Estimating Local Government Efficiency using a Panel Data Parametric Approach: The Case of Chilean Municipalities

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Estimating Local Government Efficiency using a Panel Data Parametric Approach: The Case of Chilean Municipalities*

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Abstract

Previous empirical evidence on municipal efficiency mostly uses cross-sectional data which makes it impossible to separate unobserved heterogeneity from inefficiency. Furthermore, they also typically use a two stages approach which has been widely criticized as the assumptions in the first stage are violated in the second stage, generating biased results. We present a longitudinal parametric study that analyzes municipal efficiency and its determinants using a one step procedure. Moreover, we analize overall efficiency as well as efficiency by clusters of municipalities in order to reduce heterogeneity. We use administrative datasets of Chilean municipalities for 2008-2010 period and our results suggest that Chilean municipalities have on average an inefficiency level of 32% 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.

Keywords: Efficiency, Local governments, Panel Data, Parametric Estimation, Chile.
JEL Classification: H71, H72, H83, D24, O54

1 Introduction

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

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Given their relevance, there have been a long series of studies which tried to measure the level of efficiency on municipal provision of 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 contradicts 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 has 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 have used panel data for municipal efficiency estimation. Unfortunately, the vast majority of recent previous literature have used non-parametric methods which uses a two stage approach to estimate inefficiency and their determinants (Greene 2005c). Apart from this, they face other drawbacks. In particular, 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. In this way, 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, efficiency score is computed for each single year as just in a 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 in this sense by providing a study with these characteristics. In particular, we present an efficiency analysis of 309 Chilean municipalities followed 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 goods and services. Among them the more important are: education, health, rubbish collection, maintained green areas, etc.

Results suggest that Chilean municipalities are heterogeneous in their inefficiency levels and that on average inefficiency reaches 16% approximately. This is, Chilean municipalities could provide the same amount of services but with a 16% 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 results 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 of the Fondo Comun Municipal relative self-generated revenues, higher investment as a percentage of total expenditure, a lower schooling level and a higher political concentration.

This study is organized as follows: section 2 provides the institutional framework of municipal management while section 3 presents the literature review. Section 4 presents the details of the methodology used in this work. Section 5 put fowards the procedure for the construction of municipal clusters, the data and the summary statistics. Section 6 and 7 present the results and the sensitivity analysis respectively. Finally, section 8 offers some concluding remarks.

2 Institutional Framework

Chile is organized in 15 regions.[1] Each 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 with municipal management and (ii) those attributed to the municipality as an institution. Among the former, the major has to be the legal 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.

2.1 Specific functions of the local government

The Organic Law of Municipalities (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*), promotion of comunitarian development, public transport regulation, hygiene services, urbanism and construction norms. Among the shared 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 the Organic Law of Municipalities (Law N^{o}18.695) 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 (FCM).
- 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 charge. Among these are: territorial tax, transport tax and commercial rights on alcoholic sells.
- Interests and penalties.

[1] 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.

Municipal income can be classified depending on the source of funding. There are two main funding sources: permanent self-generated revenues (IPP) and municipal common fund (*FCM*). Other sources are transfers from regional government and the central government. Among the latter are transfers for education and health services. In this way, local government act as an intermediary between local education and health services and the respective ministry. Next, we present the detail of 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 (*IPP*) and municipal common fund (*FCM*).

2.1.1 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. In this way, the sources of funding of the FCM come from municipal income and are defined by article 14^o of the Organic Law of Municipalities (Law N^o18.695) in the way presented in **Table 1**.

Regarding the mechanism of distribution of this fund, there is a defined structure which defines it. The mechanism of distribution can be observed in **Table 2**. In this way, the first 25% corresponds to 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 (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 asset (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.

2.1.2 Permanent self-generated revenues (IPP)

Permanent self-generated revenues (*IPP*) is the source of funds a local government generates from municipal management. Income generated from this source has no restriction on where or in what to invest. From article 38 of the municipal rents law N^o3,063, 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.[2] 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).[3]

Commercial rights are regulated mainly by the municipality as it chooses the tax rate to charge (subject to a range established by the law). Of the amount of income collected by commercial rights,

[2] This is regulated in the Law N^o17,235 about territorial tax.

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

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.

3 Literature Review

3.1 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. In this way, 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 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.

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. In this way, 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.[4] 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.

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

3.2 Empirical Evidence on Municipal Efficiency[5]

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)).

