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Keywords Bayesian inference, electricity distribution, dynamic effects, heterogeneity, stochastic frontier models

JEL Classification C11, C23, C51, D24, L94

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Inefficiency persistence and heterogeneity in Colombian electricity distribution utilities

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Abstract

The electricity reform in Colombia has exhibited gains in terms of reliability but its effects on firms efficiency and service quality have not been clear. Previous studies evaluating the performance of distribution companies after the reform have not found evidence of improvements, although large differences in efficiency have been found among firms. This suggests high inefficiency persistence and heterogeneity in the Colombian distribution sector. In this paper, we propose an extension of dynamic stochastic frontier models that accounts for unobserved heterogeneity in the inefficiency persistence and in the technology. The model incorporates total expenses, service quality and energy losses in an efficiency analysis of Colombian distributors over fifteen years after the reform. We identify the presence of high inefficiency persistence in the sector, and important differences between firms. In particular, rural companies and firms with small customers present low persistence and evidence the largest gains in efficiency during the period. However, increases in efficiency are only manifested during the last five years when the main improvements in service quality and energy losses are presented. Overall, inefficiency persistence, customer density and consumption density are found to be important criteria to be considered for regulatory purposes.

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1. Introduction

The electricity market reform introduced in Colombia in 1994 established a new structure of the sector and new conditions for private participation and competition. The reform was mainly motivated by an energy crisis suffered in 1992-1993 that caused major blackouts as a consequence of extreme droughts. This situation revealed the inefficiency and inability of the state-owned industry to satisfy an increasing demand and to deal with weather events. The regulatory reform adapted a version of the UK model with the creation of a pool where prices are settled in a bidding process. The Electric Law of 1994 created the regulatory commission *Comisión Reguladora de Energía y Gas* (CREG) and split the traditional vertically integrated and monopolistic system into the activities of generation, transmission, distribution and retailing. As a consequence, the seven major public holdings in charge of multiple activities from generation to distribution previous to the reform were divested into eleven companies performing only one of these activities and two companies involved in both generation and distribution. Although generation and distribution were allowed to be performed by the same company, limits to the amount of electricity that the distributor could buy from its own generation firm were set and separate managerial and accounting procedures were required.

However, privatization and competition have been slow processes in Colombia. After the reform only two of the new companies were fully privatized and, although in the following years several companies were open to private capital, in most of the cases private investors are minority shareholders and firms remain under the control of municipalities and regional governments. Certainly, privatization and competition have been identified as pending issues in Colombia in previous studies analyzing the effects of the first years of the reform (see Pombo and Taborda, 2006; Larsen et al., 2004).

Nevertheless, these processes have accelerated in recent years. From 2010 to 2012, the number of generating and retailing firms has increased by 23% and 32%, respectively, and most of the companies involved in these activities are classified as private-owned. In distribution, companies with a majority of public capital account for 62% of total firms and serve 51% of the total users. Currently there are 54 generation, 33 distribution and 85 retailing companies. Of the generation firms, 12 are also involved in distribution and 15 combine generation exclusively with retailing activities.[1]

In general, the effects of the reform have been positive in terms of the ability of the electricity sector to overcome extreme weather conditions and to satisfy the increasing demand. Since the reform, Colombia has not experienced blackouts

[1]Information provided by the national supervisory agency of public services *Superintendencia de Servicios Públicos Domiciliarios (SSPD)* in 2013.

in spite of some severe droughts that have affected the region during the 1997-1998 and 2009-2010 periods, and that have seriously affected neighbor countries. Moreover, Colombia has become an electricity exporter to Ecuador and Venezuela and it is currently planning to export electricity to other Central American and Caribbean countries.[2]

On the other hand, the effects of the reform in terms of energy losses and service quality have not been successful until recent years. During the first ten years of the reform, energy losses and electricity interruptions did not present reductions and were even higher than previous to the reform. Colombia also exhibited very bad performance in these aspects when compared to other countries in the region (see Larsen et al., 2004; Dyner et al., 2006). Only from 2008, can important reductions in energy losses be observed. In terms of the length of interruptions, although it is possible to identify some improvements since 2005, it is only until 2011 that significative reductions are evident. In both cases, these improvements are consequence of changes in the regulation, as is discussed further below.

Meeting the quality requirements and satisfying the increases in electricity consumption and users has required distribution companies to make important investments. In fact, capital and operational expenses have increased by more than 30% during the period 1998 - 2012. This suggests the need to study the effects of the reform and the latest regulations on efficiency. Concerning this issue, some few previous studies have quoted the effects on efficiency of the reform in Colombia and no major gains have been identified. Pombo and Taborda (2006) use Data Envelopment Analysis (DEA) to perform an analysis of technical efficiency of Colombian distribution firms during the period from 1985 to 2001. The authors find no major changes during the period and highlight that the most efficient firms previous to the reform continue to be in the best-practice frontier but firms which were inefficient have not been able to change this condition and present even lower efficiency scores. A similar result was found by Melo and Espinosa (2005), who measure the technical efficiency of Colombian distributors from 1999 to 2003 using Stochastic Frontier Analysis (SFA). The authors find out that public companies perform better than those privately owned but that there have not been major changes in technical efficiency in the immediate years after the reform. This Colombian evidence contrasts with the effects of the electricity reforms on performance in other South American countries (see Mota, 2003; Pollitt, 2004, 2008; Pérez-Reyes and Tovar, 2009, for the cases of Brazil, Chile, Argentina and Peru, respectively.)

Findings from these studies may suggest the presence of high adjustment costs in the Colombian distribution sector that imply inefficiency to be highly persistent

[2] In 2011, Colombia exported 1.740 GWh. Information from the Ministry of Mines and Energy.

in time. In this context, it is costly for firms to move towards optimal conditions and they may find it optimal to remain inefficient in the short-run. These studies have also evidenced the existence of important differences among firms with different characteristics in terms of their performance.

Therefore, this work has two main aims: first, to identify the presence of adjustment costs in the distribution sector after the reform and distinguish heterogeneity in the technology and the inefficiency among Colombian distributors; second, to estimate measures of efficiency that consider costs and quality of service in the Colombian electricity sector and their evolution from the first years after the reform into the following fifteen years. In particular, we focus on the last five years, when most of the changes in terms of quality, demand and costs have occurred.

For these purposes we propose a dynamic heterogeneous SFA model, which extends other dynamic specifications in the frontier efficiency literature. In particular, we extend the dynamic model introduced by Tsionas (2006) in order to allow for heterogeneous persistence and unobserved technological heterogeneity. This allow us to identify differences in the adjustment costs faced by firms and to distinguish inefficiency properly from unobserved firm characteristics. Inference of the model is performed using the Bayesian approach and the effects of the proposed specification on efficiency estimations are evaluated.

