effects or random effects model. These methods differ in terms of their treatment of heterogeneity. In particular, a fixed effects meta-regression assumes that all the heterogeneity can be explained by the covariates and leads to excessive type I errors when there is residual, or unexplained, heterogeneity (Harbord and Higgins 2008; Higgins and Thompson 2004; Thompson and Sharp 1999). Instead, a random effects meta-regression allows for such residual heterogeneity (the between-study variance not explained by the covariates) and therefore extends the fixed effects model. Formally, under the random-effects framework, eq. [2] becomes:

$$E_i^* = \beta_0 + \beta_1 S_i^* + \sum_j \beta_j X_i^* + u_i + e_i \qquad [3]$$

where $e_i \sim N(0, \sigma^2_i)$ is the disturbance and $u_i \sim N(0, \tau^2)$ is the primary study fixed effect. The parameter τ^2 is the between-study variance, which must be estimated from the data as in Harbord and Higgins (2008).[4] To provide some robustness of the results to clustering, we adopt a two-step procedure as in Gallet and Doucouliagos (2014) and adopted by Aiello and Bonanno (2017). An REML regression is run in the first step, while in the second step we run a WLS regression in which the weights also include the value of τ^2 retrieved from the first step. This ensures that the REML estimates will be robust to clustering at the study level.[5]

4.2 The explanatory variables in the meta-analysis

The right-hand side of eq. [3] includes the matrix X_i, which is related to the observed characteristics used to explain the variability in local government efficiency that we have identified on the basis of a systematic comparison of original papers. The explanatory variables are discussed in the following.

A first group of variables is anchored to the specific topic of the analysis that is the study of heterogeneity in efficiency. Then, the first distinguishing element to be considered relates to the approaches and methods used to estimate the frontier. We firstly made a broad distinction between papers using a parametric method and papers following a nonparametric approach. To this end, the dummy variable used is *Parametric* (*PARAM*), which is equal to unity for the first group of studies and zero for the others. Additionally, as we have already pointed out (cf. Introduction), nonparametric papers distinguish between DEA and FDH methods to estimate the frontier. In this respect, after restricting the sample to nonparametric papers we include

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[4] Technically, REML first estimates the between-study variance τ^2 and then estimates the coefficients, β, with the weighted least squares procedure and using as weights $1/(\sigma_i^2 + \tau^2)$, where σ_i^2 is the standard error of the estimated effect in study *i*. The term "multilevel" refers to the structure of the meta-dataset, which combines observations at the single estimate level and observations at the study level (Harbord and Higgins 2008; Thompson and Sharp 1999). The choice of using REML is also driven by the structure of our data. As our dataset contains high variability in primary studies, the fixed effects estimator is expected not to perform well because it does not allow for between-study variability. Conversely, REML fits our case well. The evidence we find supports the use of the random effects model as the between-study variance is high and significant (cf. Table 2). This holds despite the potential caveat of REML, the results of which are reliable if the random effects variance is properly estimated (Oczkowski and Doucouliagos 2014). Importantly, Stanley and Doucouliagos (2015) compare REML and WLS and their analysis is not conclusive, depending on additional extra heterogeneity and publication bias effects.

[5] To address the clustering issue with greater effectiveness, we have also taken into consideration the developments proposed by Jackson et al. (2011) and Hedges et al. (2010). Jackson et al. (2011) claim "the absence of information about the within-study correlation structure does not entirely prohibit a multivariate approach but this does present very real statistical issues and a consensus about the best approach or approaches has yet to be reached" (p. 2495). The model proposed by Hedges et al. (2010) requires knowing the dependence structure within each study. Their routine (the "robumeta" Stata command) runs after assigning a value to the parameter of dependence. This means that on the one hand, we search for a technique yielding robust standard errors and on the other hand, the advances in econometrics assume that the within-study variability is known. In other words, in Hedges et al. (2010) the standard errors are correct if and only if the assumed value of the dependence is valid and there is no way to test this assumption. It is also worth pointing out that the "robumeta" command is not yet for use in research as noted in a message that emerges when launching a regression ("*this routine needs to be verified, do not use for research purposes*"). Based on these arguments, we left the within-study issue within the REML framework for future research as it is still an open question in the econometrics of meta-analysis.