In this way, 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 (2009) 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, where the determinants of the inefficiency are estimated, showed that for Belgium, De Borger and Kerstens (1996a) find 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. 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 composition of the council versus those with a more homogeneous composition). For Peru, Herrera and Francke (2009) find that a higher participation in FONCOMUN (similar to the Chilean FCM) has 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) find 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. Cordero et al (2017) apply time-dependent conditional frontier estimators to assess the performance of the 278 Portuguese mainland municipalities for the 2009–2014 period. Following Mastromarco and Simar (2015) conditional nonparametric frontier analysis, they found that the economic and demographic indicators included as contextual variables in their model play an important role as influencing the production set, although those effects do not seem to vary much over time. This evidence was corroborated after they conducted a second-stage nonparametric regression of the conditional efficiency measures over those variables.

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

[5] For a systematic literature review on the Local governments' efficiency see Narbón-Perpiñá & De Witte (2018).

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, 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 (2000) and Worthington and Dollery (2000) 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 the result obtained about municipal efficiency is sensitive to the technique used. However, despite the magnitude of efficiency changes from method to method, the general results are very similar.

Furthermore, it is important to mention that all the parametric evidence uses cross sectional data (except Bianchini (2010) and Stastna and Gregor (2011)). This is crucial as, this kind of data, may be informative for efficiency measures but it has the drawback that it is not possible to disentangle municipal efficiency from municipal heterogeneity (see Greene 2005a, 2005b and 2005c). Bianchini (2010) and Stastna and Gregor (2011) have carried out an overall analysis. Some authors (Afonso and Fernandez 2008) have criticized this 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 because this method 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). In this way, 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).[6]

[6] In their own words:"*A more serious problem in all of the two-stage studies that we have found arises from*

To solve this problem in the parametric case Khumbhakar, Gosh and McGuckin (1991) proposed a one step estimation method where 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 in to 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. As our objective is to analyze the determinants of municipal inefficiency, we use the Battese and Coelli (1995) approach (i.e. we include the exogenous determinants into the mean of the inefficiency term), all this carried out in one step in order to avoid the problems described above. Furthermore, we also carry out both, an overall and a cluster analysis of Chilean municipalities in order to reduce 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 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.

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).

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. In general, the approach followed in the literature, either production maximization or cost minimization, depends upon 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 institutional framework is crucial, and given the Chilean institutional framework described above, where output is given by the law (i.e. exogenous) and inputs depend on municipal management, *a cost minimization approach is more adequate for our analysis.*

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 is important to notice that any deviation from cost efficiency may come from two sources: input-oriented technical inefficiency and allocative inefficiency. 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 Chilean case, 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.

Hence, Aigner, et al. (1977) and Meeusen and Van Broeck (1977) input-oriented specification, define the minimum cost level for observation i needed to produce a good and services vector given inputs prices (w_i). In this way 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 1997).[7]

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 consist on 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:

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

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 one observed. 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). This is:

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

In order to find $E\left[-u_i|\varepsilon_i\right]$ the conditional density function must be known, and this function is defined 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 the 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 the inefficiency in one step, avoiding the problems presented above when a two stage approach is carried out.

[7] 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.

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

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

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

as the joint density function ($f(u_i,\varepsilon_i)$) is unknown, the joint density function of both error term components can be estimated ($f(u_i,v_i)$) 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 $v=\varepsilon-u$ 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. On the other hand, 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 (u_i).

Finally, replacing equation (9) in to 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, we conclude that $f\left(u_i|\varepsilon_i\right)$ 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 $\phi\left(\right)$ 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 the Inefficiency

As it was previously mentioned, a branch of the stochastic frontier literature has incorporated a second stage where the determinants of the inefficiency found in the first stage are estimated. This approach has been criticized by more recent literature (Wang and Schmidt, 2002) and a one stage approach has been suggested which solves the drawbacks of the two stage approach.

In order to carry out this one stage approach, there are two alternatives: 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. On the other hand, 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 which are 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 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 inefficiency term is time invariant the Fixed Effect and the Random Effect present problems as in both approaches u_i carries both the 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). Due to this, a random effects model is preferred (see more details in **Appendix A**, available upon request). This model can be expressed as:

$$ln(C(y_{it},\beta)) = \beta_0 + \sum_{r=1}^{R}\beta_r ln(y_{rit}) + \frac{1}{2}\sum_{r=1}^{R}\sum_{k=1}^{K}\beta_k ln(y_{rit}) ln(y_{kit}) + \sum_{j=1}^{J}\beta_j x_{jt} + v_{it} + u_{it} \tag{15}$$

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 distributed as truncated-normal $(N^{+}\left(z_{it}\delta,\sigma_u^2\right))$. This is:

$$u_{it} = z_{it}'\delta + W_{it} \tag{16}$$

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 consider the joint maximization of equations (15) and (16) by maximum likelihood (ML). The estimated parameters should be replaced in equation (15) obtaining the estimated variables presented in equations (11) and (12). Then these variables are used in equation (14) to estimate municipal inefficiency.