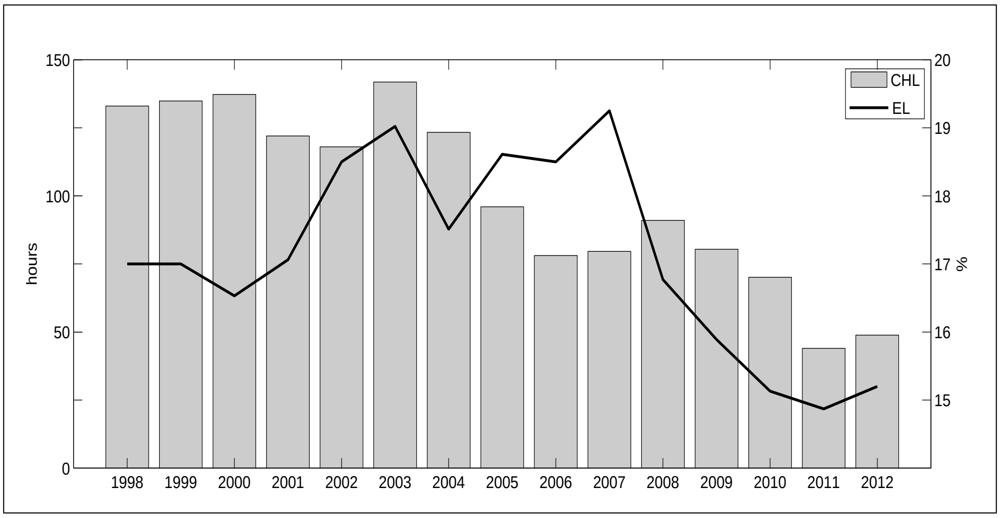
The paper is divided into six sections including this introduction. In the second section, we describe the main characteristics of the Colombian electricity distribution sector after the reform. In the third section, we review previous literature on dynamic SFA models and heterogeneity in the electricity sector, and we present the proposed model, the estimation procedure and the model specification. In the fourth section, we describe the data and the empirical model. In the fifth section, we analyze the estimation results. Finally, we present some conclusions.

2. Colombian electricity distribution sector

The activity of electricity distribution in Colombia is defined by CREG as the transportation of electricity from the national transmission system, which operates at voltages above 220 Kv, to the final user. There are four different levels of tension operated by the distributor. That is, from level 1, which involves tension levels below 1 Kv, to level 4 with tension levels between 57.5 Kv and 115 Kv. CREG establishes the pricing formula for distributors for each of the tension levels considering demand, investments, and administration, operation and maintenance costs. The length of the price review is five years and the first pricing period was 1998-2002.[3]

[3]CREG resolution 031 of 1997.

Figure 1: Average CHL and EL ratio per firm



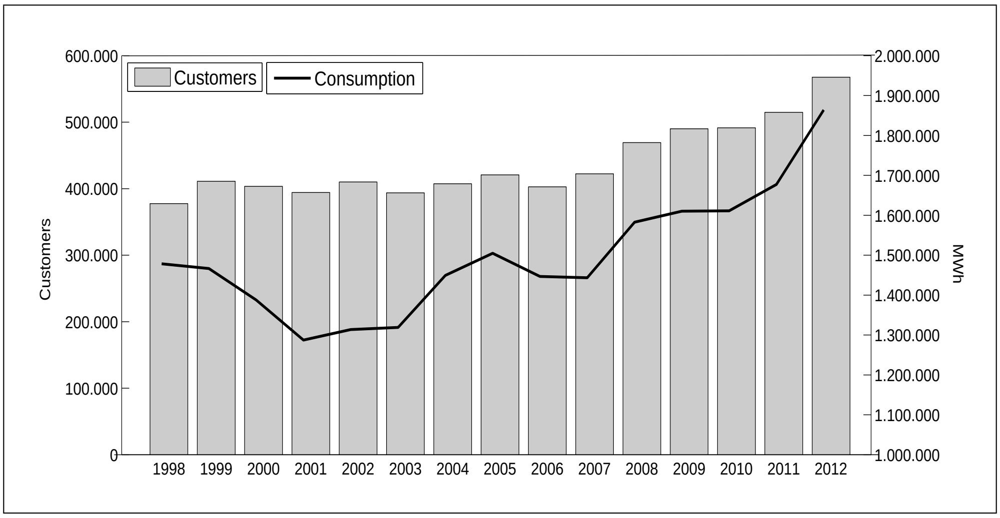
Besides prices, service quality and energy losses have also been under regulation. In 1998 CREG established maximum values for both duration and number of interruptions by tension level, as well as compensations to users when companies exceeded these maximums.[4] However, small and slow improvements motivated CREG to modify this scheme in 2008. The new regulation introduced quality incentives in the pricing formula and compensations for the most affected users.[5] Under this model, an index of service discontinuity is calculated quarterly and three ranges of values for this index are set: if distribution companies exceed an acceptable range their pricing formula is revised down; if they perform better than the acceptable values their formula is revised up; and if their discontinuity index is within the acceptable range their formula does not change. The implementation of this mechanism has been postponed and only from 2011 have all companies had to report this index. The effects of this last regulatory scheme are still uncertain. In the literature, some studies have found this direct mechanism of incentive regulation to have negative effects on quality of service (see Ter-Martirosyan and Kwoka, 2010). However, the most important reductions in the length of interruptions have occurred since then. This can be observed in Figure 1, where the evolution in customer hours lost (CHL) and energy losses (EL) from 1998 to 2012 is presented for the sample of distribution companies described in Section 4.

Regarding energy losses, new regulations were also set by CREG in 2008 by establishing a program for reducing losses and setting upper limits for the per-

[4] CREG resolution 070 of 1998.

[5] CREG resolution 097 of 2008.

Figure 2: Average number of customers and electricity consumption per firm



centage of losses recognized by users via tariff.[6] The effects of this regulation also seem to be positive (see Figure 1).

During the period 1998-2012, the electricity consumption and the number of connected users have also presented important increases (27% and 51%, respectively). Figure 2 presents this evolution for the same firms above. We can observe that, after a period characterized by economic recession and low growth rates (1999-2003), consumption and customers exhibit an upward trend with high growth in the most recent years.

Satisfying the demand and meeting the quality requirements have had effects on the costs of distribution firms. Figure 3 presents the evolution of capital and operational expenses in real US dollars of 2012 for the same companies in the figures above. We observe important increases, mainly in operational expenses, from 2007, when relatively higher capital expenses were made. The overall increase in real total expenses from 1998 to 2012 was 31%.

Higher distribution costs have had an impact on the tariff for the final user. Figure 4 plots the evolution of the tariff per kWh by decomposing it into each of their components. Although almost all the components of the tariff have increased in real terms, the proportion of the distribution component has raised from 33% to 40% during the period, with a particular increase in 2011 and 2012.

[6]CREG resolutions 199 and 121 of 2007.

