A Longitudinal Parametric Approach to Estimate Local Government Efficiency *

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Abstract

Previous empirical works on municipal efficiency have mostly used cross-sectional data which makes it impossible to separate unobserved heterogeneity from inefficiency. Furthermore, they have also typically used a two stages approach which has been widely criticized as the assumptions made in the first stage are violated in the second stage, generating biased results. We present one of the first longitudinal parametric studies that analyze municipal efficiency and its determinants using a one step procedure. Furthermore, we are the first of this kind that analize overall efficiency as well as efficiency by clusters of municipalities in order to reduce heterogeneity. We use administrative datasets of Chilean municipalities for the 2008-2010 period and our results suggest that Chilean municipalities have on average an inefficiency level of 30% with a significant variance between clusters of municipalities. Also, our results suggest that socio-economic, fiscal and political variables affect municipal efficiency. In particular, we found that municipalities with tighter budget constraints are associated with more efficient municipalities.

JEL Classification: O54, H72

1 Introduction

Local governments (municipalities) are crucial in the pursue of a decentralized system of policy making. This is because they are the closest political level to the population and their needs. Due to this, municipalities have their own budgets and are mandated to provide, independently from central government, a number of public services to their community.

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Given their relevance, there have been a long series of studies which have tried to measure the level of efficiency of municipal provision of such public services. Traditionally, previous literature have used a two stages approach, a first stage to estimate inefficiency and a second stage to estimate the determinants that affect the previously estimated inefficiency. This two-stages approach has been widely criticized (Wang and Schmidt, 2002) because the assumptions in the second stage contradict those made in the first stage, potentially biasing the results. In particular, in the first stage it is assumed that the inefficiency term is independent and identically distributed while in the second step inefficiency is deterministic. Thus, a one stage approach has been suggested to solve the drawbacks of the two stage approach.

Additionally, the vast majority of previous literature uses a cross-section approach. This formulation presents the drawback that it is not possible to separately identify inefficiency from municipal unobserved heterogeneity. In order to overcome this difficulty, models with panel data have been suggested. Recent literature has used panel data for municipal efficiency estimation. Unfortunately, most of the previous literature has used non-parametric methods which applies a two stage approach to estimate inefficiency and their determinants (Greene 2005c). Apart from this, they face other drawbacks. Particularly, non-parametric methods uses linear programing techniques instead of econometric methods which implies that the error is calculated and not estimated. This in turn implies that non-parametric techniques have a deterministic nature. Thus, any deviation from the frontier is interpreted as inefficiency even though the source of these deviations may be due to variables that are not under the control of the municipality. Furthermore, with availability of panel data, non-parametric methods have an additional drawback. As non-parametric methods optimize period by period, the efficiency score is computed for each single year as in the cross-sectional framework, therefore they ignore the panel dimension of the data.

There is a very scarce empirical literature that uses a one stage approach with parametric models and panel data to estimate municipal efficiency. We contribute to the literature by formally outlining a methodological approach to this setting and by presenting one of the first studies with these characteristics. Furthermore, unlike previous related literature we analize overall efficiency as well as efficiency by clusters of municipalities, in order to reduce heterogeneity, and thus diminishing the risk of omitted variables.For efficiency analysis, homogeneity of the municipalities under study is very important, since as pointed out by previous literature (Afonso and Fernández 2008) a highly heterogeneous group of municipalities may be the result of omitted variables and thus of a misspecified model (e.g. due to scale effects). Hence, we first estimate our model for the whole sample and then for each one of the identified clusters.

The specific application presented in this work is a stochastic frontier analysis for 309 Chilean municipalities for the period 2008-2010. For this task we use administrative data provided by the Chilean Government on the municipal provision of a series of public goods and services. Among them the more important are: education, health, rubbish collection, contributions to social organizations, maintained green areas, and access to clean water. Results suggest that Chilean municipalities are heterogeneous in their inefficiency levels and that on average inefficiency reaches 30% approximately. This is, Chilean municipalities could provide the same amount of services but with a 30% less of resources. Regarding heterogeneity, we also analyze inefficiency by more homogeneous subgroups of municipalities (clusters). We find that results go in the same direction than the general model although there are heterogeneous findings when clusters were compared. Despite this, when we analyze the most efficient municipalities per cluster, we found similar patterns in the effects of the determinants. We found that municipalities with the best results in each cluster have a higher dependency on the municipal common fund (a fund aimed at redistributing municipal income) relative to self-generated revenues, higher investment as a percentage of total expenditure, a lower schooling level and a higher political concentration.

The article is organized as follows. Section 2 discusses the theoretical background of the methodology used for our estimation. Section 3 puts forward a literature review of previous empirical works. Section 4 formally presents the proposed methodology. Section 6 provides details of the Chilean case study, discussing the institutional framework of Chilean municipal management. Section 7 outlines the procedure for the construction of municipal clusters, the data and the summary statistics. Section 8 and 9 present the results and the sensitivity analysis respectively. Finally, section 9 puts forward some concluding remarks.

2 Theoretical Background

2.1 Product maximization versus Cost minimization

Theoretical references of frontier functions go back to Farrell (1957). He proposed that efficiency of a firm consists of two components: technical efficiency and allocative efficiency. The former reflects the ability of a firm to obtain maximal output from a given set of inputs, while the latter reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices. These two measures are then combined to provide a measure of total economic efficiency. A simple example of firms which use two inputs (x_1 and x_2) to produce output (y) under an assumption of constant return to scale can be seen in Figure 1. The isoquant of the fully efficient firm is represented by *YY'* in the Figure. Knowing this isoquant allows the measurement of technical efficiency because, if a given firm uses quantities of inputs, defined by the point *P*, to produce a unit of output, the technical efficiency of that firm is defined to be the ratio *OR/OP*, which is the proportional reduction in all inputs that could theoretically be achieved without any reduction in output. Note that the point *R* is technically efficient because it lies on the technical isoquant.

If the price ratio, represented by the line *CC'* in Figure 1, is also known, allocative efficiency may also be calculated. For a firm operating at *P*, allocative efficiency is defined by the ratio *OS/OR*, since the distance *RS* represents the reduction in production costs that would occur if production were to occur at the allocatively (and technically) efficient point *R'*, instead of at the technically efficient, but allocatively inefficient, point *R*. The total economic efficiency is defined as the ratio *OR/OP*, in which the distance *RP* can also be interpreted in terms of a cost reduction.

These efficiency measures assume the production function of the fully efficient firm is known, which in practice is not the case, hence the efficient isoquant must be estimated from the sample data. Farrell suggests a parametric function, such as the Cobb-Douglas, such that no observed point should lie to the left or below it. Since then, several authors have proposed different functional forms (e.g. translog, Zellner-Revankar generalized production function, etc.).[1] The choice of functional form bring a series of implications with respect to the shape of the implied isoquant and the values of elasticities of factor demand and factor substitution, but as Greene (2005c) points out: "*the issue of functional form for the production function or cost function is generally tangential to the analysis, and not given much attention*". In empirical literature the most commonly used production functions are the Cobb-Douglas and the Translog.

Greene (2005c) argues that cost inefficiency is a blend of the two sources technical and allocative. Despite this complexity, there are several studies which analyze cost inefficiency because they allow to include multiple inputs, which is not straightforward on the production side.

It should be noted that any deviation from cost efficiency may come from two sources: input-oriented technical inefficiency and allocative inefficiency (OR/OP and RS/OP in Figure 1 respectively). In order to estimate the latter, additional data should be available, for example: the vector of inputs prices. If the additional data is not available it is only possible to estimate the input-oriented technical inefficiency. As in the case study to be presented later, we do not know all the inputs and their respective prices, we focus our attention in this study only on input-oriented technical inefficiency. Throughout this study we will refer to the input-oriented technical efficiency as cost efficiency.

In general, the approach followed (i.e. maximize production or minimize costs) in the literature depends on the exogeneity of output and inputs variables. In particular, when inputs are considered more exogenous than the product (i.e. that they do not fully depend on municipal management) product maximization is used and viceversa. In order to choose, the given institutional framework is crucial, as for the case study to be later analyzed in which output is given by law (i.e. exogenous) and inputs depend upon municipal management, a cost minimization approach will be more adequate for our analysis.

2.2 Parametric versus Non-Parametric approaches

In order to measure efficiency two types of approaches have been used: non-parametric (such as Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH)) and parametric (such as Stochastic Frontier Analysis (SFA)). On the one hand, the non-parametric approach analyzes efficiency from the data available and not from imposed functional forms. Also, it uses linear programing techniques instead of econometric methods which makes that the error is calculated and not estimated implying that non-parametric techniques have a deterministic nature. Thus, any deviation from the frontier is interpreted as inefficiency even though the source of these deviations may be due to variables that are not under the control of the municipality. Also, non-parametric methods use two stages procedures, which have been criticized because of the contradictions between the assumptions made in the first stage versus to what is estimated in the second stage. Furthermore, with availability of panel data, non-parametric methods have an additional drawback. As non-parametric methods

[1] The Zellner-Revankar form removes the return to scale restrictions, while the Translog form imposes no restrictions upon returns to scale or substitution posibilities but has the drawback of being susceptible to multicolinearity and degrees of freedom problems.

optimize period by period, efficiency score is computed for each single year as just in a cross-sectional framework, therefore they ignore the panel dimension of the data.

On the other hand, parametric methods, such as the stochastic frontier analysis, originally developed by Aigner, Lovell and Schmidt (1977) and Meeusen and Van Broeck (1977), come from an extension of Ordinary Least Squares (OLS) and Maximum Likelihood (ML). In this way, while OLS estimate the most appropriate function of medium cost, the stochastic frontier analysis estimates the maximum production or the minimum cost. Furthermore, it decomposes the deviation from the frontier in to a random component (the error term) and the inefficiency. Hence, this approach can accommodate exogenous shocks such as bad weather and separate it from inefficiency. An additional advantage of parametric methods is that, when there is panel data, they take into account the unobserved heterogeneity across municipalities, which could play a crucial role in explaining the performance of cities.[2] The drawback of parametric methods is the necessity of an assumption about the production (or cost) function. As, in this study, we use the parametric approach, we tackle its weakness by assuming different production (cost) functions in order to check if results are sensitive to them.

3 Previous Empirical Literature

The analysis of municipal efficiency has been carried out mainly in two steps models: the first one as an efficiency analysis itself and the second as an evaluation of its determinants (see Bellaguer-Coll et al. (2002), Herrera and Francke (2009), Afonso and Fernandes (2006)).

Consequently, in the first step the focus has been placed on the analysis of the productive process by which the local government utilize the available resources to generate goods and services; As such, municipal performance has been measured by the efficiency of municipal expenditure. The results obtained in previous literature, which focused in municipal efficiency, suggests that there are important inefficiencies on municipal expenditure. For example, the Afonso and Fernandez (2006) DEA study for Portugal concludes that on average municipalities of the Lisbon region could achieve the same performance with 39% less resources. Similarly, a second DEA evaluation applied to 278 Portuguese municipalities showed similar inefficiency levels (Afonso and Fernandez 2008). For Peru, the parametric cross-section analysis of Herrera and Francke (2007) showed that municipalities could achieve the same provision of good and services with 58% less resources. In the same line, Pang, Liu, Peng and Wu (2010) find inefficiency levels of 41% for Taiwanese municipalities and Balaguer-Coll et al. (2007) with a DEA and a FDH find similar results for Spain.