For the efficiency 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 described below. In this way we will consider more homogenous municipalities which will allow us to decrease the risk of omitted variables.

5 Municipal Clustering, Data and Summary Statistics

5.1 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 of self generate resources and in the way of confronting services administration and public programs. Therefore, it is important to separate municipalities into clusters where these clusters will be define according to some variables, otherwise the comparison between municipalities will be less informative as, for example, we will be comparing Las Condes (the richest municipality) with Cobquecura (a poor rural municipality).

In order to do the clustering, we use the municipal typology of the provision of municipal services elaborated by the Undersecretarship of Regional Development (*SUBDERE*).[8] This typology is elaborated based on clusters with the objective of group municipalities with a minimum internal variance between them and maximal external variance with other groups (see a detailed description of the methodology in **Appendix B**, available upon request). The conformed groups are determined by grouping variables which can not be any of the variables to be used in the estimation. This is 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 3**.

From these clusters, and using both indexes, a graphic analysis of the dispersion is presented (**Figure 1**). This figure suggests which groups can be identified. Based in this analysis and following the number of clusters of SUBDERE we define 6 clusters as presented in **Table 4**. 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 5**), where our new cluster 1 consolidates the former 1 and 2. To see their main characteristics see **Table 6**.

[8] 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.

5.2 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 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 2008-2010. The reason for this is that for some of the variables needed there are no previous information. 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 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. Therefore, we now explain which variables were included in each of them.

a) Output Variable:

Due to the inherent difficulties of quantify the output provided by municipalities, proxies will be used. These variables should consider the multiple functions assigned to municipalities and capture the results obtained in all the areas where they deliver goods and services. After the revision of the empirical literature and given the data available we include 8 output variables described below and whose summary statistics are described in **Table 7**.

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

2. 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.

3. Urbanism: another function of municipalities is to provide roads and places of recreation such as parks, squares, etc. To measure the services provided in this area we include the square meters of maintained green areas.

4. Hygiene: municipalities are in charge of basic services in order 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.

5. Social Services: 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 this kind of services we include the variable social organization which register all social organization by municipality.

6. Municipal Scale: finally, 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 services.

b) Input Variable:

After the definition of the output variables we define the resources used for the provision of public services such as those presented above. 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 route 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 expenditure 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. expenditure in: employees, consumption good and services and transfers to education and health). For this reason, we should keep in mind that for the interpretation of the results it should be considered that we are measuring efficiency on a subgroup of all the possible good and services a municipality can provide. In any case, we check the sensitivity of our results with the alternative specification below. Their summary statistics are also reported in **Table 7**.

c) Determinants of municipal efficiency:

To measure the effect of demographic, economic and fiscal factors on inefficiency, the model must incorporate some exogenous variables that may be considered relevant on municipal performance. Determinants can represent direct effect on municipal efficiency or discretionary inputs or unobservable outputs. Discretionary inputs refer to production in a favorable environment while unobservable outputs indicate service quality (as the included output variable 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 the determinants of municipal inefficiency use similar variables for this purpose and for estimating the inefficiency. These are the variables used to estimate the determinants of the inefficiency:

i. Education: a higher proportion of educated people may imply higher efficiency (De Borger and Kerstens, 1996a). The reason for this is that the municipality should have a more qualified labor force. This should also improve the accountability of the population relative to municipal performance. To approximate educational level we use the average schooling level of the population by municipality.

ii. Population (only for clusters): the hypothesis is that the bigger the population the bigger economics of scale and such municipalities could reach higher levels of efficiency on the provision of goods and services. This variable is used in the general model and not for each cluster as population was one of the variable used to construct the indexes that defined the clusters. To measure this variable in the general model we include dummy variables that accounts 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.

iii. Geography: 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. In this way, for these reasons 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. Fiscal capacity: a lower fiscal capacity of municipalities implies a tighter budget constraint reducing the operational surplus, and effect which may affect municipal efficiency. To measure this effect we use four variables: 1) dependency from the common municipal fund (FCM) relative to self-generated income, 2) percentage of investment relative to total expenditure, 3) current transfers from public institutions, where the latter is in per capita terms. These variables are included because they should measure budgetary tightness.

v. 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 to a lower efficiency because of lack of political competition (Besley et al, 2005). To measure this we use two variables: 1) a Herfindahl index to capture monopolistic degree of the City council[9] and 2) the percentage of the council who belongs to the governmental coalition.

6 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.[10] In this way, 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.