Figure 3: Average operational and capital expenses per firm

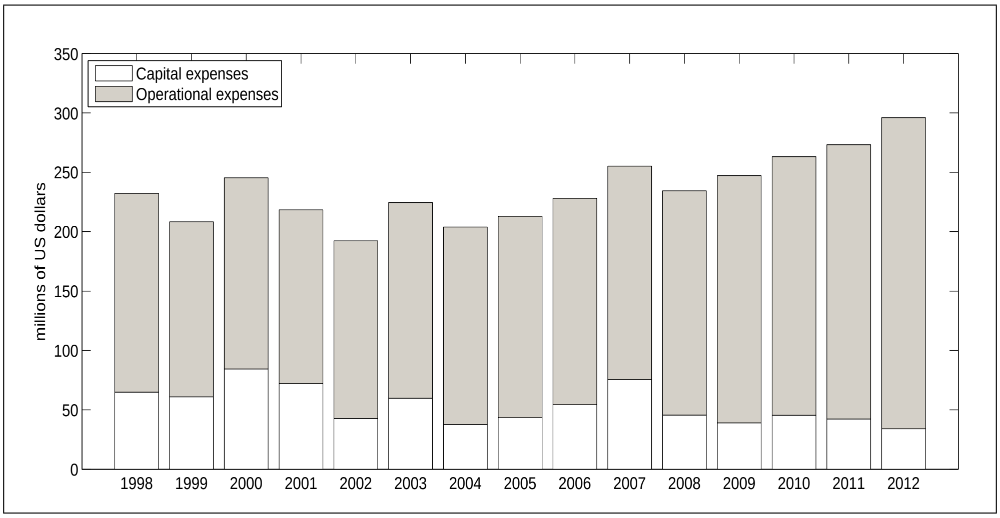
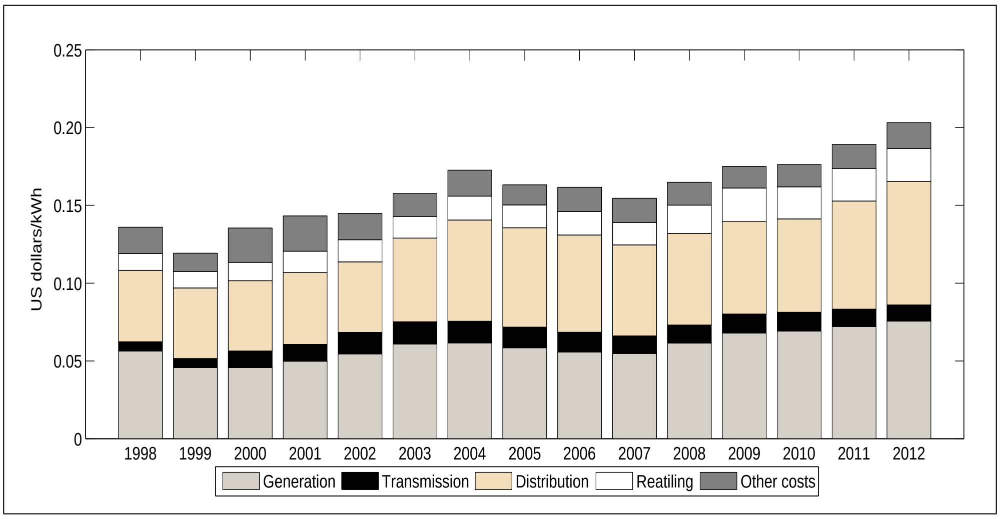


Figure 4: Evolution of tariff per kWh in Colombia in real terms of 2012



Regarding tariffs, it is important to remark that CREG establishes their value only for regulated users. After the reform, customers were separated into regulated and non-regulated users, which are differentiated in terms of their power demand and consumption. Since 2000, CREG has defined regulated users as those with power demands under 0.1 MW and monthly consumption below 55 MWh.[7] Non-regulated users are allowed to negotiate prices with retailing companies.

[7]CREG Resolution 131 of 1998.

3. Methodology

Frontier efficiency models have become a very useful tool to study the impact of the deregulation processes carried out in many countries from the 1990s and to analyze the performance of the participants in the different stages from generation to retailing. In particular, SFA, first introduced in Aigner et al. (1977) and Meeusen and van den Broeck (1977) has the advantage of allowing inferences on the parameters and considering idiosyncratic errors, in contrast to the most common non-parametric methods such as DEA. It also allows dealing easier with panel data structures and to model the evolution of efficiency over time. Two different approaches have been used in the literature for this purpose. The most common approach estimates the temporal pattern of the variation in inefficiency by using deterministic specifications of time. Here we find the proposals by Kumbhakar (1990), Battese and Coelli (1992), Lee and Schmidt (1992), and Cornwell et al. (1990). These models have the problem of imposing arbitrary restrictions on the short-run efficiency and they are not able to model firm-level dynamic behaviour. A second approach proposed by Ahn et al. (2000) and Tsionas (2006) directly incorporates the dynamic behaviour of the inefficiency by specifying an autoregressive structure that recognizes inefficiency persistence over time. In particular, Tsionas (2006) argues that adjustment costs prevent firms from making instant adjustments towards optimal conditions and causes inefficiency persistence. Rigidities derived from the nature of some inputs, regulation, transaction costs, information failures and other adjustment costs may cause firms to find it optimal to remain partly inefficient in the short-run.

3.1. Heterogeneity in the electricity sector

Accounting for both observed and unobserved heterogeneity in stochastic frontier models is still a concern since efficiency estimations are sensitive to the modeling of sources of heterogeneity. In the case of observed heterogeneity, previous applications to the electricity distribution sector have studied the effects of including different types of covariates in the frontier, in the inefficiency or both. Hattori (2002) found out that heterogeneity sources related to the load factor, customer density and consumption density affect both, the shape of the frontier and the level of technical efficiency. Goto and Tsutsui (2008) found only customer density to have impacts on the technical efficiency of US electricity distribution firms in a model that also includes consumption density, time and a deregulation index in the inefficiency distribution. In a recent study, Growitsch et al. (2012) considered weather factors and found them to be influential on costs but having limited effects in the efficiency estimations.

However, Growitsch et al. (2012) achieved more sensitivity in the efficiency estimations when unobserved heterogeneity is included by using a True Random

Effects (TRE) model as proposed by Greene (2005). Other recent studies in electricity distribution have also been found to be relevant to considering this latent source of heterogeneity in SFA models. Kopsakangas-Savolainen and Svento (2011) perform a good analysis of the effect of observed and unobserved heterogeneity and warn of the high changes produced in rankings of cost efficiency under different models.

In the context of dynamic inefficiency models, Emvalomatis et al. (2011) studied the effect of including technological unobserved heterogeneity in an application to power generation plants in the US. Their findings reveal high persistence of inefficiency over time but also biases in the efficiency estimations when unobserved factors are not considered. However, it is also possible to think of heterogeneity regarding the persistence parameters. This would be related to possible differences in the adjustment costs among firms. The only studies considering this issue have been applications to the banking sector, where this type of heterogeneity has been found to be relevant (see Huang and Chen, 2009; Galán et al., 2013a).[8]

3.2. A Dynamic Heterogeneous Model

We propose a dynamic stochastic frontier model that accounts for both observed and unobserved heterogeneity sources. This is mainly an extension of the model introduced by Tsionas (2006) that combines it with other recent proposals in the literature of dynamic SFA models. In particular, the proposed specification accounts for observed firm characteristics in the inefficiency dynamics, as in Tsionas (2006), but also captures two additional sources of unobserved heterogeneity: the first one is related to differences in the adjustment costs among firms, and we model it through a heterogeneous persistence parameter as in Galán et al. (2013a); the second one is related to unobserved sources of technological heterogeneity and we model it in a similar way to the dynamic model in Emvalomatis (2012). The general model is given by the following equations:

$$y_{it} = \alpha_i + \mathbf{x}_{it}\boldsymbol{\beta} + v_{it} - u_{it}, \qquad v_{it} \sim N(0, \sigma_v^2) \tag{1}$$

$$\log u_{it} = \omega + \mathbf{z}_{it}\boldsymbol{\gamma} + \rho_i \log u_{i,t-1} + \xi_{it}, \qquad \xi_{it} \sim N(0, \sigma_\xi^2), \qquad t = 2...T \tag{2}$$

$$\log u_{i1} = \frac{\omega + \mathbf{z}_{it}\boldsymbol{\gamma}}{1-\rho_i} + \xi_{i1}, \qquad \xi_{i1} \sim N\left(0, \frac{\sigma_\xi^2}{1-\rho_i^2}\right), \; t = 1. \tag{3}$$

Equation (1) represents the stochastic frontier, where in the case of a produc-

[8] Huang and Chen (2009) include firm specific persistence parameters in the context of models with forward-looking rational expectations while Galán et al. (2013a) include them in relation to the theory of adjustment costs.

tion function y_{it} is the output for firm i at time t, α_i is the firm specific parameter intended to capture unobserved technological heterogeneity, $\mathbf{x}_{it}$ is a row vector of the input quantities, $\boldsymbol{\beta}$ is a vector of parameters, v_{it} is the idiosyncratic error assumed to follow a normal distribution, and u_{it} is the inefficiency component. The dynamic specification for the inefficiency is represented by (2), where ω is a constant term, $\mathbf{z}_{it}$ is a row vector of firm specific heterogeneity variables, $\boldsymbol{\gamma}$ is a vector of parameters, ρ_i is the heterogeneous persistence parameter capturing, for every firm, the proportion of inefficiency that is transmitted from one period to the next, and ξ_{it} is a white noise process with constant variance σ_ξ^2, which may capture unobserved random shocks in the dynamic component. Finally, equation (3) represents the specification of the inefficiency in the first period and is intended to initialize a stationary dynamic process.