Studies focused on the second stage, in which the determinants of inefficiency are estimated, have shown, for instance for the case of Belgium, that the level of education has positive effects on municipal efficiency while average income and the amount of transfers relative to local income have negative effects on municipal efficiency, see De Borger and Kerstens (1996a). Also for Belgium, Van den Eckaut et al. (1993) find a positive relationship between municipal efficiency and political composition of the City Council (i.e. better results for municipalities with heterogeneous

[2] Parametric methods estimate the time profile of the scores endogenously in a single panel.

composition of the council versus those with a more homogeneous composition). For the case of Peru, Herrera and Francke (2009) find that a higher participation in the municipal common fund (a fund aimed at redistributing municipal income) has a negative effect on municipal efficiency while political participation affects positively municipal efficiency. The parametric and non-parametric evaluation of Greek municipalities by Anthanassopoulos and Triantis (1998) finds a negative relationship between efficiency levels and the ratio of transfers over municipal total income, population density and political affiliation (measured as parties affiliated to the central government). For Finland, Loikkanen and Susiluoto (2005) find a positive relationship between municipal efficiency and certain age groups (mainly with individuals between 35-49 years old) and a negative relationship with peripheric geographic location, high income levels, high population, transfers of good and services from other municipalities and higher participation in municipal funds. For Taiwan, Pang, Liu, Peng and Wu (2010) concluded that environmental policies adopted by municipalities were crucial for municipal efficiency.

In one of the very few parametric studies with panel data, Bianchini (2010) evaluates the efficiency of 100 Italian chief towns of Province in providing urban environmental quality during 1998-2007. She finds that, besides socio-economic variables, those which explain different municipal performance are the fiscal and political ones. The other known parametric panel data study has been carried out for the Czech Republic by Stastna and Gregor (2011). They find that population size, distance to the regional center, share of university educated citizens, capital expenditure, subsidies per capita and the share of self-generated revenues increase inefficiency.

Previous results from the literature, as those mentioned above (see a more complete list in Table 1) are based on a variety of estimation methods. On the one hand, parametric methods have been used which assume a functional form to model the relationship between the variables of input and output and on the other hand non-parametric methods have been used, which assume that any deviation from the frontier are due to inefficiency. Under this general setup, the stochastic frontier analysis is the main parametric approach while the data envelopment analysis and the free disposal hull are the main approaches in non-parametric methods. Due to the variety of techniques for the estimation of municipal efficiency, there have been some studies which focuses on the analysis of the differences of the results given by the different techniques. As such, De Borger and Kerstens (1996a and 1996b) in Belgium and Worthington (2000a and 2000b) in Australia explore the differences of the results given for the same municipalities using parametric and non-parametric methods. Similarly, Van den Eckaut et al. (1993) focused in the comparison of the results of DEA and FDH. All these studies have shown that findings obtained about municipal efficiency are sensitive to the technique applied. However, despite the magnitude of efficiency changes from method to method, the general results are very similar.

Furthermore, it is worthwhile to mention that most of the parametric evidence uses cross sectional data, being the exception the working papers of Bianchini (2010) and Stastna and Gregor (2011). This is crucial as this kind of data may be informative for efficiency measures, but it presents the drawback that it is not possible to disentangle municipal efficiency from municipal heterogeneity (see Greene 2005a, 2005b and 2005c). In addition, it should be noted that the works of Bianchini (2010) and Stastna and Gregor (2011) carried out an overall analysis. Some authors (Afonso and Fernandez 2008) have criticized this kind of approach as municipalities are very heterogeneous, which may be due to omitted variables, generating in this way a misspecified model. To reduce this risk the authors proposed to use more homogeneous clusters of municipalities.

For parametric models, the majority of the empirical evidence on technical efficiency mentioned above uses a two step approach, where the second step estimates the determinants of the inefficiency estimated in the first step. This is carried out regressing the estimated inefficiency on exogenous variables which may affect municipal performance. This two step method has been widely criticized in the literature, since it assumes that the exogenous variables included in the second step are not correlated with the variables used to estimate the inefficiency in the first step. The reason for this is that in the first step it is assumed that inefficiency is independent and identically distributed, but in the second step the assumption is that inefficiency is explained by exogenous variables, which may be a contradiction. In other words, if the variables included in the second step are not orthogonal to those included in the first step, this method will obtain biased results (Wang and Schmidt 2002). Consequently, to increase the number of input, output or exogenous variables will probably increase the probability of violating the assumption. This issue is particularly problematic for two stage studies that employ non-parametric methods (Simar and Wilson 2007).[3]

To solve this problem in the parametric case Khumbhakar, Gosh and McGuckin (1991) proposed a one step estimation method, in which determinants of inefficiency are estimated jointly with the frontier given the appropriate assumptions about the error terms. This method of estimation solves the inconsistency on the estimators due to the assumptions imposed on the inefficiency term. Exists two options for this one step estimation. The first one incorporates the exogenous determinants of the inefficiency directly into the production function (Battese and Coelli, 1992) and the second one and more used in the literature, includes the exogenous determinants into the mean of the inefficiency term (Battese and Coelli, 1995). Interpretation of results differ in each option. In the former, the effect of the determinants of the inefficiency term determines the position of the production function, whereas in the latter they are interpreted as the distance to the frontier.

In this context, this work contribute to the empirical literature by presenting one of the first longitudinal parametric studies that analyze municipal efficiency and its determinants using a one step procedure. Specifically, we include the exogenous determinants into the mean of the inefficiency term in one step procedure in order to avoid the problems described above. Furthermore, we are the first of this kind that analize overall efficiency as well as efficiency by clusters of municipalities in order to reduce heterogeneity, and thus diminishing the risk of omitted variables.

4 Methodology

4.1 Deterministic Frontier Analysis

As mentioned above there are two approaches used for the estimation of frontier functions, the parametric and the non-parametric methods. The former approach can be divided in to its deterministic versus its stochastic branch. Regarding the deterministic branch, a lengthy literature

[3] In their own words:"*A more serious problem in all of the two-stage studies that we have found arises from the fact that DEA efficiency estimates are serially correlated. Consequently, standard approaches to inference are invalid*". Furthermore, the two stage approach is routine in the DEA literature (Greene 2005c).

commencing with theoretical work by Debreu (1951) and Farrell (1957) and the pioneering empirical study by Aigner, Lovell, and Schmidt (1977) has been directed at models of production that specifically account for the proposition that a production function is a theoretical ideal. If $y = f(x)$ defines a production relationship between inputs, x, and an output, y, then for any given x, the observed value of y must be less than or equal to $f(x)$. The implication for an empirical regression model is that in a formulation such as $y = h(x, \beta) + u$, u must be negative. Because the theoretical production function is an ideal—the frontier of efficient production—any nonzero disturbance must be interpreted as the result of inefficiency. By duality the former approach presented for product maximization, can be applied for cost minimization.

Due to the limitation of the deterministic frontier approach Aigner, et al. (1977) proposed instead a formulation within which observed deviations from the production function could arise from two sources: (1) productive inefficiency, that would necessarily be negative, and (2) idiosyncratic effects that are specific to the firm and that could enter the model with either sign. The end result was what they labeled as stochastic frontier.

4.2 Stochastic Frontier Analysis

The Stochastic Frontier Analysis was developed by Aigner, et al. (1977) and Meeusen and Van Broeck (1977) as a model to estimate production and/or cost frontiers. Their input-oriented specification, defines the minimum cost level for observation i needed to produce a good and services vector given input prices (w_i). Thus, the model can be expressed as:

$$C_i = C(y_i, w_i, \beta)\ exp(v_i + u_i) \tag{1}$$

$$i = 1, ..., N \quad with \quad u_i \geq 0$$

where:

C_i	is the observed (actual) cost or expenditure of municipality i
$C(y_i, w_i, \beta)$	is the cost frontier of municipality i
y_i	is the output vector of municipality i
β	is a vector of parameters to be estimated.

v_i is an iid random variable.This variable represents exogenous factors which are not controlled by the municipality which affect the cost level (e.g. weather, luck , regulation, etc). u_i is a random variable which correspond to the inefficiency level in costs and its distribution will depend on the assumptions made (explained below).

The parameters of this model are estimated by Maximum Likelihood, given suitable distributional assumptions for the error term. Aigner, et al. (1977) assumed that v_i has a normal distribution and u_i has either the half-normal or the exponential distribution. The main criticism is that there is no a priory justification for the selection of any particular distributional form for the u_i . Since then, started a literature which have proposed more general distributional forms, such as the truncated-normal (Stevenson 1980) and the two-parameter Gamma (Greene 1990).[4]

It is crucial to notice that deviations between the observed cost (C_i) and the frontier ($C(y_i, w_i, \beta)$) can come from two sources: technical inefficiency of the municipality (u_i) or random shocks which are not under the control of the municipality (v_i). Both components are assumed to be independent from each other. The stochastic frontier method consists of the estimation of the variation of (v_i) and (u_i) in order to obtain evidence of the relative effect of each of them on costs. Thus, the cost efficiency level of a municipality (CE) will be given by the ratio between actual costs and the cost frontier in order to reach certain output y_i, given input prices w_i. Formally, this is given by:

$$CE_i = \frac{C(y_i, w_i, \beta)\ exp(v_i)}{C(y_i, w_i, \beta)\ exp(v_i + u_i)} = exp(-u_i) \tag{2}$$

when the value of equation (2) tends to 1, implies that municipality i is very efficient in terms of costs because actual costs will be similar to the cost efficient level. On the other hand, CE<1 provides a measure of the gap between the minimum possible cost and the observed one. The inefficiency term itself (u_i) is not observable, therefore $\varepsilon_i = v_i + u_i$ must be used for the estimation of equation (2). In order to do this, the estimation is carried out computing the expected value of the inefficiency term component (u_i) given the composite error term (ε_i). Hence, we obtain:

$$CE_i = E\left[exp\left(-u_i|\varepsilon_i\right)\right] = E\left[exp\left(-u_i|(v_i + u_i)\right)\right] \tag{3}$$

In order to find $E\left[-u_i|\varepsilon_i\right]$ the conditional density function must be known, and this function is given by:

$$f\left(u_i|\varepsilon_i\right) = \frac{f(u_i, \varepsilon_i)}{f(\varepsilon_i)} = \frac{f(u_i, (v_i + u_i))}{f(\varepsilon_i)} \tag{4}$$

To estimate this, it is necessary to assume a probability distribution for both error components. As it was previously mentioned, in all the models v_i is considered as independent and identically distributed following a normal distribution ($N\ \left(0, \sigma_v^2\right)$). Despite there are no consensus on which distribution to assume for u_i, the most used one in the empirical literature is the truncated-normal ($N^{\ +}\left(\mu, \sigma_u^2\right)$). The main reason for this is that this distribution allows us to estimate the determinants of inefficiency in one step, avoiding the problems presented above when a two stage approach is carried out.