6.1 General Results

From the result of the general model (i.e. without typologies) presented in column1 of **Table 8** 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) Population: results suggest that the bigger the population the higher the efficiency levels. In particular, intermediates cities are more efficient than small ones, however big cities are not statistically different in efficiency terms to small cities.

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

[10] 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).

An hypothesis to explain this result is that small municipalities face some difficulties to provide a minimum of goods and services due to their lack of economic of scale, moral hazard and political pressure from certain groups.[11] On the other hand, big municipalities even they do have economic of scale, they may not be enough to compensate the bigger demand for goods and services. Furthermore, they may be providing higher quality services, which increases costs and are not measured in the model.[12]

b) Fiscal capacity: results suggest that municipalities will have a lower fiscal capacity when the dependency of the FCM relative to their self-generated revenues increases. This lower fiscal capacity generate 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 then 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.

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 in lower income municipalities. (2) municipalities with higher schooling levels have more resources and this relax the budget constraint increasing inefficiency.

d) Political factors: results suggest that a higher level of political concentration, is associated to a higher Herfindahl index, make municipalities less inefficient. An explanation to this may be that a higher political concentration will make easier to reach consensus (or agreement) and then it will allow municipalities to make decisions faster increasing in this way their efficiency.

6.2 Results from the Clusters

Results by cluster of municipalities are presented in columns (2-6) of **Table 8** and suggest that, in general, determinants have similar effects in all of them.

From those that measure fiscal capacity, we find that dependence of 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 with the general model for all typologies (with the exception of the second and fourth typology where 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 typologies 4 and 5, it is not significant for typology 1, 2 and 3. A potential

[11] As there are negative correlations between the dependency level of the FCM and population, a municiplity with a smaller population will have higher dependency of the FCM and lower self-generated income which may induce moral hazard as resources are not generated by the municipality but transferred from others regardless of municipal financial performance.

[12] In the typology analysis quality should be less of a problem as we are using a measure of it as one of the variables to cosntruct the clusters.

explanation for this results may be that for typologies 4 and 5 there is a lack of fiscalization from the population due to: lack of knowledge (less educated people, as seen in **Table 6**), cultural effects given by friendship or family relationship (this is easier in smaller towns than in big cities) or less educated authorities (Mayor and the City Council). For typology 1, 2 and 3 those effects may be

attenuated by their higher average schooling levels and weaker family relationships.

Regarding political factors, we found that results of the Herfindhal index are similar in the clusters and in the general model, in particular for typologies 2 and 3. In the case of typologies 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 then political concentration may be less important versus familiar and/or cultural links between individuals in the area. Regarding the results of the other political variable, we found that the percentage of seats of the governmental coalition is only significantly different from zero in typologies 2 and 3 at 5%.

Finally, regarding 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.

6.3 Overall results

Regarding the overall results, **Table 8** 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 32% but after disaggregate by cluster we found that there is variance as inefficiency levels reach 14.6%, 32.2%, 14%, 13.1% and 9.3% for typologies 1, 2, 3, 4 and 5 respectively(see [1-average efficiency] in **Table 9**). These results suggests that typologies 1 and 2 have a higher level of inefficiency on the provided services. Furthermore it is important to notice the high variance on inefficiency levels between municipalities within clusters which reach between 15-19 percentage points. These results can be seen in **Figure 2**.

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

When we analyze all the typologies we found that municipalities in the top quantile of each cluster present some common characteristics. In particular, we observe in **Table 10** 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 an exception. The same is observed for some of the output variables such as: students registered, rubbish collection, houses with sewer and maintained green areas. By doing the same exercise to the determinants (**Table 11**) we found that most efficient municipalities have a higher dependency from 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 generate a tighter budget constraint and so municipalities use the resources more carefully given that they have to provide a minimum of services Similarly, results for education may be explained because municipalities with lower schooling levels have lower resources and so municipalities use the money more efficiently. The explanation for political concentration is the same given above and it relate to the fact that more concentrated City Councils take less time to reach agreements.

7 Sensitivity Analysis

In order to check the sensitivity of our results we modify some of the assumptions.

7.1 Multicollinearity

In the first place we check the correlations between the variables. This is important as the Translog function used for our analysis may be susceptible of 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 between them and the results are presented in **Table 12**. Results suggest that levels of correlation are not very high except for two variables, houses with sewer and rubbish collected. We decided to keep these two variables as their levels of correlation are only high with a few variables. Furthermore, we repeat the same exercise with the determinants. Results are presented in **Table 13** and suggest that correlations between them are not high.

7.2 Alternative Costs Function

All the analysis was carried out with a Translog cost function which gives flexibility and relax some of the assumptions of the more used Cobb-Douglas. Even though Greene (2005c) pointed 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 re estimate 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).