Stationarity is imposed by requiring the persistence parameters to satisfy $|\rho_i| < 1$. This is important in order to avoid possible divergence of $\log u_{it}$ to positive or negative infinity, which would lead to efficiencies equal to zero or to one. These results are not desirable since in the first case they would mean that completely inefficient firms remain in the market, and in the second case that firms may be fully efficient, contradicting the adjustment cost theory behind the formulation. In general, if a firm has a value of ρ_i close to 1 it would suggest that this firm presents high adjustment costs, which translates into a high proportion of inefficiency being transmitted from one period to the next. On the other hand, if this value is close to 0, a low proportion of inefficiency is persistent in time, implying that the firm may move quicker towards more optimal conditions.

The general model in (2) and (3) allows to evaluate different specifications by imposing restrictions over some parameters. If $\alpha_i = \alpha$ is assumed, then unobserved technological heterogeneity is not accounted for. If $\rho_i = \rho$ is imposed, homogeneous persistence is assumed for all companies in the sector. If $\rho = 0$ the model reduces to a static model where the inefficiency follows a log-normal distribution with firm specific mean. Finally, if no inefficiency covariates are observed, then $\boldsymbol{\gamma} = 0$ would be assumed.

3.3. Bayesian inference

Inference of the model in (1) till (3) is carried out using the Bayesian approach. Bayesian inference of stochastic frontier models was introduced by van den Broeck et al. (1994) and allows incorporating formally parameter uncertainty and obtaining posterior distributions of inefficiencies for every observation.

In general, we assume non-informative but proper prior distributions for all the parameters. For the parameter capturing unobserved heterogeneity in the frontier we define a hierarchical structure where $\alpha_i \sim N(\alpha, \lambda_{\alpha_i}^{-1})$ and the hyperparameter $\alpha \sim N(0, \lambda_\alpha^{-1})$. Priors for the precision parameters λ are set to 0.1 and 0.001 for the firm specific parameters and the hyperparameter, respectively. For parameters in $\boldsymbol{\beta}$ we assume a normal prior distribution $\boldsymbol{\beta} \sim N(\mathbf{0}, \boldsymbol{\Lambda}_{\boldsymbol{\beta}}^{-1})$ where $\boldsymbol{\Lambda}_{\boldsymbol{\beta}}$ is a precision diagonal matrix with priors set to 0.001 for all parameters. The variance of the idiosyncratic error component is assumed to follow an inverse gamma distribution $\sigma_v^2 \sim IG(a, b)$ with priors set to 0.01 and 100 for the shape and scale parameters.

The inefficiency component as defined in (2) follows a log-normal distribution where $u_{it}|u_{i,t-1}, \omega, \mathbf{z}_{it}, \boldsymbol{\gamma}, \rho_i, \sigma_\xi^2 \sim LN(\omega + \mathbf{z}_{it}\boldsymbol{\gamma} + \rho_i \log u_{i,t-1}, \sigma_\xi^2)$ for $t = 2...T$. For $t = 1$, the inefficiency is distributed $u_{i1}|\omega, \mathbf{z}_{i1}, \boldsymbol{\gamma}, \rho_i, \sigma_\xi^2 \sim LN\left(\frac{\omega+\mathbf{z}_{i1}\boldsymbol{\gamma}}{1-\rho_i}, \frac{\sigma_\xi^2}{1-\rho_i^2}\right)$.

Regarding the parameters in the inefficiency, the distribution for the common constant term is $\omega \sim N(\mu_\omega, \lambda_\omega^{-1})$ with priors set to -1.5 and 1 for the mean and precision parameters, respectively. The distribution for the parameters of observed heterogeneity is: $\boldsymbol{\gamma} \sim N(\mathbf{0}, \boldsymbol{\Lambda}_{\boldsymbol{\gamma}}^{-1})$ where $\boldsymbol{\Lambda}_{\boldsymbol{\gamma}}^{-1}$ is a diagonal matrix of precisions with priors set to 0.1 for every precision parameter. For the persistence parameters, we impose $|\rho_i| < 1$ to assure stationarity and we define a hierarchical structure with $\rho_i = 2k_i - 1$, where $k_i \sim \beta(k, 1-k)$. The hyperparameter is distributed $k \sim \beta(r, s)$ with priors set to 0.5 for shape parameters. The variance of the inefficiency component is assumed to follow an inverse gamma distribution where $\sigma_\xi^2 \sim IG(n, d)$ with priors set to 10 and 100 for the shape and scale parameters, respectively.[9]

Sensitivity analysis is performed on priors in the inefficiency component. Different values are used for prior parameters in the distributions of ω, k and σ_ξ^2 and posterior results are found to converge to approximately the same values.[10] We also found posterior results to be robust to the use of a truncated normal distribution for parameters ρ_i and ρ.

The specification proposed accounts for firm specific effects in the frontier and the inefficiency persistence. However, firms in the sector share a common long-run dynamic component ω, common elasticities for the covariates given by $\boldsymbol{\gamma}$, and are linked through common parameters ρ and α that are present in the hierarchical structures defined.

As introduced by Koop et al. (1995), Markov Chain Monte Carlo (MCMC) methods and, in particular, the Gibbs Sampling algorithm with data augmentation can be used. We carry out the implementation of the proposed model using the WinBUGS package (see Griffin and Steel, 2007, for a general procedure in applications to SFA). For all the estimated models we use 5,000 iterations for posterior inference. The MCMC algorithm involves 50,000 iterations with 10,000 discarded in a burn-in phase and a thinning equal to 8 is used to remove autocorrelations.

[9] This is the same prior used by Tsionas (2006) and Galán et al. (2013a).

[10] The priors used centre the efficiency prior distributions at 0.8.

3.3.1. Comparison criteria

Using the MCMC output, we compare the different models derived from (1) till (3) using a robust version of the Deviance Information Criterion (DIC) and a criterion for predictive performance, which is the Log Predictive Score (LPS).[11]

DIC is a within-sample measure of fit introduced by Spiegelhalter et al. (2002) and defined as: $DIC = 2\overline{D(\theta)} - D(\bar{\theta})$ with $D(\theta) = -2\log f(\mathbf{y}|\theta)$, where $D(\theta)$ defines the deviance of a model with parameters θ and data $\mathbf{y}$. The version of this criterion used here is the DIC_3, as developed in Richardson (2002) and Celeux et al. (2006), and its formulation is the following:

$$DIC_3 = -4E_\theta[\log f(\mathbf{y}|\theta)|\mathbf{y}] + 2\,\log \widehat{f}(\mathbf{y}). \tag{4}$$

This alternative uses an estimator of the density $f(\mathbf{y}|\theta)$ instead of the posterior mean $\bar{\theta}$ and has been found to be more stable in models with random effects, mixtures and with data augmentation (see Li et al., 2012).