the dummy *FDH*, which is unity when efficiency scores are derived from primary studies using the FDH (the controlling group comprises the point observations from papers using DEA). Furthermore, to control for efficiency type we include the dummy *TE*, taking the value of 1 if the primary estimation refers to technical efficiency (the controlling group is the efficiency obtained from the cost frontiers). Finally, there is another factor belonging to this groups that ought to be taken into account,[6] which is related to the assumption on returns to scale: in this respect we consider the dummy variable *VRS* which is equal to 1 if the primary study assumes VRS and zero otherwise (the controlling group comprises the point-observations from studies using constant returns to scale, CRS). As parametric studies do not provide any information regarding the returns to scale assumption, we restrict the test to the nonparametric studies.

Secondly, a number of regressors is from the literature on meta-regression which gives some guidance regarding the issue to be addressed in the analysis. A distinction to be made is between the efficiency obtained in papers using cross-sectional data and that derived from studies based on panel data. The dummy variable *Panel* is equal to unity if the original works used panel data and zero otherwise. We also control for the time effect by using the *Year of publication* of the primary paper. Furthermore, we consider the variables l*DIM*, given by the sum of the number of inputs and outputs of the frontier (in logs) and l*SIZE*, which is the number of observations used in primary papers when estimating the efficiency score. In such a case, we also include the interaction *lSIZE*MANY* for testing if the sample size has an effect of the primary estimated efficiency when they refer to a high number of municipalities (*MANY* is a binary variable equal to 1 if the number of municipalities is greater than 2000).

Thirdly, our MRA includes the dummy D_{REG}, which distinguishes between the efficiency observations for a specific sample of municipalities belonging to one or specific regions of a country (D_{REG}=1) and observations referring to national local government as a whole (D_{REG}=0). The coefficient of D_{REG} is expected to vary moving from national to sub-national groups of municipalities, although there is no *a priori* expectation on its sign. The result depends on the homogeneity of the sample of municipalities used in estimating the frontier: if regional municipalities are homogenous, then the estimated efficiency score will be expected to be higher than that obtained from heterogeneous samples (i.e. all municipalities of a specific country): all else being equal, similar municipalities exhibit similar behaviour and thus are more clustered around a frontier than different municipalities with divergent goals. In addition, to control for geographical differences, we consider the dummy variable *Europe*, which are equal to 1 if the study used data from an European country (in estimating the MRA, the controlling group comprises efficiency scores from papers focusing on the rest of the world).

At this stage of the discussion, it is worth mentioning that the numerous different ways of performing an efficiency study make conclusive expectations of the impact of each regressor difficult. Indeed, despite the high degree of specialization in the use of various methods, the effect of some methodological choices is still not certain. For example, efficiency in parametric studies may be higher or lower than that obtained in nonparametric papers, depending on the nature of disturbances from the frontier (Nguyen and Coelli 2009). The use of panel data would generate higher efficiency levels than those from cross-sectional data. Finally, efficiency would increase with the number of variables included in the frontier, while it would decrease with

[6] When performing an efficiency study based on parametric methods, researches make another choice in their study design, which is related to the functional form of the frontier. This choice has proven to impact on the heterogeneity of results (Aiello and Bonanno 2017; Ngujen and Coelli 2009). However, our MRA disregard this issue because the observations from parametric studies are few (only 38, table 1), thereby limiting the possibility to run a regression. The number of efficiency scores from translog function forms are only 10, the Cobb-Douglas sample comprises 27 observations (10 of which are without standard errors, cfr. § 3). The metadata also contains 1 observation from a parametric study using the Distribution Free Approach.

small sample sizes and the assumption of CRS (Berger and Humphrey 1997; Coelli 1995; Fethi and Pasourias 2010; Nguyen and Coelli 2009). However, while theory predicts the likely impact of any choice, the actual measure of how sensitive the results are to the study design is an issue to be addressed empirically.