7.3 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. In this way we are considering all the current resources used by municipalities on the provision of good and services. From **Table 15** we observe that results are similar when input variable is slightly modified.

7.4 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 is implicitly imposed. This relates to the assumption that there is no correlation between the covariates and the composed error term. As in the error term unobserved heterogeneity is included, this is included in our assumption. As in the municipal case, it could be questionable that unobserved heterogeneity is not correlated with the covariates, we relax the assumption by using Mundlak's (1978) approach. This approach consist on 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 the original model without Mundlak's parametrization.

7.5 Quality

As previously stated, we did not include quality measures in our determinants and thus the general model focuses in quantity of services provided. Despite this, we indirectly take quality into account when municipal clusters were defined as one of the variables used for that classification was PSU average score (were PSU is the national test taken after high school in order to get access to college and should capture in some degree quality of schooling). Thus, the model estimated for each cluster considers municipalities with similar PSU scores, and thus with similar schooling quality. In order to further investigate this, we reestimate the general model but now controlling by the number of students who obtained more than 450 points at the PSU test score as a determinant. Results are presented in **Table 17** and suggest that the effect of quality is not significantly different from zero (at least in schooling).

8 Conclusion

This study estimates a stochastic frontier model in order to analyze municipal efficiency and its determinants. To estimate the model, unlike most of previous literature, we use panel data from 2008-2010 of 309 Chilean Municipalities and a one stage approach in order to avoid the problems from the two stages approach.

Results suggest that, in general, Chilean municipalities have on average an inefficiency level of 32%. This imply that municipalities can provide the same services but with 16% less resources. In particular, results suggest that a higher population, a longer distance to the regional capital, a higher dependency of the FCM 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. On the other hand, a higher per capita capital expenditure, higher per capita current transfers from public institutions and higher average schooling levels are related to lower efficiency levels.

Given the high municipal heterogeneity, we reestimate the previous model but at a lower level. This 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 the clusters are 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 of 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 was due to unmeasured quality. We include some quality determinants but their effect 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 the law, municipalities with tighter budget constraint use their resources more carefully and tend to be more efficient on the provision of public services.

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Table N^{o}1: Sources of Funding of the FCM

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}2: Mechanism of Distribution of the FCM

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

Table N°3: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 N^{o}4: 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 N^{o}5: 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 N°6: 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 N°7: 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 N^{o}8: Results for the General model and the five clusters

Determinants	**General** (1)	**C1** (2)	**C2** (3)	**C3** (4)	**C4** (5)	**C5** (6)
Constant	-1.521***	1.098	1.900***	0.543	-2.211*	-3.398***
Population Dummy 2	-0.109**					
Population Dummy 3	-0.113*					
Population Dummy 4	-0.071					
Distance to Regional Capital (ln Km)	-0.018*	0.209***	-0.083***	0.055	0.010	0.148***
$\frac{FCM}{IPP}$	-0.728***	-1.442***	-0.790***	-1.203***	-1.629***	-0.789***
$\frac{Investment}{Total\ Expenditure}$	-0.665***	-0.574	-0.350*	-1.305***	0.650*	-0.944***
$\frac{Public\ Transfers}{Population}$	0.008*	0.067***	0.003*	0.014**	0.014*	0.027***
Average Schooling (ln)	1.229***	-0.647	-0.103	0.584	1.393***	1.588***
Herfindhal Index	-0.000***	0.001	-0.000***	-0.000***	0.000	0.000
% Governmental Coalition seats	0.006	-0.076	0.425***	-1.281***	0.424*	0.381
σ^2	0.057***	0.014***	0.005***	0.019***	0.031***	0.031***
γ	0.403***	0.000***	0.000	0.000*	0.006***	0.000
LR test on $\sigma_u^2 = 0$	79.71***	92.28***	117.57***	84.62***	81.56***	83.86***

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

Table N^{o}9: Ranking Clusters

Cluster	**Average Efficiency**	**S. Deviation**	**Maximum***	**Minimum**
1	0.854	0.198	0.988	0.296
2	0.678	0.151	1.000	0.421
3	0.860	0.185	1.000	0.357
4	0.869	0.192	1.000	0.350
5	0.907	0.157	1.000	0.399

*The maximum may not reach 100%. This is because what it is being reported is the maximum of the average across three years. i.e. Municipality k might be first in the ranking with 100% in 2008 and 2009, but second with 97% in 2010, reaching an average of 99%.