After both distributions are defined, their distributions functions should be obtained:

[4] Truncated normal and the two-parameter Gamma were introduced because the Half-normal and exponential distributions both have a mode at zero. This causes conditional technical inefficiency scores, specially in the neighbourhood of zero that can involve artificially high technical efficiency levels. The Truncated Normal is more flexible since the modal efficiency value can also be away from one, and for this reason in most empirical works it is preferred relative to the Half Normal.

$$f\left(v_i\right) = \frac{1}{\sigma_v\sqrt{2\pi}} exp\left(\frac{-v^2}{2\sigma_v^2}\right) \tag{5}$$

$$f\left(u_i\right) = \frac{2}{\sigma_u\sqrt{2\pi}} exp\left(\frac{-u^2}{2\sigma_u^2}\right) \tag{6}$$

as the joint density function ($f(u_i, \varepsilon_i)$) is unknown, the joint density function of both error term components can be estimated as ($f(u_i, v_i)$) and replaced it in the term $v_i = \varepsilon_i - u_i$. As u_i and v_i are independent to each other, the joint density function corresponds to the product of the individual density functions such as:

$$f(u_i.v_i) = f(u_i)\ f(v_i) = \frac{2}{2\pi\sigma_v\sigma_u} exp\left(\frac{-u^2}{2\sigma_u^2} - \frac{v^2}{2\sigma_v^2}\right) \tag{7}$$

by replacing $v = \varepsilon - u$ in equation (7)we obtain the joint density function of u_i and ε_i:

$$f(u_i.\varepsilon_i) = \frac{2}{2\pi\sigma_v\sigma_u} exp\left(\frac{-u^2}{2\sigma_u^2} - \frac{(\varepsilon - u)^2}{2\sigma_v^2}\right) \tag{8}$$

Now, to find the denominator of equation (4), we integrate equation (8) to get:

$$f(\varepsilon_i) = \int_0^\infty f(u_i.\varepsilon_i)du = \frac{2}{\sqrt{2\pi}\sigma}\left[1 - \Phi\left(-\frac{\varepsilon\lambda}{\sigma}\right)\right] exp\left(\frac{-\varepsilon^2}{2\sigma^2}\right) \tag{9}$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \frac{\sigma_u}{\sigma_v}$ and $\Phi()$ is the cumulative distribution function of a standard normal. Using this parametrization, λ is the ratio of the variability coming from each of the variables that conform the composite error term. Therefore, if $\sigma_u^2 \rightarrow 0$ (and thus $\lambda \rightarrow 0$), it is the random effect the one that predominates relative to the inefficiency and thus the density function of the composite error term tends to a normal. By contrast, if $\sigma_u^2 \rightarrow \infty$ (and thus $\lambda \rightarrow \infty$) the gap between the minimum cost and the actual cost will be mainly determined by the inefficiency term component (u_i).

Finally, replacing equation (9) into equation (4) we obtain the density function of u given ε:

$$f\left(u_i|\varepsilon_i\right) = \frac{f(u_i, \varepsilon_i)}{f(\varepsilon_i)} = \frac{1}{\sqrt{2\pi}\sigma^*\left[1 - \Phi\left(-\frac{\mu^*}{\sigma^*}\right)\right]} exp\left(\frac{-(u - \mu^*)^2}{2\sigma^{*2}}\right) \tag{10}$$

where:

$$\mu^* = \frac{-\varepsilon\sigma_u^2}{\sigma^2} \tag{11}$$

$$\sigma^{*2} = \frac{\sigma_u^2\sigma_v^2}{\sigma^2} \tag{12}$$

From the above formulation, we conclude that $f\,(u_i|\varepsilon_i)$ is the density function of a variable that distributes $N\ ^+\left(\mu^*, \sigma^{*2}\right)$.Once this distribution is known, and given that the value of cost inefficiency u_i is not observable, it is possible to use the expected value $E(u_i|\varepsilon_i)$ as the estimator of the cost inefficiency of each municipality.

$$E(u_i|\varepsilon_i) = \mu^* + \sigma^* \left[\frac{\phi\left(\frac{-\mu_i^*}{\sigma^*}\right)}{1 - \Phi\left(\frac{-\mu_i^*}{\sigma^*}\right)}\right] \tag{13}$$

where $\phi\,()$ is the density function of a standard normal. Thus, the cost efficiency function for a municipality is:

$$CE_i = E\left[exp\left(-u_i|\varepsilon_i\right)\right] = \frac{1 - \Phi\left(\sigma^* - \frac{\mu_i^*}{\sigma^*}\right)}{1 - \Phi\left(-\frac{\mu_i^*}{\sigma^*}\right)} ex\ p\left\{-\mu_i^* + \frac{\sigma^{*2}}{2}\right\} \tag{14}$$

4.3 Determinants of Inefficiency

In order to implement a one stage approach to stochastic frontier analysis, there are two options: the first one incorporates the determinants directly as regressors in the non-stochastic component of the cost frontier. The second one, incorporates indirectly the determinants in the stochastic component, in particular on the variable u_i. Thus, in the first approach, it is assumed that determinants affect directly the cost frontier by moving it. By contrast, the second approach assumes that determinants affects the costs inefficiency levels. This latter approach was introduced in the literature by Battese and Coelli (1995) and it allows to find the determinants of the estimated inefficiency. Therefore, the interpretation of the results corresponds to the distance between the effective costs and the cost frontier.

There is no consensus in the literature on which of the previous alternatives is preferred (Greene 2005c). Due to this and given our objective of finding the determinants of the inefficiency, we use the Battese and Coelli (1995) approach.

4.4 Estimation Method

When panel data is available, there are two main approaches for the estimation of frontier functions: fixed and random effects. In order to choose the more appropriate method it is important to consider the assumptions about the inefficiency term and the linearity of the production function. If the production function is not linear, then the within estimator will be inconsistent as the difference with respect to the mean may not eliminate the unobserved heterogeneity, furthermore, in short panels (as in our case) fixed effects suffer of what is known as the *incidental parameter problem* and random effects should be used. If the production function is linear, then in principle both methods may be appropriate depending on the assumptions made on the inefficiency term.

When the inefficiency term is time invariant Fixed Effects and Random Effects present problems as in both approaches u_i carries both: inefficiency and, in addition, any time invariant municipal specific heterogeneity. Additionally, for both approaches, the time invariance assumption in long time series of data, is likely to be a particularly strong assumption.

For these reasons, recent literature have promoted models with a time varying inefficiency term. Even in this context, fixed effects do not take into account time invariant covariates (which is our ultimate interest in this study). We now formally analyze whether a random effects model is preferred to a fixed effects approach, or vicevera, for this particular setting.

- Fixed Effects approach

If the inefficiency term is time invariant (u_i) the Schmidt and Sickles fixed effects formulation implies that:

$$y_{it} = \alpha - u_i + \beta' x_{it} + v_{it} \tag{15}$$

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it} \tag{16}$$

The model is reinterpreted by treating α_i as the firm specific inefficiency term. There are three important restrictions in this model. First, any time invariant unobserved heterogeneity will be pushed into α_i and ultimately into $\hat{u}_i$, where:

$$\hat{u}_i = max_i \hat{\alpha}_i - \hat{\alpha}_i \tag{17}$$

Second, with longer time periods the assumption that inefficiency is time invariant is complicated, as in general, individuals learn with experiences. Finally, since this approach precludes covariates that do not vary through time, such variables cannot appear in this model. To overcome these first two shortcomings Greene (2003, 2005a, 2005b and 2005c) proposed the true Fixed Effect model, given by:

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it} - u_{it} \tag{18}$$

This model introduces new problems. As Greene (2003, 2005a, 2005b and 2005c) recognizes, the first one is that if this model is estimated by the brute force approach ($LSDV$), it would be impractical for cases in which there are many municipalities as perhaps thousands of parameters must be estimated. A second and more difficult issue is the incidental parameters problem. With small T (group size—in our applications, T is 3), many fixed effects estimators of model parameters are inconsistent and are subject to a small sample bias. To date, there has been no systematic analysis of the estimator for the stochastic frontier model.[5] Greene (2005c) finds that the incidental parameter problem affects the variances and not the slopes and that the transmission of the biases are not as large as expected.[6]

- Random Effects approach

For the case of random effects, the model can be expressed as follows:

$$y_{it} = \alpha + \beta' x_{it} + v_{it} - u_i \tag{19}$$

The random effects model has three noteworthy shortcomings. The first two are common between Fixed and Random effects models. The first problem with the random effects model is its implicit assumption that inefficiency is the same in every period, which for a long time series of data is likely to be a particularly strong assumption. The second shortcoming of this model, regardless of how it is formulated, is that in this model, u_i carries both the inefficiency and, in addition, any time invariant municipal specific heterogeneity. The third shortcoming is its implicit assumption that inefficiency is not correlated with the included variables. Given these problems, several studies suggest to modify this by proposing the true random effect model with a time variant inefficiency term. Among these works are: Battese and Coelli (1995) and Kumbhakar and Orea (2003). The former proposed the one presented in equation (3) while the latter proposed a more general form. Thus, including the time variant inefficiency term the true random effects model becomes:

$$y_{it} = \alpha + w_i + \beta' x_{it} + v_{it} - u_{it} \tag{20}$$

where w_i is the random municipality specific effect. We can formulate this model for a stochastic frontier with a municipal specific random constant term as follows:

[5] As Greene (2005c) points out, the analysis has an additional layer of complication because unlike any other familiar setting, it is not parameter estimation that is of central interest in fitting stochastic frontiers. No results have yet been obtained for how any systematic biases (if they exist) in the parameter estimates are transmitted to the JLMS estimates of the inefficiency scores.

[6] If there is persistent inefficiency, it would be completely absorbed in the municipal specific constant term which is also capturing any time invariant heterogeneity. Ultimately, $\alpha_i + v_{it} - u_i$ contains both municipal specific heterogeneity and inefficiency and both may have invariant and time varying elements. Thus, there is no perfect way to disentangle them based on observed data (Greene 2003).

$$y_{it} = (\alpha + w_i) + \beta' x_{it} + v_{it} - u_{it} \tag{21}$$

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it} - u_{it}$$

The time invariant random constant term embodies the unobserved municipal heterogeneity. This form of the model overcomes the first two shortcomings of the random effects models mentioned above. The only remaining issue here is the assumption of no correlation between inputs and any part of the error term $(\alpha_i + v_{it} - u_{it})$. By construction v_{it} is white noise. The correlation between inputs and inefficiency (u_{it}) could be reduced through the inclusion of environmental effects $(z's)$ in the mean and/or variance of the distribution of the inefficiency term (as equation (4)). Finally, the assumption of no correlation between the individual effect (α_i) and the covariates becomes difficult to defend, Mundlak´s (1978) approach can be used to capture the correlation between the individual effect (α_i) and the average of the regressors. Thus, we propose the following:

$$\alpha_i = \alpha_0 + \alpha_1' \overline{x_i} + j_i \tag{22}$$

where j_i is white noise $(j_i \sim N\left[0, \sigma_j^2\right])$. This is the more general formulation and the one that allows us to overcome the mentioned shortcomings (except the assumption of no correlation between the covariates and $(v_{it} - u_{it})$.

Consequently, we postulate that in this context a random effects model, that follows the formulation outlined above, is preferred to a fixed effects approach. Hence, the basic model we propose for the estimation of fronteir functions can be expressed as follows:[7]

$$ln(C(y_{it}, \beta)) = \beta_0 + \sum_{r=1}^{R} \beta_r ln(y_{rit}) + \frac{1}{2} \sum_{r=1}^{R} \sum_{k=1}^{K} \beta_k ln(y_{rit}) ln(y_{kit}) + \sum_{j=1}^{J} \beta_j x_{jt} + v_{it} + u_{it} \tag{23}$$

where $C(y_{it}, \beta)$ is the cost function of municipality i in period t. y_{it} is the output of municipality i in period t; β is a vector of unknown parameters to be estimated; We also include the variable x_t which are dummies that control for time. v_{it} is a white noise which is assumed independent and identically distributed (iid) $N\left(0, \sigma_v^2\right)$ and independent of u_{it}. u_{it} represents the non negative inefficiency term which may vary over time and is distributed as truncated-normal $(N^{+}\left(z_{it}\delta, \sigma_u^2\right))$. This is:

$$u_{it} = z_{it}' \delta + W_{it} \tag{24}$$

[7] It should be noted that we did not include in this formulation the input prices variable, w_i, see (1). The reason for this is the typical limited available information on input prices at the municipal level. In addition, much of the associated prices correspond to salaries, which in the municipal sector are typically set by law, and therefore are quite similar, the exception being rural areas in which a premium is usually paid. While, we do not have this specific information for all the cases, as we are dealing with panel data and since these salaries do not change much through time, not including these input prices should not affect much the results of the study.

where z_{it} are the determinants of the inefficiency of municipality i at time t, δ is a vector of unknown parameters to be estimated and W_{it} is a white noise distributed $N^{+}\left(0, \sigma_u^2\right)$.Finally, as the cost measure is usually specified in natural logs, the inefficiency term, u_{it}, can be interpreted as the percentage deviation of observed performance from the municipality's own frontier (at least for small deviations).