5. Fitted models and analysis

5.1 Fitted models and diagnostics As the underlying idea is to test the robustness of the results (sign, magnitude and significance) when moving from basic to extended regressions, in presenting the results, we start from a regression just including the dummies relating to the regional/national samples of the primary papers (D_{REG}) and to the geographical areas (*Europe*) which the primary analysis refers to. Results are displayed in Table 2, model 1. Model 2 adds the variables related to the efficiency and data type (*TE* and *PANEL*, respectively), the methods (*PARAM*), the number of variables (*lDIM*) and the sample size (*lSIZE*) used to estimate the efficiency scores of municipalities in primary studies. [8] Finally, we also include the *Year of publication*. In model 3, the interaction *lSIZE*MANY* allows to to test the effect of sample size when the number of municipalities is high.

Table 3 reports the evidence we find for specific sub-samples of observations belonging to the class of nonparametric studies. In this case, we test the convexity hypothesis of the production set in performing a nonparametric efficiency study. To this end, we introduce the dummy *FDH*, which is equal to 1 when the primary studies relax the convexity hypothesis (Model 4). In addition, we include *VRS* to control for the heterogeneity depending on the hypothesis of returns to scale (Models 5 and 6). Lastly, we carried out a sensitivity analysis to test whether the evidence is robust to the substitution of the variable *Year of publication* with the variable *Year of estimation*, which the primary study refers to (Table 4).

Before presenting the results, it is worth discussing some diagnostics. The main evidence regards $\hat{\beta}_0$, the parameter used as a test for publication bias. If $\beta_0 = 0$ (FAT) then there will be asymmetry in the estimates and publication selection (Stanley 2005, 2008). $\hat{\beta}_0$ is significant in models 1, 2 and 3, but not in models 4, 5 and 6, indicating that when the focus is on nonparametric studies there is no evidence of publication bias in REML regressions with the covariates. The estimation of $\hat{\beta}_0$ remains significant when performing the sensitivity analysis (Table 4).

Furthermore, we present some statistics at the bottom of each table that we retrieved from the Stata command “metareg”, developed by Harbord and Higgins (2008). As can be seen, the proportion of the residual variance that is attributable to between-study heterogeneity is

[8] The dummy associated with TE enters into the regression not to provide a ranking across efficiency types, but simply to check if the main results hold when controlling for the frontiers to which the single observation refers. Furthermore, the MRA collects observations from very different papers and thus there is no expectation on TE compared to cost efficiency (CE). We can use an example to explain the issue. When estimating a cost frontier with input-oriented technology for a given sample of local governments, say sample A, we know that a municipality is inefficient because its technical and/or allocative efficiency is low. Therefore, for this sample, the cost efficiency, say CE_A, is at best equal to the technical efficiency TE_A. This ranking TE≥CE is predicted by theory (Kumbhakar and Lovell 2000: 54). However, any empirical outcome is admitted when comparing efficiency scores retrieved from different samples, even when the analytical framework remains the same (which in our example is a cost frontier with input-oriented technology). In this respect, let us consider another sample of municipalities, say B. It is true that $TE_B \geq CE_B$, but if in sample B the overall level of efficiency is very high, CE_A may be higher than TE_B. Then, the result that cost efficiency is higher than technical efficiency might be misleading when referring to a specific setting (i.e. a cost frontier with input orientation and a given sample), but is admitted in the empirics of MRA. Finally, it is noteworthy to say that the evidence CE>TE holds in the descriptive summary, whilst regression results show that TE>CE.

very high: in Model 1 it is 99.94%. Again, in the same regression, the proportion of between variance explained by the covariates is 31.63%, the measure of within-study sampling variability. When we include additional regressors, between-study heterogeneity tends to decrease (in Model 3 it is equal to 70.19%), while the proportion of between variance explained by the covariates tends to increase (in Model 3 it becomes 58.60%). Finally, the joint significance of the explanatory variables is high in each model. To ensure clarity in the presentation of the results, the discussion is divided into three sub-sections. The first is devoted to the role of data aggregation and geographical context. The second sub-section focuses on the estimating methods, while the third looks at the effects exerted by the features and the study-design of primary-papers.