We also implement a criterion for evaluating out-of-sample behaviour of the models, which is LPS. This criterion was first introduced by Good (1952) and is intended to examine model performance by comparing its predictive distribution with out-of-sample observations. For this purpose the sample is split into a training and a prediction set. Our prediction set consists of observations corresponding to the last two observed years of every firm in the sample, and the training set contains all the rest. The formula is the following:

$$LPS = -\frac{1}{k}\sum_{i=1}^{k}\log f(y_{i,t_i}|\text{previous data}), \tag{5}$$

where y_{i,t_i} represents the observations in the predictive set for the k firms in the sample and t_i represents the penultimate time point with observed data for firm i.

3.4. Stochastic input distance function

Given that electricity distributors do not have control over electricity consumption and the number of users, which are their natural outputs, it is only possible to use input-oriented models for measuring technical efficiency. In this context, we assume that distribution firms use an $N \times 1$ vector of inputs $\mathbf{x} = (x_1, x_2, \ldots, x_N)'$ to provide an $M \times 1$ vector of outputs $\mathbf{q} = (q_1, q_2, \ldots, q_M)'$. Thus, we define an input set as follows:

$$L_g(q) = \mathbf{x} : \mathbf{x}\,\text{and technology}\; g\,\text{can produce}\;\mathbf{q}, \tag{6}$$

[11] Applications of both criteria to Bayesian SFA models can be found in Griffin and Steel (2004); Ferreira and Steel (2007); Galán et al. (2013b).

where the technology g satisfies the axioms of closeness, boundedness, strong disposability and convexity as described by Färe and Primont (1995). This technology can be represented by an input distance function, which is defined as:

$$D_I(\mathbf{x}, \mathbf{q}, g) = \sup_{\lambda}\{\lambda : \mathbf{x}/\lambda \in L_g(\mathbf{q}) \geq 1\}, \quad (7)$$

where λ denotes the maximum amount by which an input vector can be radially contracted while the output vector remains constant. We assume that every distribution firm employs the best available technology in each period. Thus, the Debreu-Farrell input-oriented measure of technical efficiency (TE) for firm i in period t is:

$$TE(x_{it}, q_{it}, t) \equiv 1/D_I(x_{it}, q_{it}, t). \quad (8)$$

The input distance function has the following features: it is homogeneous of degree one, a non-decreasing concave function of inputs, and a non-increasing quasi-concave function of outputs (see Färe and Primont, 1995). Linear homogeneity implies that it is possible to normalize all the inputs in the distance function by an arbitrarily chosen input $x_{N_{it}}$:

$$1/x_{N_{it}} = D_I(x_{it}/x_{N_{it}}, q_{it}, t)\exp(-u_{it}), \quad (9)$$

where $u_{it} \equiv \ln D_I(x_{it}/x_{N_{it}}, q_{it}, t) \geq 0$. Then, a firm is technically efficient if and only if $u_{it} = 0$ or similarly, $TE(x_{it}, q_{it}, t) = 1$.

Regarding the technology representation, we use a translog functional form to parameterize the distance function. So, we define $v_{it} \equiv \ln D_I(x_{it}/x_{N_{it}}, q_{it}, t) - TL(x_{it}/x_{N_{it}}, q_{it}, t)$, where $TL(.)$ is the translog function. In this case, (9) becomes:

$$y_{it} = TL(x_{it}/x_{N_{it}}, q_{it}, t) + v_{it} - u_{it}, \quad (10)$$

where $y_{it} \equiv -\ln x_{N_{it}}$. If any outputs or normalized inputs are stochastic then v_{it} is stochastic and (10) becomes a standard translog stochastic frontier model. For estimation purposes, the random noise term v_{it} is assumed to follow a normal distribution and the inefficiency component u_{it} is assumed to follow a nonnegative distribution. Using the results for individual inefficiencies, TE in each period is calculated as:

$$TE_{it} = \exp(-u_{it}). \quad (11)$$

4. Data and empirical model

Information on expenses, consumption, users, network length and quality indicators was collected for a sample of 21 electricity distribution firms during the period 1998 - 2012. The main data sources are CREG, SSPD and annual reports of the companies. Firms in the sample distributed 81% of the total consumed KwH in Colombia during the period and share 98% of total customers in the country. The data set is an unbalanced panel with a total of 246 observations. Table 1 presents a summary of statistics of the main variables. Monetary values are expressed in thousands of US dollars in real terms of 2012 after deflating by the consumer price index.

Table 1: Summary statistics

Variable	Mean	SD	Minimum	Maximum
Residential consumption (MWh)	785,665	1,118,006	13,499	4,687,938
Non-residential consumption (MWh)	729,120	1,138,132	9,069	5,637,621
Residential customers (#)	405,457	491,828	34,365	2,247,024
Non-residential customers (#)	40,672	57,430	2,935	294,734
Network length (Km)	16,587	15,673	232	70,795
Customer hours lost ($hours$)	89.12	101.94	6.20	580.89
Energy losses (%)	16.25	7.45	4.02	38.57
Consumption density ($kWh/user$)	2,836	1,120	436	6,642
Customer density ($users/Km$)	43.41	45.42	9.85	194.42
Total Expenses (thousands USD)	239,034	363,063	1,395	1,768,163

From these variables two outputs and three inputs are selected for the specification of the input distance function. Consumption and number of customers are the standard outputs in electricity distribution; however, they are usually highly correlated (0.95 in our sample) and one of them should be chosen to avoid collinearity problems. In our case, we select the number of users divided into residential (y_1) and non residential users (y_2). Inputs are total expenses (x_1), energy losses (x_2) and customer hours lost (x_3). Total expenses is the sum of operational and capital expenses. The former include administrative, operative and maintenance expenditures and the latter corresponds to the value of new investments in network cables, lines, ducts, tunnels and other machinery, plant and equipment. Considering overall total expenses is desirable for benchmarking electricity utilities (see Giannakis et al., 2005). Moreover, since we also account for quality measures, including total expenses recognizes that distribution firms adopt different strategies mixing capital and operating investment inputs in order to improve quality of service (see Jamasb et al., 2012). We also include energy losses and the length of interruptions as inputs where reductions are desirable. This approach has been used before in applications to the electricity sector using SFA models with distance functions (see Growitsch et al., 2009; von Hirschhausen et al., 2006; Tovar et al., 2011). Giannakis et al. (2005) and Yu et al. (2009) have also found these variables to be relevant in performing electric utilities benchmarking analysis explicitly including quality of service. Energy losses is the percentage of energy lost due to technical reasons and customer hours lost is the duration of service interruptions measured in hours per customer. We also include the network length measured in kilometers (km) as a characteristic of the output which is not directly under the control of firms.

Finally, we consider two inefficiency heterogeneity variables. These are consumption density (z_1) and customer density (z_2). Consumption density is measured as the number of KwH consumed per customer and customer density is measured as the number of users per kilometer. Both variables are expected to affect the inefficiency negatively in the sense that firms serving areas with low customer and consumption density may face a higher input-output relationship and more managerial difficulties in providing optimal service quality and resources allocation. Previous studies have also modeled these variables in the inefficiency distribution. Hattori (2002) and Goto and Tsutsui (2008) found these density characteristics to be relevant technical inefficiency drivers in the US and to produce changes in the results when they are omitted from the inefficiency distribution. Growitsch et al. (2009) found similar effects for eight European countries when including customer density in the mean of a truncated normal distributed inefficiency. In the case of Colombia, Melo and Espinosa (2005) have tested the inclusion of both density variables in the frontier and the inefficiency and have concluded about relevant effects of these variables as inefficiency drivers.