The model follows Battese and Coelli (1995) but applied to cost minimization. Their model considers the joint maximization of equations (23) and (24) by maximum likelihood (ML). The estimated parameters should be replaced in equation (23) obtaining the estimated variables presented in equations (11) and (12). Then these variables are used in equation (14) to estimate municipal inefficiency.

For the effciency analysis, homogeneity of the municipalities under study is important. Previous literature (Afonso and Fernández 2008) have pointed out the importance of homogeneity as a highly heterogeneous group of municipalities may be the result of omitted variables and thus of a misspecified model (e.g. due to scale effects). The authors suggest the use of clusters of municipalities. Given this, we estimate the model explained above for the whole sample first, and then for each of the clusters defined with the methodology later specified (see appendix). In this way we will consider more homogenous municipalities which will allow us to decrease the risk of omitted variables.

5 The Case of Chilean Municipalities: Institutional Framework

Chile is organized in 15 regions.[8] Each one of them has provinces (54 in total) and each of the provinces has municipalities (345 in total). The Organic Law of Municipalities (Law N^{o}18.695) establishes how municipalities are constituted (i.e. the Major and the City Council), how their authorities are elected and their attributions. The major has two main attributions: (i) those related to municipal management and (ii) those attributed to the municipality as an institution. Among the former, the major is the only legally responsible individual in judicial and extra-judicial cases and also he/she is the responsible for the municipal budget. On the other hand, the city council is in charge of fiscalization and enhancement of community participation.

5.1 Specific functions of the local government

The Law N^{o}18.695 establishes that the local government has 6 exclusive responsibilities and 13 shared with other institutions. Among the former are: the planification and management of the development communal plan (*PLADECO*, in Spanish), promotion of comunitarian development, public transport regulation, hygiene services, urbanism and construction norms. Among the shared

[8] Arica and Parinacota, Tarapacá, Antofagasta, Atacama, Coquimbo, Valparaíso, Región Metropolitana, del Libertador Bernardo O'Higgins, Maule, Bío-Bío, Araucanía, de Los Ríos, de Los Lagos, Aysén and Carlos Ibañez del Campo and Magallanes and Chilean Antartica.

responsibilities are those which attributes to municipalities the main responsibility for education and health at the local government area.

Regarding financial matters, article 13^o of Law N^o18.695 establishes the main source of municipal assets, among which are:

- All real state goods they acquire.
- Transfers from the regional government.
- Resources from the municipal common fund.
- Benefits obtained from the services they deliver and for any concession (rights) or permits they give.
- Income received as a result of their activities and activities in related dependencies.
- Income collected from all the taxes the law allows local government to levy. Among these are: territorial tax, transport tax and commercial rights on alcoholic sells.
- Interests and penalties.

Municipal income can be classified depending on the source of funding. There are two main funding sources: permanent self-generated revenues and the municipal common fund. Other sources are transfers from the regional government and the central government. Among the latter, there are transfers for education and health services. Thus, local government acts as an intermediary between local education and health services and the respective ministry. Next, we give below some details regarding the income sources of the municipal budget coming from non-conditional transfers of the central government (education and health), i.e. permanent self-generated revenues and municipal common fund.

5.1.1 Municipal Common Fund (FCM)

The Municipal common fund is a fund created by the local government reform in 1979. The objective is to redistribute communal income in order to guarantee the achievement of municipal functions and its adequate functioning. Hence, the sources of funding of the FCM come from municipal income and are defined by article 14^o of Law N^o18.695 in the way presented in Table 2.

Regarding the mechanism of distribution of this fund, there is a determined structure which defines it. The mechanism of distribution is presented in Table 3. Thus, the first 25% corresponds to an amount transferred to be distributed in the same proportion in all the municipalities in the country. The next 10% is distributed depending on poverty levels of each municipality (i.e. number of poor people relative to poor people in the country). The next 30% is distributed according to the number of assets exempt of territorial tax relative to the total of exempts assets (regarding territorial tax only) in the country. Finally, the last 35% is transferred to those municipalities which generate lower permanent self-generated revenue (IPP) per capita than the national average.

5.1.2 Permanent self-generated revenues (IPP)

Permanent self-generated revenues (*IPP*) are the sources of fundings that local governments generate from municipal management. Income generated from these sources has no restriction for the municipality in what and where to invest it. From article 38 of the municipal rents law N^{o}3,063, IPP are composed by: municipal rights income, hygiene rights, concessions, municipal property rents, percentage of the income from territorial tax and transport tax, among others. From these sources most of the income of IPP comes from: territorial tax, commercial rights and transport tax. The first one is a tax imposed to agricultural and non-agricultural land.[9] From this source of income, only 40% remains in the municipality for its own funding and the other 60% is directed to the municipal common fund (FCM).[10]

Commercial rights are regulated mainly by the municipality as it chooses the tax rate to charge (subject to a range established by law). Of the amount of income collected by commercial rights, only the richest four municipalities (Santiago, Providencia, Las Condes and Vitacura) transfer a proportion to the FCM: Santiago 55% and the other three 65%. Finally, regarding transport tax, from the amount collected the 37,5% goes for municipal benefit and the rest (64,5%) go to the FCM.

6 Municipal Clustering, Data and Summary Statistics

6.1 Municipal Clustering

Chilean municipalities are highly heterogeneous regarding their territory, financial capacity and human resources (Valenzuela 2008). These differences impact directly on municipal organization, in their capacity to self generate resources and in the way municipalities confront the administration of services and public programs. Therefore, it is key to separate municipalities into clusters according to specific variables, otherwise the comparison among municipalities will be less informative as, for example, comparing *Las Condes* (the richest municipality in Chile) with *Cobquecura* (a poor rural municipality).

In order to perform the clustering analysis, we use the municipal typology of the provision of municipal services elaborated by the Chilean Under Secretary of Regional Development (*SUBDERE*).[11] This typology is elaborated based on clusters with the objective of grouping municipalities with a minimum internal variance between them and maximal external variance with other groups (see a detailed description of the methodology in the appendix). The conformed groups must be determined by grouping variables different than those used in the econometric estimation. This is

[9] This is regulated in the Law N^{o}17,235 about territorial tax.

[10] For the four richest municipalities, Santiago, Providencia, Las Condes and Vitacura percentage are: 35% and 65% respectively.

[11] It is a governmental Institution in charge of local governments, regions and provinces of Chile. SUBDERE publishes a document with the typology named "Tipología Comunal para la Provisión de Servicios Municipales", División de Municipalidades, Departamento de Finanzas Municipales. SUBDERE, Ministerio del Interior.

because we want to obtain unbiased and consistent results. In the municipal typology elaborated by SUBDERE, municipalities are clustered following two concepts: socio-territorial and socio economic indexes, which are described in Table 4.

From these clusters, and using both indexes, a graphic analysis of the dispersion is presented in Figure 2. This figure suggests which groups can be identified. Based on this analysis and following the number of clusters put forwatd by SUBDERE we define 6 clusters as presented in Table 5. For our estimations presented below, we grouped clusters 1 and 2 into one cluster due to few observations in cluster 1. Thus, we use 5 clusters for our analysis, see Table 6, in which our new cluster 1 consolidates the former 1 and 2. To see their main characteristics see Table 7.

6.2 Data description and Summary Statistics

The data for this study comes from the National System of Municipal Information (*SINIM*). This system is a management tool which consolidate a group of variables and statistical data of Chilean municipalities. *SINIM* is updated once a year and has information of all 345 municipalities in Chile from 2001 to 2010. For this study we use data for the period 2008-2010. The reason for this is that for some of the variables there are no data for previous years. The main sources of information for *SINIM* are municipalities (40% of the information) and ministries or other public services (60%). *SINIM* is the main source of information for municipal issues in Chile as it includes information on management, finance, human resources and municipal characterization.

For our analysis we use output and input variables as well as determinants. We now explain which variables were included in each one of them.

a) Output Variables:

The output variables here presented are the ones denoted by y_{it} in equation (23). Due to the inherent difficulties for quantifying the output provided by municipalities, proxies will be used (for details see Bradford et al., 1969; Levitt and Joyce, 1987). These variables should consider the multiple functions assigned to municipalities and capture the results obtained in all the areas in which they deliver goods and services. After the revision of the empirical literature and given the data available, we include 6 output variables described below and whose summary statistics are described in Table 8.

1. Municipal Scale: we consider the scale (size) of the municipality as an output (for the general model only, as this is an important variable for clustering) as bigger municipalities should provide more public goods and services.

2. Education: one of the main services provided by municipalities is education. Municipalities provide education through municipal schools. To measure the amount of education provided we use 2 variables: number of schools and the monthly average of registered students at those schools.

3. Health: this is another of the most important services provided by municipalities. To capture the amount of health services provided we use the number of health centres.

4. Urbanism: another function of municipalities is to provide roads and places for recreation such as parks, bike lanes, and so on. To measure the services provided in this area we include the square meters of maintained green areas.

5. Hygiene: municipalities are in charge of basic services to promote wellbeing. In order to have a measure of the amount of services provided in this item we use two variables: tons of collected rubbish and houses with sewer.

6. Social Services: finally, we consider services provided to social organizations which have municipal promotion and funding such as sport clubs, municipal services, elderly clubs, etc. To measure the amount of these kinds of services we include the variable social organization which registers all formal social organizations by municipality.

b) Input Variable:

After the definition of output variables we define the resources used for the provision of public goods and services such as those presented above. This is known as the input variable and is denoted by $C(y_{it}, \beta)$ in equation (23). Previous literature use current (i.e. operational) expenditure as input. The reason for this is because capital expenditure is highly volatile. We follow the same approach in this work as in the Chilean case capital expenditure is also volatile. Additionally, current expenditure represents more than 75% of total expenditure, hence we are covering the majority of it. Given this, we have two alternatives: (a) use total current expenditure or (b) use current expenditure of those services provided. The differences between the two is that the former also includes expenditures on items that are not easily or directly attributed to some particular output. For this reason we choose to use as input the current expenditure of those services provided (i.e. employees, consumption goods and services and transfers for education and health). We should also keep in mind for the interpretation of results that we are measuring efficiency on a subgroup of all the possible goods and services a municipality can provide. In any case, we check the sensitivity of our results with the alternative specification.The summary statistics for bothe specifications of input variables are also reported at the bottom of Table 8.

c) Determinants of municipal efficiency:

To measure the effect of demographic, economic and fiscal factors on inefficiency, the model has also incorporate some exogenous variables that may be considered relevant to municipal performance. Determinants can represent a direct effect on municipal efficiency, discretionary inputs or unobservable outputs. Discretionary inputs refer to production in a favorable environment while unobservable outputs indicate service quality (as the included outputs variables in the model above do not measure quality but quantity).