5.2 Data aggregation and geographical context Estimations referring to a specific region of a nation yield lower efficiency scores on average respect to estimations made on a country as a whole. This holds for all the estimated models. The parameter $\hat{\beta}_2$ associated to dummy D_{REG} ranges between -0.25 in Model 6 to -0.15 in Model 1 (the lowest value is estimated in Model 2, but only in this case $\hat{\beta}_2$ results not significant). The implication of this evidence may be useful for scholars, as one may expect a lower level of efficiency when focusing on sub-national areas (the municipalities of a region/province) than when addressing the efficiency issue of a national local government system. We also find that studies focusing on municipalities of European countries yield on average lower efficiency scores than papers that analyse the local government of other nations. Indeed, the parameter $\hat{\beta}_3$ associated to dummy *EUROPE* assumes values between -0.24 in Model 6 and -0.09 in Model 2.

5.3 The role of estimating methods Regarding the methods used to estimate efficiency in primary papers, we find that the coefficient associated to dummy *PARAM* is significant and positive ($\hat{\beta}_6 = 0.16$) in Model #. This also occurs in the sensitivity analysis, as $\hat{\beta}_6 = 0.13$ is Model 2bis, while $\hat{\beta}_6 = 0.15$ in Model 3bis of table #. The conclusion is that parametric studies achieve higher efficiency level than nonparametric estimations, thereby confirming that method type matters for explicating heterogeneity in local governments' efficiency. This is in line with a high and negative movement of the random component, as depicted by Nguyen and Coelli (2009). It is also worth pointing out that the parametric effect in the other MRA applications is found to be neutral with respect to the counterpart, as documented by the inconclusive evidence provided by Thiam et al. (2001) for agriculture in developing countries, Nguyen and Coelli (2009) for hospitals, Brons et al. (2005) for transport and Kolawole (2009) for Nigerian agriculture. Conversely, some discrepancies with our evidence is found in Bravo-Ureta et al. (2007) with regard to agricultural efficiency in developed and developing economies and in Odeck and Bråthen (2009) for efficiency in seaports and Aiello and Bonanno 2017) for banking.

The issue of the method-heterogeneity nexus can be explored in a deep analysis when focusing on nonparametric studies only. Table 3 shows a strongly significant coefficient for dummy *FDH*. In detail, when primary papers use FDH method, efficiency scores are higher than those estimated through *DEA*. This result is in line with the evidence showing that relaxing the hypothesis of convexity of production set matters and holds in the sensitivity analysis (Table 4). Finally, the estimated coefficient of *VRS* is positive, which means that models using the VRS hypothesis yield higher efficiency scores than models based on CRS.

5.4 Features and study-design of primary papers We proceed by discussing if estimation results differ by efficiency type. All else being equal, performing a study of technical efficiency yields higher scores on average than when estimating a cost frontier and this holds true regardless of the model to which we refer to. In Model 3, that is the most complete regression for all sample, the parameter associated with the variable *TE* is significant and it is around 0.18. We find the same finding when the estimations focus on nonparametric studies ($\hat{\beta}_4$ is 0.22, 0.9 and 0.2 in Models 4, 5, and 6, respectively). This outcome deserves attention as it is in line with one might expect. Theory states that technical efficiency is higher than cost efficiency with input-oriented technology (Kumbhakar and Lovell 2000: 54), which is an assumption made in a few papers in our meta-dataset (on this, see footnote 8).