We use a translog representation of the technology for the input distance function derived in (10). The estimated model with the dynamic specification presented in (1) till (3) is the following:

$$\begin{aligned}
-\ln x_{1_{it}} = \;& \alpha_i + \textstyle\sum_{m=1}^{2} \beta_m \ln y_{m_{it}} + \beta_{m+1} \ln km_{it} + \sum_{r=1}^{2} \delta_r \ln\left(\frac{x_{r_{it}}}{x_{1_{it}}}\right) \\
& + \tfrac{1}{2} \textstyle\sum_{m=1}^{2} \sum_{n=1}^{2} \beta_{mn} \ln y_{m_{it}} \ln y_{n_{it}} + \frac{1}{2} \sum_{r=1}^{2} \sum_{s=1}^{2} \delta_{rs} \ln\left(\frac{x_{r_{it}}}{x_{1_{it}}}\right) \ln\left(\frac{x_{s_{it}}}{x_{1_{it}}}\right) \\
& + \textstyle\sum_{m=1}^{2} \sum_{r=1}^{2} \eta_{mr} \ln y_{m_{it}} \ln\left(\frac{x_{r_{it}}}{x_{1_{it}}}\right) + \kappa_1 t + \frac{1}{2} \kappa_2 t^2 + \sum_{m=1}^{2} \phi_m t \ln y_{m_{it}} \\
& + \textstyle\sum_{r=1}^{2} \varphi_r t \ln\left(\frac{x_{r_{it}}}{x_{1_{it}}}\right) - u_{it} + v_{it} \\
& \log u_{it} = \omega + \textstyle\sum_{p=1}^{2} \gamma_p z_{p_{it}} + \rho_i \log u_{i,t-1} + \xi_{it};\; \xi_{it} \sim N(0, \sigma_\xi^2);\; t = 2...T \\
& \log u_{i1} = \frac{\omega + \sum_{p=1}^{2} \gamma_p z_{p_{i1}}}{1-\rho_i} + \xi_{i1};\; \xi_{i1} \sim N\left(0, \frac{\sigma_\xi^2}{1-\rho_i^2}\right);\; t = 1.
\end{aligned} \tag{12}$$

Total expenses are used as a numeraire to accomplish linear homogeneity in inputs and cross-effects symmetry is imposed by requiring $\beta_{mn} = \beta_{nm}$ and $\delta_{rs} = \delta_{sr}$.

5. Estimation Results

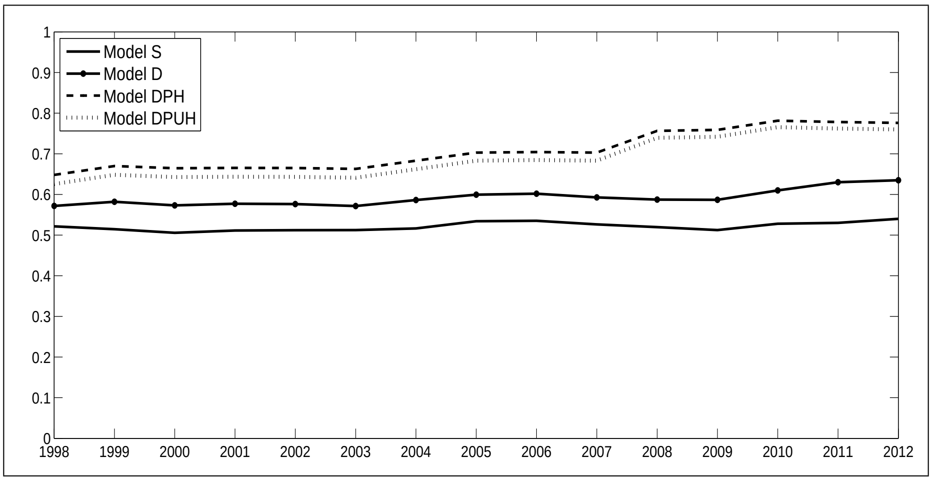
We estimate four different models derived from (12). The first three models do not account for unobserved technological heterogeneity, that is, $\alpha_i = 0$. In addition, model (S) restricts $\rho_i = 0$, so the model becomes static and the inefficiency term follows a log-normal distribution with observed heterogeneity in its location parameter. The second model (D) restricts $\rho_i = \rho$, which implies a dynamic model with fixed persistence parameter. The third model (DPH) allows heterogeneous persistence through ρ_i. Finally, the fourth model (DPUH) is the complete model in (12), which is dynamic and allows for heterogeneous persistence and unobserved heterogeneity. Results of the estimations are presented in Table 2.

Table 2: Posterior mean and standard deviation of parameter distributions

Parameters	**Model S**		**Model D**		**Model DPH**		**Model DPUH**	
	$\alpha_i = \alpha, \rho_i = 0$		$\alpha_i = \alpha, \rho_i = \rho$		$\alpha_i = \alpha, \rho_i \neq \rho$		$\alpha_i \neq \alpha, \rho_i \neq \rho$	
Parameter	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
ID function								
α	-13.4149	1.2091	-12.6924	0.7935	-11.4653	0.6624	-11.4045	0.5543
$\beta_1(\ln y_1)$	-0.1902	0.1215	-0.0379	0.0257	-0.0346	0.0219	-0.1082	0.0266
$\beta_2(\ln y_2)$	-0.0968	0.0991	-0.1200	0.0806	-0.0712	0.0530	-0.0463	0.0248
$\beta_3(\ln x_2)$	0.0115	0.0087	0.0244	0.0135	0.0060	0.0050	0.0149	0.0134
$\beta_4(\ln x_3)$	0.0116	0.0088	0.0485	0.0168	0.0232	0.0197	0.0075	0.0056
$\beta_5(\ln km)$	-0.3494	0.0739	-0.3265	0.1074	-0.1265	0.0491	-0.1413	0.0625
$\beta_6(t)$	-0.1724	0.1217	-0.0932	0.1336	-0.0616	0.0808	-0.0730	0.0684
$\beta_7(t^2)$	0.0032	0.0010	0.0046	0.0012	0.0049	0.0006	0.0050	0.0005
$\phi_1(1/2 \ln y_1^2)$	-1.0098	0.3705	-1.3391	0.5202	1.6021	0.7925	1.5440	0.6968
$\phi_2(\ln y_1 \ln y_2)$	0.4733	0.3262	0.8353	0.5289	-1.4377	0.6969	-1.3677	0.6227
$\phi_3(1/2 \ln y_2^2)$	0.1132	0.3291	-0.2584	0.5504	1.2588	0.6821	1.2503	0.6303
$\phi_4(1/2 \ln x_2^2)$	0.0868	0.0463	0.0470	0.0450	0.0105	0.0362	0.0005	0.0346
$\phi_5(\ln x_2 \ln x_3)$	-0.0951	0.0224	-0.0652	0.0321	-0.0160	0.0147	-0.0037	0.0147
$\phi_6(1/2 \ln x_3^2)$	0.0302	0.0174	0.0209	0.0194	0.0164	0.0112	0.0138	0.0124
$\delta_1(\ln y_1 \ln x_2)$	-0.2636	0.1341	-0.2488	0.1303	0.2395	0.1451	0.1911	0.1275
$\delta_2(\ln y_2 \ln x_2)$	0.4149	0.0977	0.3551	0.1001	-0.2212	0.1136	-0.1622	0.0967
$\delta_3(\ln y_1 \ln x_3)$	0.0175	0.0822	-0.0168	0.0767	-0.0375	0.0563	0.0140	0.0554
$\delta_4(\ln y_2 \ln x_3)$	-0.2235	0.0728	-0.1163	0.0623	0.0371	0.0542	0.0035	0.0525
$\kappa_1(t \ln y_1)$	0.0252	0.0211	0.0353	0.0238	0.0192	0.0157	0.0175	0.0141
$\kappa_2(t \ln y_2)$	-0.0238	0.0196	-0.0233	0.0211	-0.0142	0.0138	-0.0150	0.0126
$\kappa_3(t \ln x_2)$	-0.0063	0.0075	0.0032	0.0074	0.0020	0.0047	0.0004	0.0041
$\kappa_4(t \ln x_3)$	0.0064	0.0040	0.0045	0.0040	0.0022	0.0025	0.0025	0.0022
Inefficiency								
ω	-1.4049	0.8467	0.0205	0.0050	0.0017	0.0002	0.0028	0.0002
ρ			0.8366	0.0846	0.6532	0.0850	0.6507	0.0868
$\gamma_1(\ln z_1)$	-0.3443	0.1008	-0.0424	0.0081	-0.0317	0.0024	-0.0314	0.0168
$\gamma_2(\ln z_2)$	-0.4407	0.0838	-0.1277	0.0394	-0.1258	0.0553	-0.1009	0.0452
σ_v	0.1653	0.0315	0.1314	0.0194	0.0943	0.0017	0.0977	0.0018
σ_ϵ	0.1610	0.0517	0.0613	0.0023	0.0406	0.0038	0.0347	0.0029
Mean eff.	0.5173		0.5841		0.6478		0.6373	
SD eff.	0.1205		0.1551		0.2600		0.2420	
DIC_3	-119.12		-253.28		-339.49		-349.86	
LPS	35.79		21.06		9.74		6.53	