Table N^{o}10: **Municipal Characterization by its efficiency level (Outputs and Input)**

		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Current Expenditure	Top Quantile	14,881	4,468	2,429	1,375	1,414
(Millions of $)	Average Cluster	16,959	7,788	2,686	1,914	1,345
Average Students Registered	Top Quantile	13,615	5,918	3,853	1,601	1,756
	Average Cluster	12,048	9,108	4,017	2,290	1,519
Average Schools (N^o)	Top Quantile	23.1	16.4	22.1	15.8	16.8
	Average Cluster	21.3	23.3	20.0	13.5	13.8
Average Health Centres (N^o)	Top Quantile	13.4	7.3	7.2	5.5	7.0
	Average Cluster	10.0	9.7	6.6	5.1	5.7
Green Areas (m^2)	Top Quantile	855,871	155,693	142,928	97,920	33,714
	Average Cluster	744,209	363,194	381,033	88,770	29,810
Rubbish (Tons)	Top Quantile	100,102	50,929	11,467	4,242	3,357
	Average Cluster	75,986	44,921	11,175	6,711	3,105
Average Houses with sewer	Top Quantile	51,689	13,864	6,046	1,846	1,771
	Average Cluster	42,459	19,832	6,388	3,319	1,696
Social Organizations	Top Quantile	1,823	1,539	676	790	435
	Average Cluster	1,507	1,521	676	501	367

Tables N^{o}11:Municipal Characterization by its efficiency level (Determinants)

		C 1	C 2	C 3	C 4	C 5
Population	Top Quantile	170,871	43,826	37,357	13,201	13,275
	Average Cluster	190,407	98,644	32,355	18,457	10,473
Av. Distance to Regional Capital (Km)	Top Quantile	2.88	60.67	80.50	117.53	90.94
	Average Cluster	2.50	62.97	107.24	115.40	179.95
$\frac{FCM}{IPP}$	Top Quantile	0.53	0.56	0.68	0.76	0.85
	Average Cluster	0.37	0.43	0.66	0.60	0.80
$\frac{Investment}{Total\ Expenditure}$	Top Quantile	0.07	0.20	0.15	0.25	0.28
	Average Cluster	0.06	0.12	0.16	0.18	0.19
Current Transfers from Public Inst.	Top Quantile	12.50	12.12	9.27	10.72	10.47
	Average Cluster	12.70	11.92	10.77	10.48	10.26
Average Schooling	Top Quantile	10.28	9.85	8.86	8.01	7.40
	Average Cluster	10.79	10.00	8.96	8.77	7.91
Herfindhal Index	Top Quantile	2.938	2.407	2.556	2.407	2.426
	Average Cluster	2.193	2.188	2.276	2.364	2.253
% of seats of Gov. Coalition	Top Quantile	0.42	0.52	0.53	0.37	0.34
	Average Cluster	0.44	0.41	0.38	0.40	0.40

Table N^{o}12: Multicollinearity of Output variables

Output Variables	**v1**	**v2**	**v3**	**v4**	**v5**	**v6**	**v7**	**v8**
Population (v1)	1.00							
Monthly Registered Students (v2)	0.79	1.00						
Number of Public Schools (v3)	0.45	0.69	1.00					
Number of Health Centres (v4)	0.51	0.61	0.76	1.00				
Maintained Green Areas (v5)	0.50	0.42	0.25	0.36	1.00			
Rubbish Collected (v6)	0.92	0.75	0.40	0.49	0.45	1.00		
Social Organizations (v7)	0.58	0.58	0.50	0.50	0.29	0.57	1.00	
Houses with Sewer (v8)	0.96	0.84	0.47	0.51	0.51	0.91	0.60	1.00

Table N^{o}13: Multicollinearity of Determinants

Determinants	**v1**	**v2**	**v3**	**v4**	**v5**	**v6**	**v7**	**v8**
Per capita Capital Expenditure (v1)	1.00							
Distance to Regional Capital (v2)	0.21	1.00						
$\frac{FCM}{IPP}$ (v3)	0.27	0.24	1.00					
$\frac{Investment}{Total\ Expenditure}$ (v4)	0.56	0.07	0.35	1.00				
Transfers from Public Institutions (v5)	-0.20	-0.11	-0.23	-0.19	1.00			
Average Schooling (v6)	-0.19	-0.04	-0.71	-0.43	0.28	1.00		
Herfindhal Index (v7)	0.08	0.06	-0.04	0.03	-0.01	-0.01	1.00	
% of seats of Governmental Coalition (v8)	-0.02	-0.06	-0.18	-0.19	0.04	0.13	0.37	1.00