Another robust evidence regards the effect of data type on primary efficiency scores. All regression results suggest that efficiency obtained from cross-sectional data differs from that for panel data, as $\hat{\beta}_5$ is always significant and positive in any REML regression (Table 2 and 3), expect for the sensitivity analysis (Table 4). This evidence is in line with the argument according to which panel data yield more accurate efficiency estimates given that there are repeated observations of each unit (see, among many others, Greene 1993) and with the empirical results of Bravo-Ureta et al. (2007) and Thiam et al. (2001). Additionally, we find that the average level of estimated efficiency tends to decrease with the temporal dimension ($\hat{\beta}_7$ is always negative). This happens either in models using *Year of publication* of the variable *Year of estimation*. The time effect results not significant in nonparametric samples.

With regard the role of *Dimension*, we find that $\hat{\beta}_8$ is positive: an increase in the number of inputs and/or outputs included in the frontier translates into an increase in the mean efficiency, so confirming the hypothesis of a positive link between the goodness of fit and the level of efficiency. Nguyen and Coelli (2009), Kolawole (2009) and Thiam et al. (2001) found a positive impact of Dimension on efficiency. Due to the use of logs, the marginal effect is 0.009 when *Dimension* is 8 (close to 8.15, which is the overall mean of our sample; 8.35 is the average level of dimension for nonparametric studies) ($\hat{\beta}_8 = 0.0705$ in Model 3, $\hat{\beta}_8 = 0.0685$ in Model 6). Figure 3a highlights the pattern of the marginal effect on mean efficiency when *Dimension* ranges between its minimum and maximum values: when the number of inputs and outputs equal to 7, the marginal effect of *Dimension* of efficiency tends to 0.

The analysis of the relationship between bank efficiency and the number of observations used in estimating the frontier produces interesting findings. The continuous variable *Sample Size* enters our regressions in log form as we try to control for a potential non-linear effect. It is likely that the impact of sample size diminishes as the observations increase. We also introduce the interaction term *lSIZE*MANY* to verify whether the effect of sample size differs between an analysis conducted on a number of municipalities $\leq$2000 and an analysis conducted on a number of municipalities >2000. In model 3, the parameter $\hat{\beta}_{10}$ is negative (-0.055), thus when estimations refer to larger numbers of municipalities the effect of *Sample Size* becomes negative (figure 3b).

Figure 3 Marginal effects of dimension and sample size

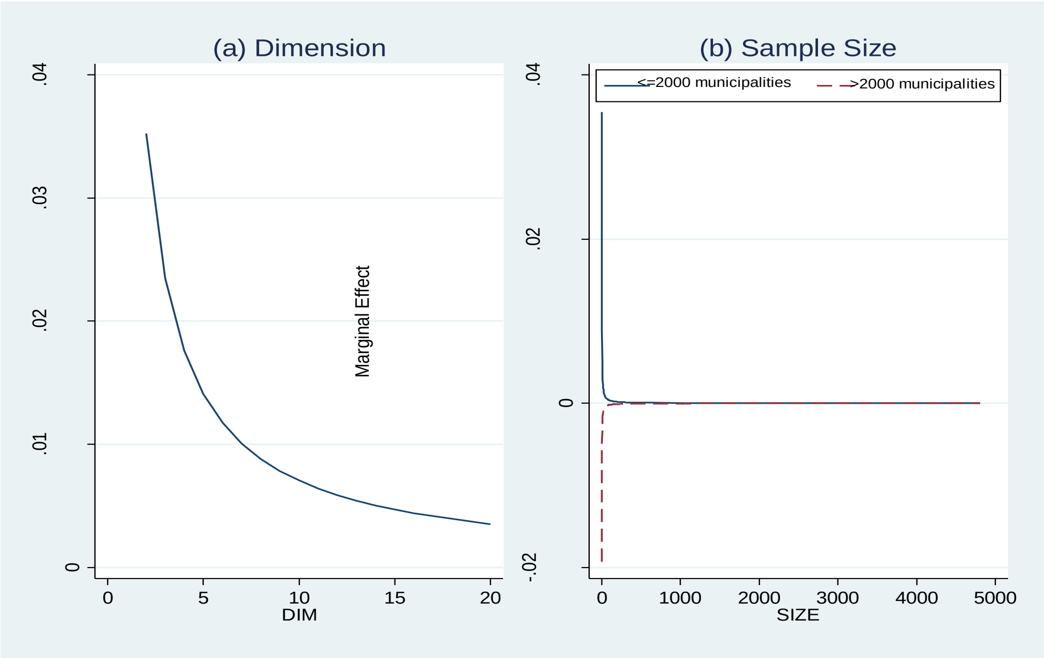

Table 2 Meta-regression analysis of Local Governments efficiency scores (All sample)