We observe that the more flexible is the model in terms of accounting for dynamic effects and heterogeneity, the better the values obtained for DIC_3 and LPS. Lower values for these criteria suggest better fit and predictive performance. Moreover, high inefficiency persistence is estimated by the dynamic models suggesting the presence of important adjustment costs in the Colombian distribution sector. Model D estimates around 84% of the inefficiency being transmitted from one period to the next, which is very similar to the average firm specific persistence estimated under models DPH and DPUH.[12] It can be also seen that not only is the average technical efficiency in the whole sector higher in the more flexible models, but also its dispersion. This may suggest that introducing dynamic effects and unobserved heterogeneity sources distinguishes the presence of adjustment costs and heterogeneity from technical inefficiency and also differentiates firms depending on their specific characteristics. These effects can also be observed in Figure 5, where the evolution of efficiency over time under the four models is plotted. We can also observe that the dynamic models accounting for persistence heterogeneity (DPH and DPUH) identify larger improvements in TE during the period.

Figure 5: Evolution of posterior mean TE under different models

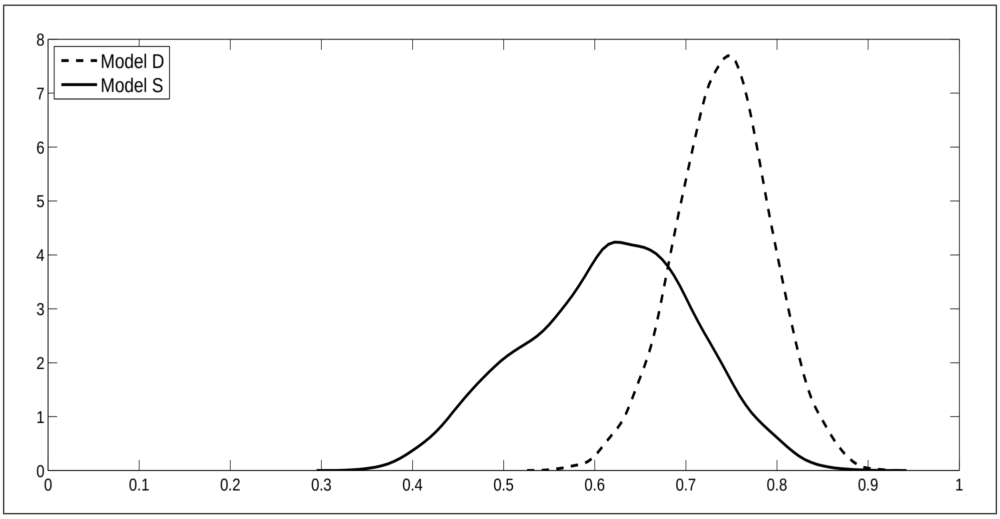


In order to understand better the effects of the different specifications on the efficiency estimates, we analyze the results at firm level and their evolution over time by comparing the models derived from (12) from the most to the least restrictive. In Figure 6, we compare the posterior efficiency distribution for a firm with median values for customer and consumption density in 2012 under static and dynamic formulations. We observe that introducing dynamic effects alter not

[12]Recently, Poudineh et al. (2014) found also very high inefficiency persistence in an application of a dynamic model to Norwegian electricity utilities.

only the location of the distribution, by estimating higher values for technical efficiency, but also that the dispersion is lower, which allows more certainty on the individual efficiency estimations.

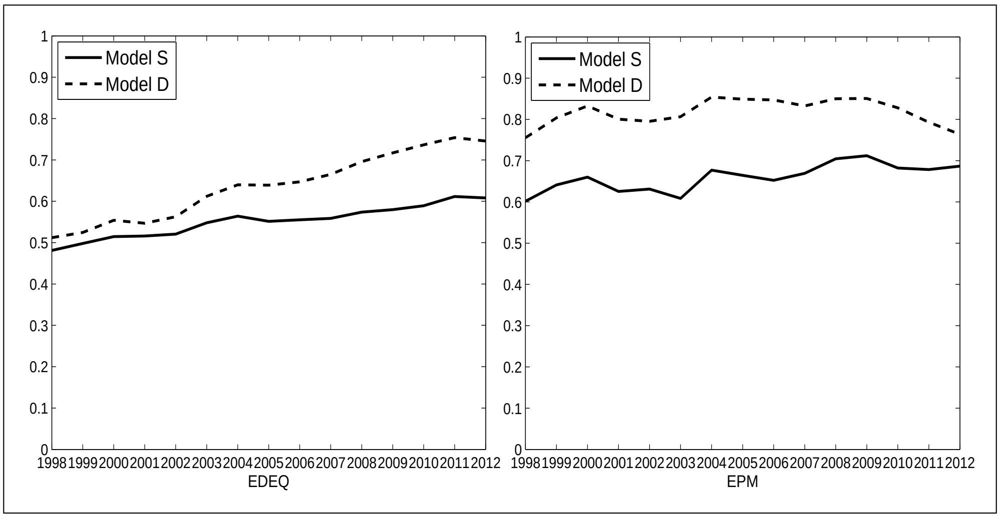
Figure 6: Posterior efficiency distribution for a representative firm in 2012



These differences in the posterior distributions also affect the estimation of the evolution of technical efficiency over time. Figure 7 presents the posterior mean efficiency estimations during the period for two firms, *Electrificadora del Quindio* (EDEQ) and *Empresas Públicas de Medellín* (EPM). We observe that for EDEQ, the dynamic specification estimates gains in technical efficiency that are not identified under the static model. This may suggest that the improvements made by this firm during the period are more important in relative terms given the presence of high adjustment costs in the sector. In the case of EPM, results imply that, given the adjustment costs faced by all firms in the sector, this firm did not improve enough to identify efficiency gains.These findings are important from the point of view of the regulator because they suggest that firms could not explain poor performance on the basis of modelled adjustment costs.