Determinants can have several effects on inefficiency, thus it is complex to identify the limits of the effect of each determinant. Previous literature on determinants of municipal inefficiency use similar variables for this purpose and for estimating inefficiency. The variables we used to estimate the determinants of inefficiency are the following:

i. Fiscal capacity: a lower fiscal capacity of municipalities implies a tighter budget constraint reducing the operational surplus, an effect which may affect municipal efficiency (De Borger, Kerstens 1996; Balaguer-Coll el at 2007). To measure this effect we use four variables: 1) dependency on the common municipal fund (FCM) relative to self-generated income (IPP) (Balaguer-Coll el at 2007), 2) percentage of investment relative to total expenditure (Athanassopoulos, Triantis 1998), 3) current transfers from public institutions, where the latter is in per capita terms. These variables are included in order to measure budgetary tightness (Kalb 2010; De Borger et al 1994).

ii. Education: a higher proportion of educated people may imply higher efficiency (De Borger and Kerstens, 1996a). The reason for this is that municipalities can in this way count with a more qualified labor force. This also should improve the accountability of the population relative to municipal performance. As a proxy of educational level we use the average schooling level of the population by municipality.

iii. Population (only for clusters): the hypothesis is that the larger the population the larger the economics of scale and so such municipalities could reach higher levels of efficiency on the provision of goods and services (Prud'homme, 1995). This variable is used in the general model and not for the cluster analysis as population was one of the variables used to construct the indexes that defined the clusters. To measure this variable in the general model we include dummy variables that account for quarters of population. In this way we include three dummies leaving the first quarter as the base category. The four categories are: 1) 1-9,027; 2) 9,028-17,963; 3) 17,964-51,838; 4) more than 51,838 inhabitants.

For the cluster analysis we include the variable distance to the regional capital. As Stastna and Gregor (2011) pointed out, the hypothesis is that the closer the geographic distance between the municipality and the regional centre the more intense will be the competition between them and at the same time access to regional public services gets easier. Thus, we should observe that closer municipalities relative to the regional centre would be more efficient. To capture this we include a variable that measures distance to the regional capital.

iv. Political factors: political characteristics of a municipality may affect efficiency in an important way. The hypothesis is that a high level of political concentration is associated with a lower efficiency because of a lack of political competition (Besley et al, 2005). To measure this we use two variables: 1) a Herfindahl index to capture the monopolistic degree of the city council[12] and 2) the percentage of council representatives who belongs to the governmental coalition.

7 Results

The model is estimated by maximum likelihood using the R-Project programme. This software uses the parametrization of Battese and Corra (1977) which gives $\gamma = \frac{\sigma_u^2}{\sigma^2}$ instead of $\lambda = \frac{\sigma_u^2}{\sigma_v^2}$. By replacing $\sigma^2 = \sigma_v^2 + \sigma_u^2$ we obtain $\gamma = \frac{\sigma_u^2}{\sigma_v^2+\sigma_u^2}$, which has a value in the range (0-1). The software allows us to test the significance of the parameter γ in order to evaluate the existence of inefficiency.[13] Thus, if the null hypothesis $\gamma = 0$ is not rejected, implies that $\sigma_u^2 = 0$ and then the term u should be dropped from the model allowing the estimation by OLS.

[12] This index was constructed using the seats of each political party in the Council.

[13] The generalized statistic LR, λ, is defined as: $\lambda = -2ln(\frac{L(H_0)}{L(H_1)})$, where H_0 and H_1 are the null and the alternative hypothesis respectively.If H_0 is true then λ asymptoticaly distributes as chi-squared. If H_0 includes $\gamma = 0$ (as in our case), then λ distributes as a combined chi-squared. The critical values for this test were obtained from Table 1 of Kodde and Pam (1986).

7.1 General Results

From the interpretation of the general model (i.e. without tipologies) it can be inferred that γ takes the value 0.346 being statistically significant at 1%. This parameter can take a value in the range 0 to 1, indicating how much of the error term variance is due to the inefficiency term u_i. Thus, in this case it can be noted that a great part of this variance is explained by white noise: v_i. However, an important part is also explained by the inefficiency term. Furthermore, a LR test for the null hypothesis was performed, testing that the elasticities of the variables of the inefficiency model are jointly equal to 0. The result of this statistical test was 72.47, which means that the null hypothesis can be rejected and that the model does present inefficiency.

The average efficiency level for the 309 Chilean municipalities included in the analysis for period 2008-2010, is shown in figure 2. From the results obtained it is important to note that the efficiency level of the municipalities under study is, on average, 70.1% for the period. This implies that, on average, municipalities bear a 30% in exceess of the required costs to operate over the efficiency cost frontier. Furthermore, 55% of the studied municipalities show an efficiency level lower than the 80%, and municipalities over this level account for 16% of the total. This latter group is the more concentrated one, being in the range 90-95%, see figure 3.

From the result of the general model (i.e. without typologies) presented in column1 of Table 9 it can be seen that most of the determinants are significant at 5% with the exception of the last dummy of population, distance to the regional capital and the political variable percentage of the council who belongs to the governmental coalition.

a) Fiscal capacity: results suggest that municipalities will have a lower fiscal capacity when the dependency on the FCM relative to their self-generated revenues increases. This lower fiscal capacity generates a tighter budget constraint, decreasing in this way current expenditure. Similarly, results suggest that when the percentage of investment over total expenditure increases municipalities will have a tighter budget constraint and therefore a lower current expenditure increasing in this way the level of efficiency. In the same line, higher current transfers from public institutions improve municipal fiscal capacity and then increases their current expenditure, lowering their efficiency.

b) Political factors: results do not support the hypothesis that a higher level of political concentration, associated with a higher Herfindahl index, making municipalities less inefficient. On the contrary, the coefficient associated with the Herfindahl index has a negative sign and is statistically significant. A plausible explanation to this relationship might be that higher political concentration can make it easier to reach consensus (or agreements) among the members of the city council and the major, making more expedite and ultimately more efficient the decision-making process of municipalities. On the other hand, the variable estimating the percentage of the city council belonging to the government party does not have a significant effect on the efficiency level of municipalities.

c) Education: results are unexpected since they suggest that the higher the schooling level the higher the inefficiency. There are two potential explanations for this: (1) municipalities with higher levels of schooling have, in general, more resources, and therefore face a higher quality demand from the community in the provision of good and services than those in lower income municipalities. (2) municipalities with higher schooling levels have more resources and this relax the budget constraint increasing inefficiency.

7.2 Results from the Clusters Analysis

Results by cluster of municipalities are presented in columns (2-6) of Table 9 and suggest that, in general, the determinants have similar effects in all of them.

From those that measure fiscal capacity, we find that dependence on the FCM relative to self-generated revenues, current per capita transfers from public institutions and percentage of investment on total expenditure, point to the same direction of the results found for the general model for all typologies (with the exception of the third and fourth typology, in which we found no significant results at 5%, although they are at 10%, for current transfers and investment).

Regarding the effects of education, we found that its impact is similar to the one estimated for the general case for all typologies, however results are not statistically significant for typologies 2 and 3.

In relation to political factors, we found that results for the Herfindhal index are similar to those found in the general model, in particular for typologies 2 and 3. For the case of typologies 1, 4 and 5 results are not significantly different from zero (at 5%). An explanation for this could be that these two typologies are smaller and poorer than the rest and therefore political concentration may be less important versus familiar and/or cultural links between individuals in the area. In regard to the results of the other political variable, we found that the percentage of seats of the governmental coalition is only significantly different from zero for typologies 2, 3 and 4 at 5%.

Finally, considering geographical determinants we found that distance to the regional capital is significant (at 5%) for typologies 1, 2 and 5. We found that a further distance to the regional capital decreases inefficiency for typology 2 but increases inefficiency for typology 1 and 5.

7.3 Overall Results

Concerning overall results, Table 9 suggests that Chilean municipalities have a significantly different from zero degree of inefficiency (i.e. the LR test $H_0: \sigma_u^2 = 0$, rejects the null). In particular, the aggregate inefficiency reaches about 30% but after disaggregating these results by cluster we found that there is variance as inefficiency levels reach 23%, 45%, 15%, 11% and 57% for typologies 1, 2, 3, 4 and 5 respectively. These results suggests that typology 5 has a higher level of inefficiency for the provided services. Furthermore, it should be noted that the high variance on inefficiency levels among municipalities within clusters which reaches between 15-19 percentage points. These results can be seen in Figure 3.

It is crucial to remember that this study does not directly measure quality on the services provided, which can play an important role in some services provided such as education. We tackle somehow this issue in the next section.

When we analyze all typologies we found that municipalities in the top quantile of each cluster present some common characteristics. In particular, Table 10 shows that, in general, the most efficient municipalities (i.e. in the top quantiles) per cluster are those whose current expenditure in services are lower than the average of the quantile, with typology 5 being the exception. The same is observed for some of the output variables such as: students registered and houses with sewer, while for rubbish collection, and maintained green areas.the evidence is less strong. By doing the same exercise to the determinants (see Table 11) we found that most efficient municipalities have a higher dependency on the FCM relative to their self-generated revenues, a higher proportion of investment relative to total expenditure, a lower schooling level and a higher political concentration (as measured by the Herfindhal index).The results for the first two determinants may be explained by the fact that these variables imply a tighter budget constraint and so municipalities use resources more carefully given that they have to provide a minimum quantity of goods and services. Similarly, results for education may be explained because municipalities with lower schooling levels have lower resources and so they use money more efficiently. The explanation for political concentration is the same given above and it relates to the fact that more concentrated City Councils take less time to reach agreements.

8 Sensitivity Analysis

In order to check the sensitivity of the results we modify some of the key assumptions of the model and thus test the consistency of our findings.

8.1 Multicollinearity

In the first place we check the statistical correlations among the variables. This is important as the Translog function used for our analysis may be susceptible to multicollinearity and degrees of freedom problems. Hence, in order to check the level of multicollinearity of the output variables included in the model, we analyze the correlation among them, results are presented in Table 12.

Results suggest that the variable showing a high correlation with all the other variables is population. This is to be expected since the level of population of the municipality determines somehow, the number of schools in a municipality, the same for social organizations, health centres and so on. Therefore, despite this high level of correlation of this variable with respect to the others, we decided to keep it given its importance in the determination of the level of services given by each municipality

In addition, results also suggest that levels of correlation are low except for the number of social organizations. We decided to keep this variable, since it allows us to measure the amount of services provided by each municipality.

Furthermore, we repeat the same exercise with the determinants. Results are presented in Table 13 and suggest that correlations among them are not signifficantly high.

8.2 Alternative Costs Functions

All the analysis was carried out using a Translog cost function which gives flexibility and relax some of the assumptions of the more commonly used Cobb-Douglas production function. Even though Greene (2005c) points out that results are overall similar irrespective of the function, we now check how our results change when we vary the cost function. For this, we reestimate the baseline general model but now using the more restrictive Cobb-Douglas instead of the Translog. Results are presented in Table 14 and suggest that the overall results are indeed similar (rankings of municipalities are similar as well) to the ones reported in section 7.

8.3 Alternative Definition of Inputs

As current expenditure on the services included in our model was used as input for our estimations, we now check the sensitivity of our results to a slight modification of the input variable. We reestimate the model but now using total current expenditure. Thus, we are considering all the current resources used by municipalities on the provision of good and services. From Table 15 we can infer that results are very similar to those obtained when the input variable is slightly modified.