Variable		Model 1		Model 2		Model 3	
Constant	β_0	0.9284	***	20.7125	***	18.8669	***
1/S	β_1	-0.000011	**	-0.000006		0.000011	
D_{REG}	β_2	-0.1464	***	-0.1158		-0.1685	***
EUROPE	β_3	-0.1544	**	-0.0945	*	-0.1748	***
TE	β_4			0.0759		0.1799	**
PANEL	β_5			0.1667	***	0.1103	**
PARAM	β_6			0.1500		0.1646	*
Year of publication	β_7			-0.0100	***	-0.0092	***
lDIM	β_8			0.0399		0.0705	*
lSIZE	β_9			-0.0006		0.0355	**
lSIZE*MANY	β_{10}					-0.0548	***
Observations		308		294		294	
tau^2 (between-study variance)		0.0192		0.0171		0.0121	
% residual variation due to heterogeneity		99.94%		74.22%		70.16%	
Adj R-squared		31.63%		41.58%		58.60%	
F- Fisher		23.86		13.32		19.08	

Legend: * p<0.2; ** p<0.1; *** p<0.05.
Note: The statistical significance of the REML results is robust to clustering at the study level, as in Gallet and Doucouliagos (2014).

Table 3 Meta-regression analysis of Local Governments efficiency scores from nonparametric studies

Variable		Model 4		Model 5		Model 6	
Constant	β_0	5.0604		1.4620		3.6452	
1/S	β_1	0.000002		-0.000014		0.000003	
D_{REG}	β_2	-0.2466	***	-0.2032	**	-0.2527	***
EUROPE	β_3	-0.2340	***	-0.1608	***	-0.2369	***
TE	β_4	0.2152	**	0.0949		0.2003	*
PANEL	β_5	0.1099	**	0.1802	***	0.1217	***
FDH	β_6	0.2308	***	0.2918	***	0.2454	***
Year of publication	β_7	-0.0022		-0.0003		-0.0015	
lDIM	β_8	0.0756	**	0.0376		0.0685	**
lSIZE	β_9	0.0022		-0.0308	*	0.0050	
lSIZE*MANY	β_{10}	-0.0533	***			-0.0520	***
VRS	β_{11}			0.0657	**	0.0544	**
Observations		267		267		267	
tau^2 (between-study variance)		0.0097		0.0137		0.0091	
% residual variation due to heterogeneity		70.58%		70.55%		66.28%	
Adj R-squared		67.99%		54.64%		69.86%	
F- Fisher		25.16		17.74		24.24	

Legend: * p<0.2; ** p<0.1; *** p<0.05.
Note: The statistical significance of the REML results is robust to clustering at the study level, as in Gallet and Doucouliagos (2014).

Table 4 Robustness check: Meta-regression analysis of Local Governments efficiency scores