Table N^{o}14: Alternative Costs Functions

Determinants	Translog	Cobb-Douglas
Constant	-3.065***	-1.521***
Population Dummy 2	-0.214***	-0.109***
Population Dummy 3	-0.094*	-0.113*
Population Dummy 4	-0.150	-0.071
Distance to Regional Capital (ln Km)	-0.057*	-0.018*
$\frac{FCM}{IPP}$	-0.549***	-0.728***
$\frac{Investment}{Total\ Expenditure}$	-0.772***	-0.666***
$\frac{Public\ Transfers\ from\ Institutions}{Population}$	0.004**	0.008**
Average Schooling (ln)	2.036***	1.229***
Herfindhal Index	-0.000**	-0.000**
% Governmental Coalition seats	0.163	0.006
σ^2	0.079***	0.057***
γ	0.600***	0.403***
LR test on $\sigma_u^2 = 0$	15.140***	79.710***

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

Table N^{o}15: Alternative Input variable

Determinants	Current Expenditure	Total Current Expenditure
Constant	-1.521***	-1.952***
Population Dummy 2	-0.109**	-0.172***
Population Dummy 3	-0.113*	-0.158**
Population Dummy 4	-0.071	-0.121
Distance to Regional Capital (ln Km)	-0.018*	-0.020*
$\frac{FCM}{IPP}$	-0.728***	-0.693***
$\frac{Investment}{Total\ Expenditure}$	-0.666***	-0.660***
$\frac{Public\ Transfers}{Population}$	0.008**	0.009**
Average Schooling (ln)	1.229***	1.461***
Herfindhal Index	-0.000**	-0.000**
% Governmental Coalition seats	0.006	0.033
σ^2	0.057***	0.064***
γ	0.403***	0.614***
LR test on $\sigma_u^2 = 0$	79.710***	72.173***

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

Table N^{o}16: **Parametrization of Unobserved Heterogeneity (Mundlak)**

Determinants	**Random Effect**	**Random Effect + Mundlak**
Population Dummy 2	-0.109**	-0.115**
Population Dummy 3	-0.113*	-0.105*
Population Dummy 4	-0.071	-0.003
Distance to Regional Capital (*ln* Km)	-0.018*	-0.016*
$\frac{FCM}{IPP}$	-0.728***	0.732***
$\frac{Investment}{Total\ Expenditure}$	-0.666***	-1.248***
$\frac{Public\ Transfers}{Population}$	0.008**	0.007**
Average Schooling (*ln*)	1.229***	0.517***
Herfindhal Index	-0.000**	-0.000**
% Governmental Coalition seats	0.006	0.015
σ^2	0.057***	0.044***
γ	0.403***	0.489***
LR test on $\sigma_u^2 = 0$	79.71***	189.864***

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

Table N^{o}17: Introducing Quality

Determinants	**General Model**	**General Model with PSU score**
Constant	-1.521***	-1.515***
Population Dummy 2	-0.109**	-0.107**
Population Dummy 3	-0.113*	-0.111*
Population Dummy 4	-0.071	-0.070
Distance to Regional Capital (ln Km)	-0.018*	-0.019*
$\frac{FCM}{IPP}$	-0.728***	-0.724***
$\frac{Investment}{Total\ Expenditure}$	-0.666***	-0.664***
$\frac{Public\ Transfers}{Population}$	0.008***	0.008***
Average Schooling (ln)	1.229***	1.222***
Herfindhal Index	-0.000**	-0.000**
% Governmental Coalition seats	0.042	0.043
Average PSU score		0.010
σ^2	0.057***	0.057***
γ	0.403***	0.397***
LR test on $\sigma_u^2 = 0$	79.71***	79.75***