8.4 Unobservable Heterogeneity

As previously pointed out, parametric methods can take into account unobserved heterogeneity in explaining municipal performance. As a random effect approach is used in this study, an assumption that is implicitly imposed is that there is no correlation between the covariates and the composed error term. Since in the error term unobserved heterogeneity is included, we consider it as an implicit assumption of our model. In the municipal case, it could be questionable that unobserved heterogeneity is not correlated with the covariates, hence we relax the assumption by using Mundlak's (1978) approach. This approach consists of parameterizing the unobserved heterogeneity with the average (across time) of the time variables covariates. Results with the Mundlak parametrization are shown in Table 16 and suggest that there are no significant differences relative to the original model without Mundlak's parametrization.

8.5 Quality

As previously stated, we did not include quality measures in our determinants and thus the general model focuses on the quantity of services provided. Despite this, we indirectly took quality into account reestimating the general model but this time including a variable with the SIMCE average score, for mathematics and spanish, (SIMCE stands for the Chilean national test taken to fourth grade students). SIMCE was included in order to control in some way the quality of schooling by municipalities. Results are presented in Table 17 and suggest that the effect of quality is not significantly different from zero. The reasons behind this result might be the following: a) the school listed at the bottom of its typology are indeed inefficient, b) quality does not have significant effects and there would be other variables that could explain this difference or c) the measurement of quality by the SIMCE variable is not a good representation of the quality of municipalities services.

9 Concluding Remarks

This work contributes to the literature by formally presenting a methodology to estimate municipal efficiency with a one stage approach using a parametric model and panel data. Moreover, unlike previous related literature it analizes overall efficiency as well as efficiency by clusters of municipalities, in order to reduce heterogeneity, and thus diminishing the risk of omitted variables.

In particular, the application presented in this paper estimates a stochastic frontier model to analyze municipal efficiency and its determinants.using panel data from 2008-2010 of 309 Chilean Municipalities. Results suggest that, in general, Chilean municipalities have on average an inefficiency level of about 30%. We found that a higher population, a longer distance to the regional capital, a higher dependency on the municipal common fund (a fund aimed at redistributing municipal income) relative to self-generated revenues, a higher proportion of investment relative to total expenditure and a higher political concentration at the local level increases municipal efficiency in the provision of education, health, rubbish collection, contributions to social organizations, maintained green areas, and access to clean water.

Given high municipal heterogeneity, we reestimated the previous general model but at a lower level. That is, we use more homogeneous groups (clusters) of municipalities. Results are, in general, similar to those found for the general model. However, we observed that the difference in inefficiency levels between clusters are quite significant. Despite this, when we analyze the most efficient municipalities per cluster, we found similar patterns in the effects of the determinants. We found that municipalities with the best results in each cluster have a higher dependency on the FCM relative self-generated revenues, higher investment as a percentage of total expenditure, a lower schooling level and a higher political concentration.

Finally, we analyze if the differences in efficiency levels were due to unmeasured quality. We include some quality determinants but their effects were not significantly different from zero. Therefore, our results suggest that, in general and given the fixed costs on the provision of the minimum amount of public services established by law, municipalities with tighter budget constraints use their resources more carefully and tend to be more efficient on the provision of public services.

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Appendix

Methodology for Municipal Clustering

For the construction of the territorial index, primary variables are used where these primary variables are conformed by secondary variables. To estimate primary variables, we transform the secondary variables in "more urban" (1) to "less urban" (0) and then they were averaged to construct every primary variable. In this way all secondary variables will be in the (0-1) range. It is important to notice that 1 corresponds to most populated, less dispersion, more political-administrative hierarchy and more territorial complexity from the urbanic point of view.

Let us consider any of the variables that conform each of the considered dimensions to be named as variable X: There are two types of possible transformation:

i) The case where the variable is directly correlated with the 0-1 range previously described (e.g. population), the procedure is the following:

$$H_i = \frac{(X_i - Min\{X_i\})}{Max\{X_i\} - Min\ \{X_i\}} \quad \forall\ i = 1, ..., 345$$

where:

Max(X) = maximum value of the variable X.
Min(X) = minimum value of the variable X.
X = value of variable X for municipality i.

ii) In the case when the variable is inversely correlated (e.g. rurality level) with the (0-1) range, the procedure is the following:

$$H_i = \frac{(Max\{X_i\} - X_i)}{Max\{X_i\} - Min\ \{X_i\}} \quad \forall\ i = 1, ..., 345$$

Once the variables are transformed, they are averaged in order to get one value by index (territorial and socio-economic), then the next step is to construct the clusters.

In order to construct the clusters the K-medias methodology is used. This method uses an heuristic algorithm, because it has a highly computational complexity which requires the number of clusters to be used. The algorithm consist on the random election of K-centroides and it determines the elements of the K-clusters based on the distance to the k previous points. Then, the centroids of those clusters are determined and the process is repeated until some criteria of convergence is achieved. This process give us the clusters to be used.

Table N^{o}1
Summary of previous Literature on Municipal Efficiency

Author	Year	Country	N^o Municipalities	Methodology
De Borger	1994	Belgium	589	FDH
De Borger and Kerstens	1996	Belgium	589	FDH & DEA
De Borger and Kerstens	1997	Belgium	590	SFA
Anthanassopoulos and Triantis	1998	Greece	173	SFA & DEA
Sousa and Ramos	1999	Mina Gerais (Brazil)	701	FDH & DEA
Worthington	2000	Australia	166	DEA
Worthington	2001	Australia	167	SFA
Prieto and Zofio	2001	Castilla and Leon (Spain)	209	DEA
Ballaguer-coll et al.	2002	Valencia (Spain)	258	DEA
Afonso and Fernández	2005	Lisbon Region (Portugal)	51	DEA
Loikkanen and Susiluoto	2005	Finland	353	DEA
Arcelus	2007	Navarra (Spain)	263	SFA
Balaguer-Coll	2007	Valencia (Spain)	414	DEA & FDH
Afonso and Fernández	2008	Portugal	278	DEA
Geys and Moesen	2009	Belgium	300	SFA
Geys	2010	Germany	1,021	SFA
Kalb	2010	Germany	245	SFA
Bianchini	2010	Italy	100	SFA
Stastna and Gregor	2011	Czech Republic	202	SFA & DEA

Table N^{o}2

Structure of FCM	Municipal Contribution	Contribution from the wealthiest Municipalities*
Territorial Tax	60%	65%
Commercial Rights	0%	55% Santiago and 65% Providencia, Las Condes and Vitacura
Transport Tax	62.5%	62.5%
Vehicles Transfers	50%	50%
Penalties and Fines	100%	100%
Central Government Transfers	218,000 UTM	218,000 UTM

*Santiago, Providencia, Las Condes and Vitacura

Table N^{o}3

Indicator	Percentage
same proportion	25%
Poverty	10%
Exempted Land	30%
Permanent Self-generated Revenue (IPP)	35%
Total	**100%**

Table N^{o}4
Socio-Territorial and Socio-Economic Indexes

	Socio-Territorial	
Dimension	**Description**	**Variables**
Size	Quantitative dimension of the population and housing	Population (Census updated to 2008), Number of habitable non-agricultural land
Dispersion	Concentration of population on a given territory	Rurality level (census 2002), Populational density (2008) and Entrophy*
Political-administrative hierarchy	Measures the political and administrative relevance of the municipality weighted by the size of its region and/or province	Capital of the region situation and/or Capital of the Province situation.
Type of locality	Takes into account a group of relations and functions which occur inside the territory and allow identification of rural-urban situations	Score assigned given according to the definition of the Housing and Urbanism Ministry.
	Socio-Economic	
Dimension	**Description**	**Variables**
Communal Assets	Corresponds to the communal commercial activities and the communal land assets.	Average total value, percentage of the value affected to taxes, per capita average collection of commercial rights.
Human Capital	Schooling level and educational capacity	Average schooling, weighted average at PSU**, % of literacy.
Socio-economic characteristics of the population	Material conditions of the communal population	% of poverty (CASEN), Average monetary income of the household.

*Entrophy refers to a variable which measures the order-disorder within a system. For our case means the concentration or dispersion of the population in a given territory. To apply this concept, housing distribution by city or town is used (Chilean National Institute of Statistics).

**PSU is the national entry test to apply for places at superior education (e.g. University).

Table 5
Constructed Clusters

Clusters	N^o Municipalities	Cluster Name	Population	% of Population
1	8	Big Metropolitan Municipalities, High development	1,010,515	6%
2	39	Big Metropolitan/Urban Municipalities,medium develop.	7,595,844	45%
3	37	Major Urban Municipalities, medium development	3,543,432	21%
4	56	Medium Urban Municipalities, medium development	1,777,524	11%
5	96	Semi-Urban and Rural Municipalities, medium develop.	1,718,931	10%
6	109	Semi-Urban and Rural Municipalities,low develop.	1,117,127	7%
TOTAL	**345**		**16,763,373**	

Table 6
Used Clusters

Clusters	N^o Municipalities	Cluster Name	Population	% of Population
1	45	Big Metropolitan Municipalities, High +medium development	8,568,303	53.1%
2	34	Major Urban Municipalities, medium development	3,353,886	20.8%
3	52	Medium Urban Municipalities, medium development	1,682,469	10.4%
4	85	Semi-Urban and Rural Municipalities,medium develop.	1,568,817	9.7%
5	93	Semi-Urban and Rural Municipalities,low develop.	974,023	6.0%
TOTAL	**309**		**16,147,498**	

Table 7
Clusters characteristics

Cluster	Average Density	% Urban Population	% Poverty	Average Schooling
1	5,669	100%	18%	12.1
2	200	89%	16%	9.9
3	60	76%	21%	8.8
4	15	60%	11%	8.7
5	12	65%	20%	6.7

Table 8
Output variables summary statistics (average)

		All	**C 1**	**C 2**	**C 3**	**C 4**	**C 5**
Output	**Variables**	(1)	(2)	(3)	(4)	(5)	(6)
Municipal Scale	Comunal Population	52,257	190,407	98,644	32,355	18,457	10,473
Education	Average Monthly Registered students	4,520	12,048	9,108	4,017	2,290	1,519
	Mun. Schools	17	21	23	20	13	14
Health	Mun. Health Centres	7	10	10	7	5	6
Urbanism	Squared meters of green areas	245,856	744,209	363,194	381,033	88,770	29,810
	Houses w/ sewer	10,864	42,459	19,832	6,388	3,319	1,696
Hygiene	Rubbish Collected (Tons)	20,670	75,986	44,921	11,175	6,711	3,105
Social Services	Social Organizations	749	1,507	1,521	676	501	367
Input							
Expenditure	Current Exp. (M$)	4,831	17,697	7,788	2,690	1,950	1,387
	Current Exp. on selected services	4,710	16,959	7,701	2,686	1,914	1,345