Variable		Model 2 bis		Model 3 bis		Model 4 bis		Model 5 bis		Model 6 bis	
Constant	β_0	17.3949	***	16.6965	***	11.5074	**	9.2130	**	10.9047	**
1/S	β_1	-0.0000120		0.0000063		0.0000003		-0.0000170	**	0.0000007	
D_{REG}	β_2	-0.1265	***	-0.1790	***	-0.2395	***	-0.1949	***	-0.2446	***
EUROPE	β_3	-0.0692	*	-0.1544	***	-0.2103	***	-0.1375	***	-0.2135	***
TE	β_4	0.0654		0.1745	*	0.2139	***	0.0938		0.2012	**
PANEL	β_5	0.0766		0.0227		0.0546		0.1405	**	0.0691	
PARAM	β_6	0.1302	*	0.1478	*						
FDH	β_7					0.1585	**	0.2203	***	0.1686	***
Year of estimation	β_8	-0.0083	***	-0.0081	***	-0.0054	**	-0.0042	*	-0.0052	**
lDIM	β_9	0.0429		0.0767	*	0.0847	***	0.0456	*	0.0785	***
lSIZE	β_{10}	-0.0056		0.0320	***	0.0050		-0.0309		0.0076	
lSIZE*MANY	β_{11}			-0.0574	***	-0.0561	***			-0.0549	***
VRS	β_{12}							0.0618	**	0.0498	**
Observations		294		294		267		267		267	
tau^2 (between-study variance)		0.0154		0.0102		0.0088		0.01325		0.008377	
% residual variation due to heterogeneity		75.00%		72.25%		72.30%		71.75%		67.89	
Adj R-squared		47.19%		65.13%		70.83%		56.25%		72.34	
F- Fisher		15.88		23.42		27.75		18.70		26.49	

Legend: * p<0.2; ** p<0.1; *** p<0.05.

Note: The statistical significance of the REML results is robust to clustering at the study level, as in Gallet and Doucouliagos (2014).

6. Conclusions

This paper collected 360 observations of local government efficiency from 54 primary studies published from 1993 to 2016. It used a meta-analysis to evaluate the impacts of a number of related factors on the heterogeneity of efficiency in primary studies. Our results show that methodological choices cause heterogeneities in the efficiency scores that one obverses when referring the literature of local government efficiency.

First of all, it is noteworthy to point out that the descriptive section of our meta-dataset highlights the fact that efficiency scores are highly heterogeneous. To be precise, significant differences in means are found when grouping efficiency on the basis of different criteria. For instance, cost efficiency is significantly lower than production efficiency. Furthermore, the unconditioned mean of efficiency scores from parametric studies is higher than that from nonparametric studies. Within the latter, the average of efficiency in DEA papers is lower than that collected from FDH studies. Besides differences in means, the data also emphasize the existence of substantial differences in the form and shape of efficiency distributions.

Secondly, it emerges from the meta-analysis that some methodological choices can significantly affect the efficiency of local government. The meta-regression results indicate that studies using parametric methods provide higher efficiency scores on average than papers based on nonparametric models. A significant impact is also exerted by the modelling choices regarding returns to scale: as we find that studies assuming VRS yield higher efficiency levels than papers based on CRS. Moreover, the efficiency estimated in nonparametric frontiers estimated under the convexity hypothesis, that is the FDH papers, is higher than that obtained from DEA studies. Again, the use of panel data does produce different efficiency scores compared to the use of cross sectional data.

Thirdly, the analysis indicates that the estimated values of local government efficiency depend on other specific factors in primary papers. For instance, the number of inputs and outputs included in frontier models of primary studies also affects the results, with more inputs and outputs leading to high efficiency; as the regressor is in logs, the marginal effect decreases as the dimension increases. Finally, we provide robust evidence that the heterogeneity in results is significantly dependent on the sample size used in primary papers.

In conclusion, this study organizes the flood of estimates stemming from the literature on efficiency in local government. While many individual papers present conflicting arguments concerning the advantages of the various methodologies, we provide clear-cut quantitative effects on efficiency caused by alternative methodological choices. Therefore, our MRA results will we hope provide some insights for researchers who are interested in estimating efficiency in local government and testing the sensitivity of their findings to the choice of study design. However, while our main results are robust to different samples of observations, the study has some limitations depending on data quality. Indeed, many authors of primary papers do not report any detail regarding their empirical setting. A lesson that we have learnt from this paper is that it is a good practice for primary papers to provide full explanations, not only so that readers are informed concerning each single study, but also because it would help the understanding of some key issues in the efficiency literature. For instance, it would be valuable for academics to know if heterogeneity in local government efficiency might be explained by orientation in technology (input- versus output-oriented models). Similarly, the data available for our MRA do not allow us to determine whether efficiency differs according to the municipality size analysed in the primary papers (i.e. small versus large municipality). Researchers might address these issues in future work by performing a new MRA. However, this is feasible only if primary papers provide more detailed information than those used in this meta-study.