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

Figure N^{o}1: Municipal Clustering

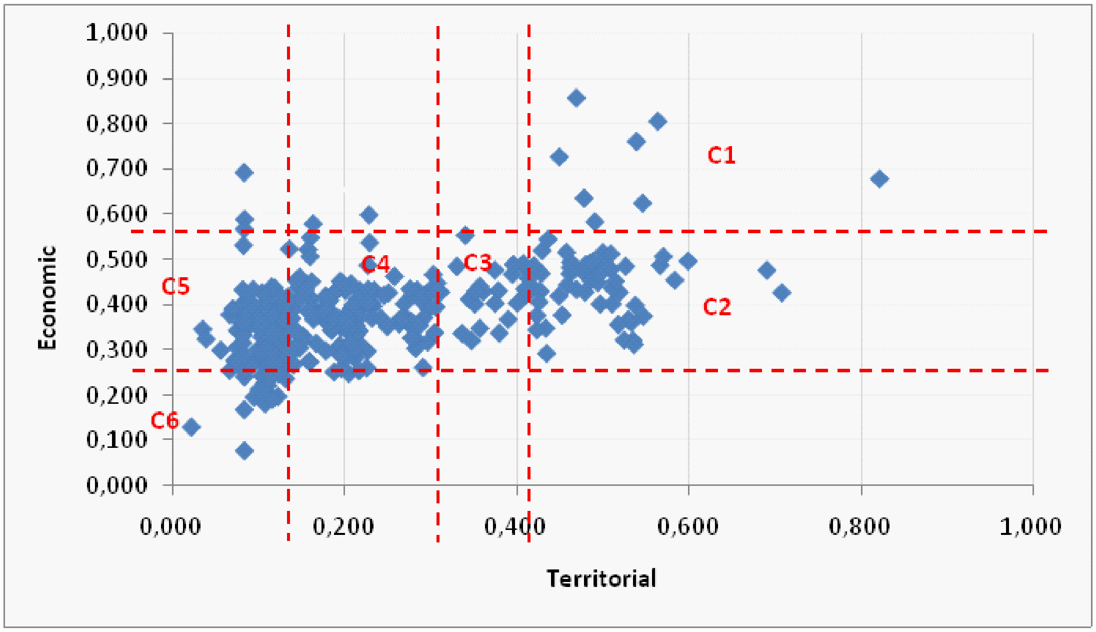
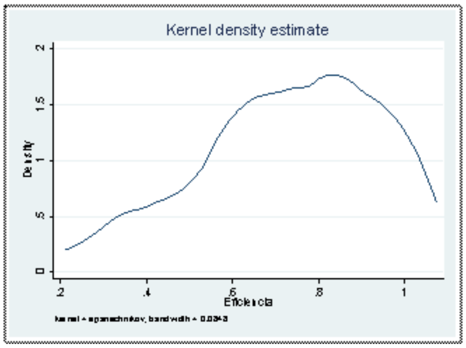
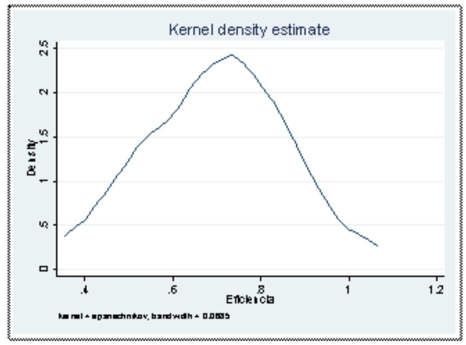


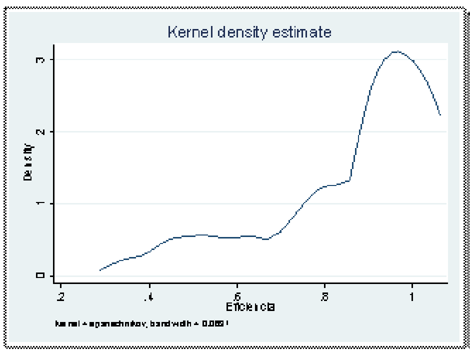
Figure N^{o}2: Histogram of Inefficiency



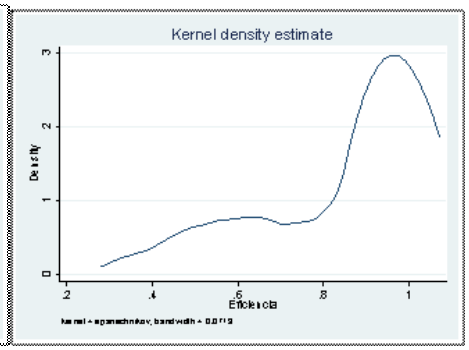
Cluster 1



Cluster 2



Cluster 3



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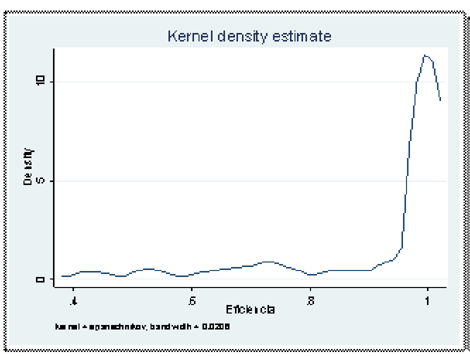
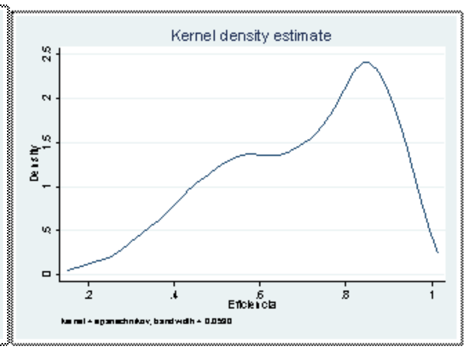


Cluster 5



General Case