Table 9
Results for the General model and the five clusters

Determinants	**General** (1)	**C1** (2)	**C2** (3)	**C3** (4)	**C4** (5)	**C5** (6)
Constant	-1.6453***	-0.4530	2.5357***	1.0521	-1.9469*	-0.5946
Municipal Population over Regional Population	-0.1811					
Distance to Regional Capital (ln Km)		0.0634*	-0.1002***	0.0976	0.0034	0.0721***
$\frac{FCM}{IPP}$	-0.7237***	-1.0425***	-0.7275***	-1.3239***	-1.6731***	-0.4340***
$\frac{Investment}{Total\ Expenditure}$	-0.6782***	-0.6017	-0.4329*	-1.3878***	0.6875*	-0.2038
$\frac{Public\ Transfers}{Population}$	0.0027***	0.0016	0.0040**	-0.0070	0.0060	0.0324***
Average Schooling (ln)	1.2060***	0.5363	-0.3638	0.5863	1.2443***	0.5864***
Herfindhal Index	-0.0001**	0.0000	-0.0002***	-0.0003***	-0.0001	0.0000
% Governmental Coalition seats	0.0805	-0.5505**	-0.2011	-1.9548***	0.4359*	-0.0687
σ^2	0.0559***	0.0156***	0.0042***	0.0289***	0.0311***	0.0297***
γ	0.3464**	0.0000***	0.0000	0.5216*	0.0104***	0.9587***
LR test on $\sigma_u^2 = 0$	72.47***	83.34***	122.49***	84.37***	81.57***	92.76***
Avg Efficiency 2008-2010	**0.7018**	**0.7603**	**0.5486**	**0.8474**	**0.8830**	**0.4292**

***p<1%, **p<5%, *p<10%

Table 10
Municipal Characterization by its efficiency level (Outputs and Input)

		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Current Expenditure	Top Quantile	8,256,110	4,031,309	2,651,006	1,316,849	838,938
(Millions of $)	Average Cluster	16,959,276	7,788,779	2,686,765	1,914,994	1,345,108
Population	Top Quantile	130,485	57,130	33,546	9,631	3,939
	Average Cluster	190,407	98,644	32,355	18,457	10,473
Built Areas (m^2)	Top Quantile	18,794	45,350	21,069	5,190	1,339
	Average Cluster	128,551	105,697	241,693	816,319	188,236
Average Students	Top Quantile	7,587	4,422	4,472	1,391	508
Registered	Average Cluster	12,048	9,108	4,017	2,290	1,519
Average Schools (N^o)	Top Quantile	16.9	11.5	25.1	12.9	7.2
	Average Cluster	21.3	23.3	20.0	13.5	13.8
Average Health	Top Quantile	10.6	5.7	8.7	4.1	2.7
Centres (N^o)	Average Cluster	10.0	9.7	6.6	5.1	5.7
Green Areas (m^2)	Top Quantile	255,395	188,712	137,061	54,405	13,948
	Average Cluster	744,209	363,194	381,033	88, 770	29,810
Rubbish (Tons)	Top Quantile	50,898	53,070	12,407	3,412	1,295
	Average Cluster	75,986	44,921	11,175	6,711	3,105
Average Houses	Top Quantile	31.045	11.407	6.655	1.585	467
with sewer	Average Cluster	42.459	19.832	6.388	3.319	1.696
Social Organizations	Top Quantile	1.528	911	803	781	136
	Average Cluster	1.507	1.521	676	501	367

Tables 11
Municipal Characterization by its efficiency level (Determinants)

		C 1	**C 2**	**C 3**	**C 4**	**C 5**
Av. Distance to Regional Capital (Km)	Top Quantile	3.71	52.57	101.65	139.41	108.16
	Average Cluster	2.50	62.97	107.24	115.40	179.95
$\frac{FCM}{IPP}$	Top Quantile	0.78	0.63	0.72	0.82	0.89
	Average Cluster	0.37	0.43	0.66	0.60	0.80
$\frac{Investment}{Total\ Expenditure}$	Top Quantile	0.10	0.14	0.17	0.23	0.19
	Average Cluster	0.06	0.12	0.16	0.18	0.19
Current Transfers from Public Inst.	Top Quantile	64.60	31.95	32.01	12.29	5.95
	Average Cluster	93.33	64.00	27.96	16.87	12.78
Average Schooling	Top Quantile	2.27	2.29	2.16	2.09	2.05
	Average Cluster	2.37	2.30	2.19	2.17	2.06
Herfindhal Index	Top Quantile	2.027	10	9	8	2.253
	Average Cluster	2.193	2.188	2.276	2.364	2.253
% of seats of Gov. Coalition	Top Quantile	0.28	0.48	0.54	0.37	0.47
	Average Cluster	0.44	0.41	0.38	0.40	0.40

Table 12
Multicollinearity of Output variables

Output Variables	**v1**	**v2**	**v3**	**v4**	**v5**	**v6**	**v7**	**v8**
Population (v1)	1							
Monthly Registered Students (v2)	0.799	1						
Number of Public Schools (v3)	0.448	0.692	1					
Number of Health Centres (v4)	0.508	0.612	0.770	1				
Maintained Green Areas (v5)	0.503	0.425	0.246	0.355	1			
Rubbish Collected (v6)	0.923	0.754	0.400	0.492	0.449	1		
Social Organizations (v7)	0.967	0.843	0.468	0.515	0.507	0.913	1	
Houses with Sewer (v8)	0.582	0.583	0.498	0.501	0.292	0.571	0.599	1

Table 13
Multicollinearity of Inefficiency Determinants

Determinants	**v1**	**v2**	**v3**	**v4**	**v5**	**v6**	**v7**	**v8**
Per capita Capital Expenditure (v1)	1							
Distance to Regional Capital (v2)	-0.0553	1						
$\frac{FCM}{IPP}$ (v3)	-0.3024	0.2373	1					
$\frac{Investment}{Total\ Expenditure}$ (v4)	-0.1447	0.0728	0.3532	1				
Transfers from Public Institutions (v5)	0.6029	-0.1846	-0.4578	-0.3355	1			
Average Schooling (v6)	0.3241	-0.0409	-0.7111	-0.4334	0.5489	1		
Herfindhal Index (v7)	-0.0959	0.0566	-0.0407	0.0265	-0.1749	-0.0054	1	
Governmental Coalition Seats (%) (v8)	-0.0205	-0.0571	-0.1781	-0.185	0.0461	0.1331	0.3674	1

Table 14
Alternative Costs Functions

Determinants	**Translog**	**Cobb-Douglas**
Inefficiency Constant	-1.6453***	-3.230***
Municipal Population over Regional Population	-0.1811.	-0.397***
$\frac{FCM}{IPP}$	-0.7237***	-0.655***
$\frac{Investment}{Total\ Expenditure}$	-0.6782***	-0.850***
$\frac{Public\ Transfers\ from\ Institutions}{Population}$	0.0027***	0.006***
Average Schooling (ln)	1.2060***	1.892***
Herfindhal Index	-0.0001**	0.000*
% Governmental Coalition seats	0.0805	0.171*
σ^2	0.0559***	0.073***
γ	0.3464**	0.420***
LR test on $\sigma_u^2 = 0$	72.47***	-22.44***
Average Efficiency	**0.7018**	**0.6756**

***p<1%, **p<5%, *p<10%

Table 15
Alternative Input variable

Determinants	**Current Expenditure**	**Total Current Expenditure**
Inefficiency Constant	-1.6453 ***	–2.167 ***
Municipal Population over Regional Population	-0.1811	-0.250 *
$\frac{FCM}{IPP}$	0.7237 ***	-0.683 ***
$\frac{Investment}{Total\ Expenditure}$	-0.6782 ***	-0.674 ***
$\frac{Public\ Transfers}{Population}$	0.0027 ***	0.004 ***
Average Schooling (ln)	1.2060 ***	1.450 ***
Herfindhal Index	-0.0001 **	0.000 *
% Governmental Coalition seats	0.0805	0.0805
σ^2	0.0559 ***	0.063 ***
γ	0.3464 **	0.575 ***
LR test on $\sigma_u^2 = 0$	72.47 ***	58.38 ***
Average Efficiency	**0.7018**	**0.6581**

***p<1%, **p<5%, *p<10%

Table 16
Parametrization of Unobserved Heterogeneity (Mundlak)

Sigma-squared 0,0559*** 0,0560***

Determinants	**Random Effect**	**Random Effect + Mundlak**
Inefficiency Constant	-1.6453***	-0.4819
Municipal Population over Regional Population	-0.1811	-0.1675
$\frac{FCM}{IPP}$	-0.7237***	-1.3855***
$\frac{Investment}{Total\ Expenditure}$	-0.6782***	-0.6059**
$\frac{Public\ Transfers}{Population}$	0.0027***	-0.0015*
Average Schooling (ln)	1.2060***	0.7549**
Herfindhal Index	-0.0001**	-0.0001**
% Governmental Coalition seats	0.0805	0.1108
σ^2	0.0559***	0.0560***
γ	0.3464**	0.3610**
LR test on $\sigma_u^2 = 0$	72.47***	143.187***
Average Efficiency	**0.7018**	**0.8476**

***p<1%, **p<5%, *p<10%

Table 17
Introducing Quality

Determinants	**General Model**	**General Model with PSU score**
Inefficiency Constant	-1.6453***	-1.629***
Municipal Population over Regional Population	-0.1811	-0.180
$\frac{FCM}{IPP}$	-0.7237***	-0.754***
$\frac{Investment}{Total\ Expenditure}$	-0.6782***	-0.689***
$\frac{Public\ Transfers}{Population}$	0.0027***	0.002**
Average Schooling (ln)	1.2060***	1.198***
Herfindhal Index	-0.0001**	0.000*
% Governmental Coalition seats	0.0805	0.091
σ^2	0.0559***	0.055***
γ	0.3464**	0.332**
LR test on $\sigma_u^2 = 0$	72.47***	80.90***
Average Efficiency	**0.7018**	**0.7092**