Appendix A

This appendix summarizes the methods applied to estimate the frontier. While the concept of efficiency is subject to different interpretations (Aigner et al. 1977; Battese et al. 2005; Farrell, 1957), there is consensus in considering efficiency to be the degree of proximity of an actual production process to a standard of optimality. Efficiency can be thought of as the ability of a decision unit to minimize the amount of input for the production of a certain output (input-oriented TE) or to maximize the amount of output given a certain amount of input (output-orientated TE), for any level of technology. Furthermore, efficiency may be evaluated and interpreted from different perspectives, depending on whether the focus is on production or costs. Since efficiency is evaluated in relation to the best-practice, the key concerns in this field of research come from the methods.The proposed classification reports, method by method, the requirements regarding the functional form to be assigned to the frontier, the assumptions regarding the disturbances (existence and composition) and some specificities of the efficiency scores (time-invariant, punctual estimates). A number of advantages/caveats are highlighted for each technique. A common criterion of classification distinguishes between parametric and nonparametric approaches. Parametric methods assign density functions to the stochastic component of the model, while nonparametric methods only define the deterministic part. The SFA, the DFA and the Thick Frontier Approach (TFA) are parametric methods and are all based on a specific functional form of the output-variable (i.e. production, profit, cost or revenue), assign a distribution to the error term and allow to do inference. The DEA and the Free Disposal Hall Approach (FDH) are nonparametric methods. The group name refers to the fact that these methods do not assign a distribution function to the error term. Another criterion is based on how the distance from the frontier should be understood. In this respect, we have stochastic or deterministic methods. The first group admits that a bank may be far from the frontier due to randomness and/or inefficiency. In other words, a stochastic method, such as the SFA, allows the decomposition of the error into two parts, one attributable to inefficiency and the other to random error. On the other hand, when using a deterministic approach, the distance from the frontier is seen as being entirely due to inefficiency. In other words, the determinist approach ignores the existence of pure random disturbance, which may be, for example, due to measurement errors or unforeseen events.

Table A1 A breakdown of some methods used to estimate efficiency

	Nonparametric and determinist approaches		Parametric and stochastic approaches		
	DEA	**FDH**	**SFA**	**DFA**	**TFA**
Functional Form of the Frontier	Not specified	Not specified	To be specified	To be specified	To be specified
Erratic Disturbance	Not allowed	Not allowed	Composite term - inefficiency - random error	Composite term - inefficiency - random error	Composite term - inefficiency - random error
Efficiency	- Time variant - Point estimates	- Time variant - Point estimates	- Time variant - Point estimates	- Time variant - Point estimates	- Time variant - Only general estimate
Advantages	- No constraint to assign a functional form to frontier - No constraint regarding error distribution - Point estimates of each DMU	- No constraint to assign a functional form to frontier - No constraint regarding error distribution - Point estimates of each DMU - No assumption of production set convexity	- Composite error split into a component relating to efficiency and another due to randomness - Point estimates of each DMU	- Composite error split into a component relating to efficiency andanother due to randomness - Point estimates of each DMU	- Composite error split into a component relating to efficiency and another due to randomness
Caveats	- No randomness - No parametric test for inference	- No randomness - No parametric test for inference	- Arbitrary choice of distribution for the error tem - Arbitrary choice of functional form of frontier	- Arbitrary choice of functional form for the frontier - Efficiency is assumed to be time-invariant	Arbitrary choice of functional form for the frontier Arbitrary choice of distribution for the error tem - No point estimates - Arbitrariness in the division of the distribution in quartiles

Legend: DEA = Data Envelopment Analysis; FDH = Free Disposal Hall; SFA: Stochastic Frontier Approach; DFA = Distribution Free Approach; TFA = Thick Frontier Approach.

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