***p<1%, **p<5%, *p<10%

Figure 1
Allocative and Technical inefficiency

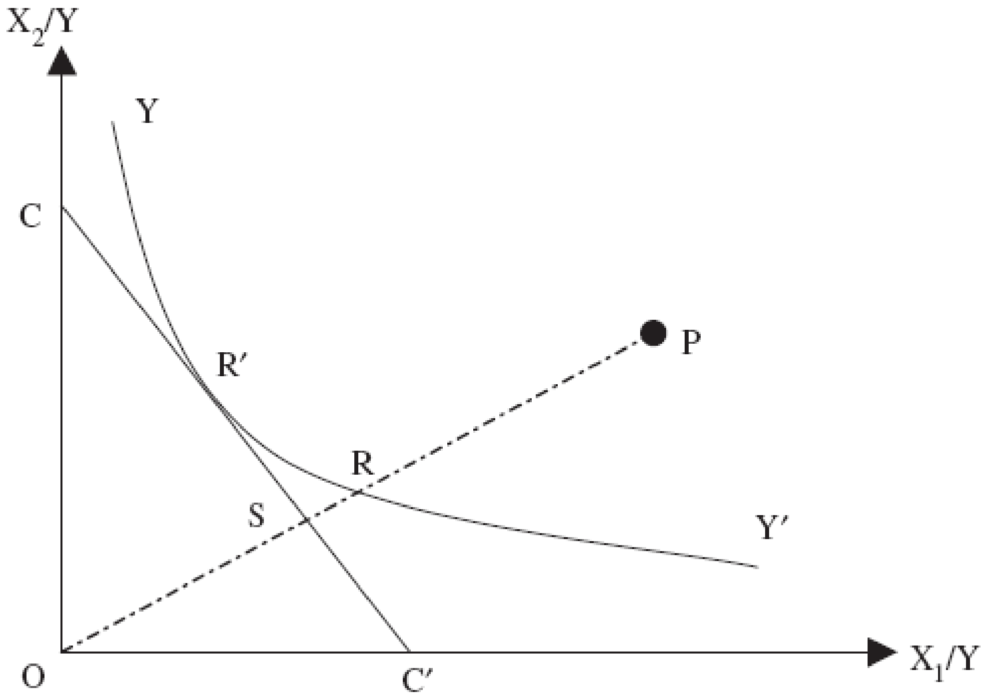


Figure 2
Municipal Clustering

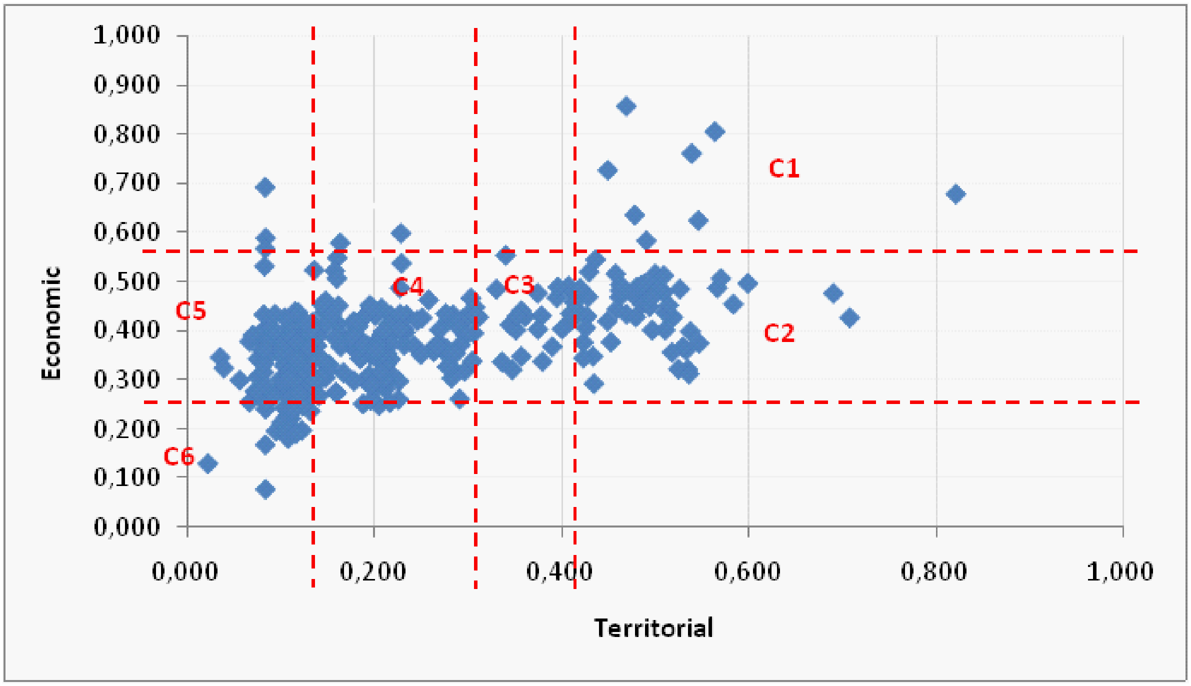


Figure 3
Municipalities by Cost Efficiency Level, Average 2008-2010

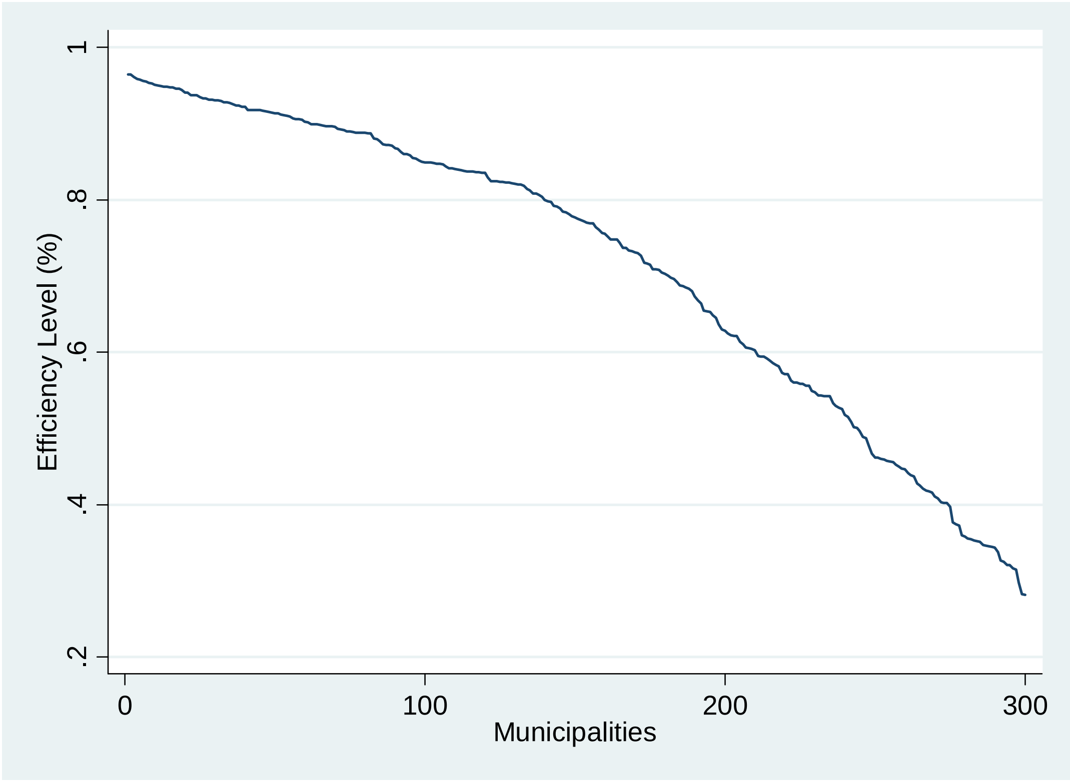


Figure 4
Cumulative Frequency of Municipalities by Efficiency Level

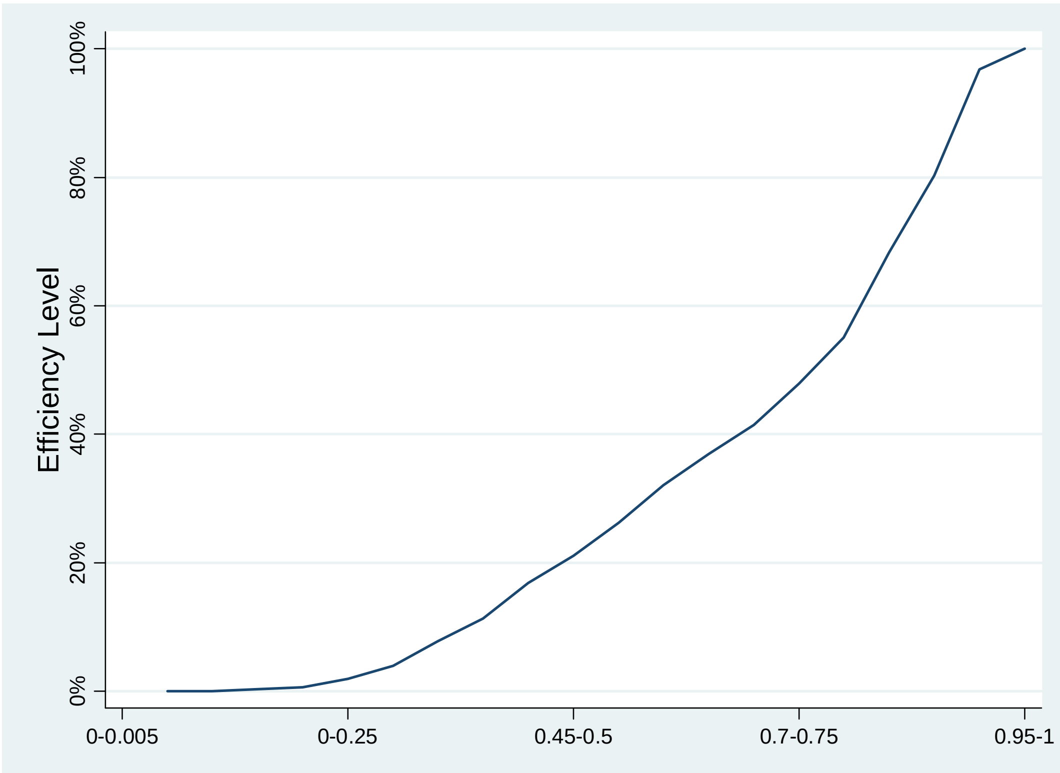
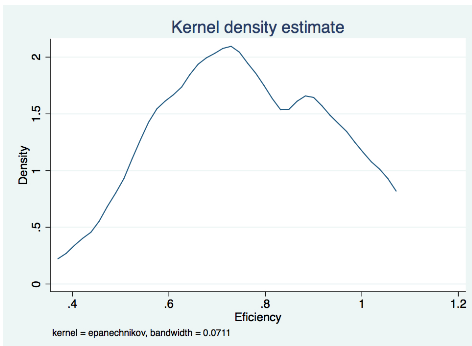
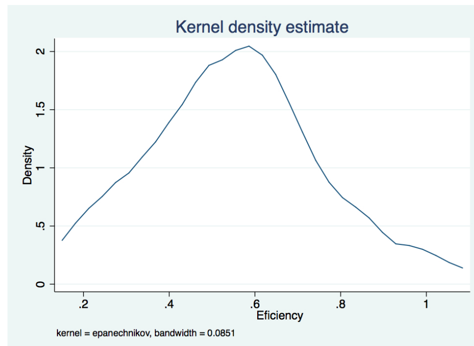


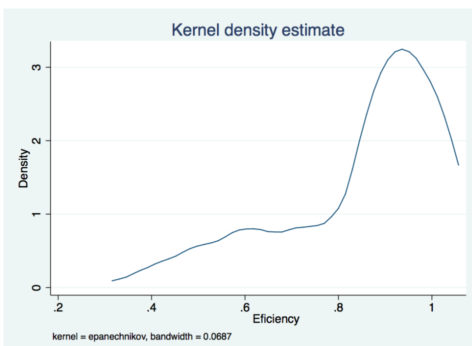
Figure 5
Histogram of Inefficiency



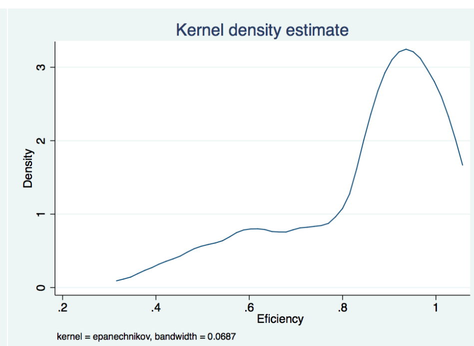
Cluster 1



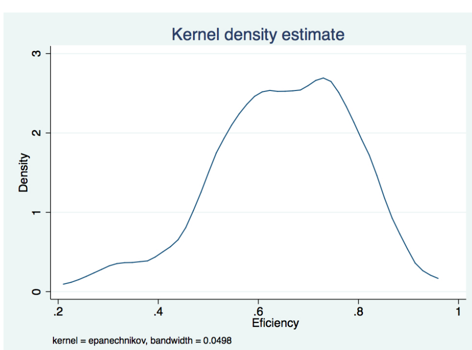
Cluster 2



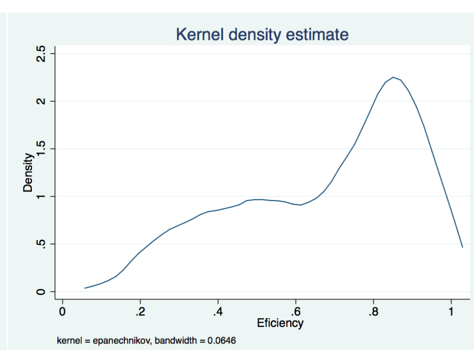
Cluster 3



Cluster 4



Cluster 5



General Case