The dynamic model analyzed assumes that all distribution firms face the same adjustment costs in terms of being able to adjust the same proportion of inefficiency from one period to the next. However, firms with different characteristics may present different adjustment costs, so Model DPH allows for firm specific persistence parameters. Figure A.1 in the appendix exhibits the 95% probability intervals for the persistence estimations of every firm. Important differences in the individual posterior estimations of persistence are found, ranging from 0.31 to 0.99.

Figure 7: Evolution of posterior mean efficiencies for EDEQ and EPM



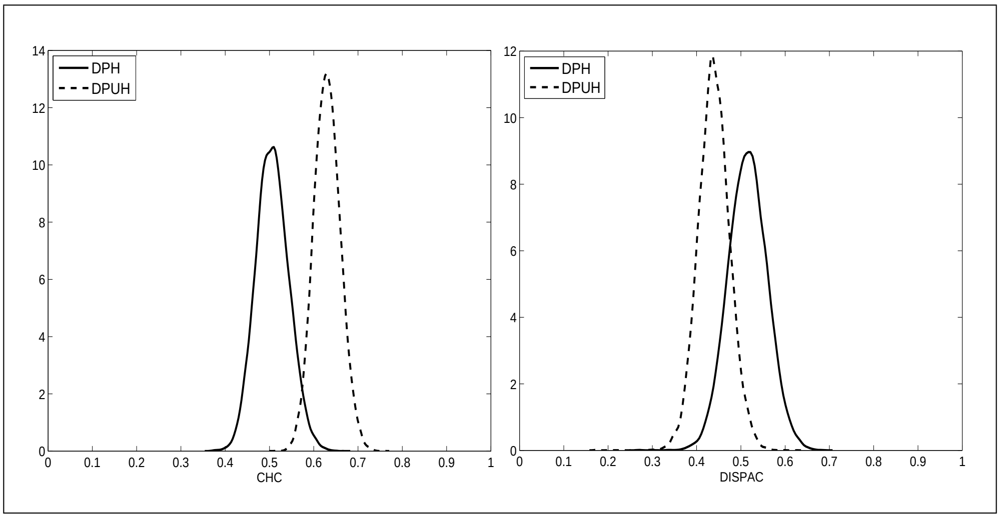
This suggests large heterogeneity in the adjustment costs of electricity distributors that could be related to certain characteristics of these firms and the incentive regulation that they have faced, as is discussed further below. These findings illustrate the importance of accounting for firm specific persistence parameters, which have implications for the efficiency estimations and their evolution over time as is observed in Figure 5.

Finally, the full model in (12) is estimated accounting not only for heterogeneous persistence but also for unobserved technological heterogeneity. Although the evolution of efficiency is similar to that estimated under Model DPH (see Figure 5), Model DPUH identifies unobserved firm effects that distinguish them in terms of the estimated efficiency. Figure 8 compares the posterior efficiency distributions for a low and a high efficient firm under models DPH and DPUH.[13] We observe that their posterior distributions move and shrink, implying a reduction in the uncertainty of the individual estimations. It is also important to notice that estimations of firm specific persistence parameters do not present important changes compared to those obtained in Model DPH.

Focusing on our preferred model (DPUH), we can identify some links between differences in adjustment costs and firm characteristics. We plot in Figure 9 the average posterior distributions of the persistence parameter by groups of firms. In general, we observe that firms with a higher proportion of rural and small

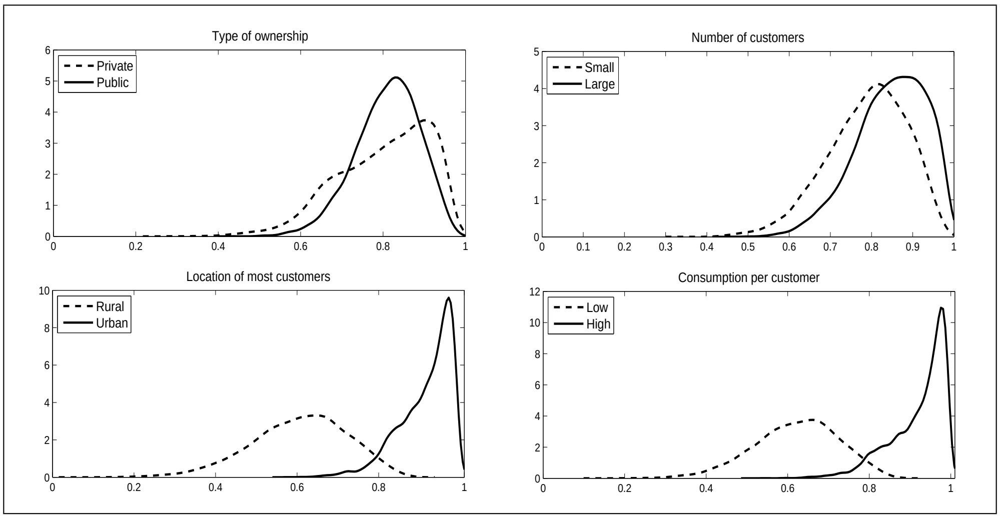
[13]The selected firms are *Central Hidroeléctrica de Caldas* (CHC) and *Empresa Distribuidora del Pacífico* (DISPAC).

Figure 8: Posterior efficiency distributions for CHC and DISPAC



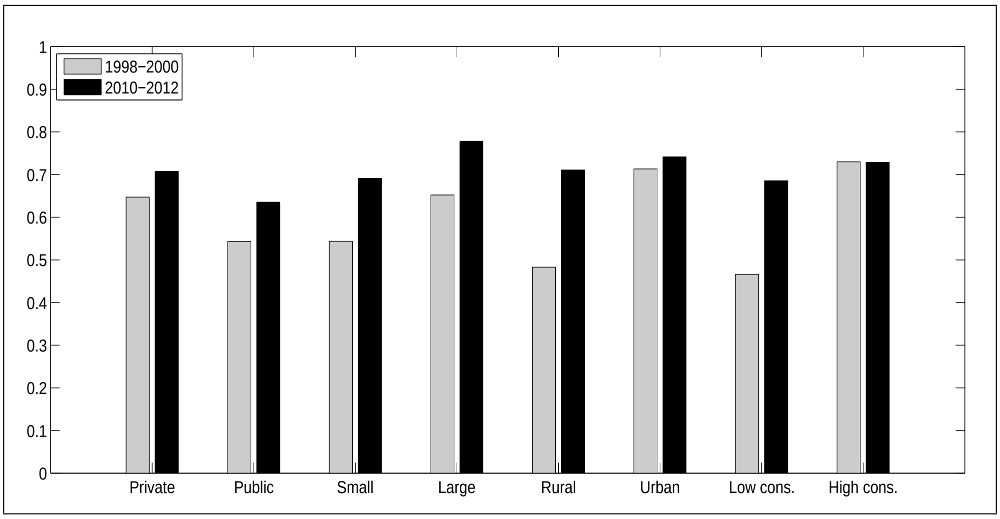
customers present lower adjustment costs than those which are mainly urban and serve larger customers. In contrast, by type of ownership and number of customers, no major differences can be observed between firms in terms of inefficiency persistence. This would imply that rural firms and those with small customers have been able to adapt more easily towards optimal performance.

Figure 9: Average posterior distribution of ρ_i by groups of firms



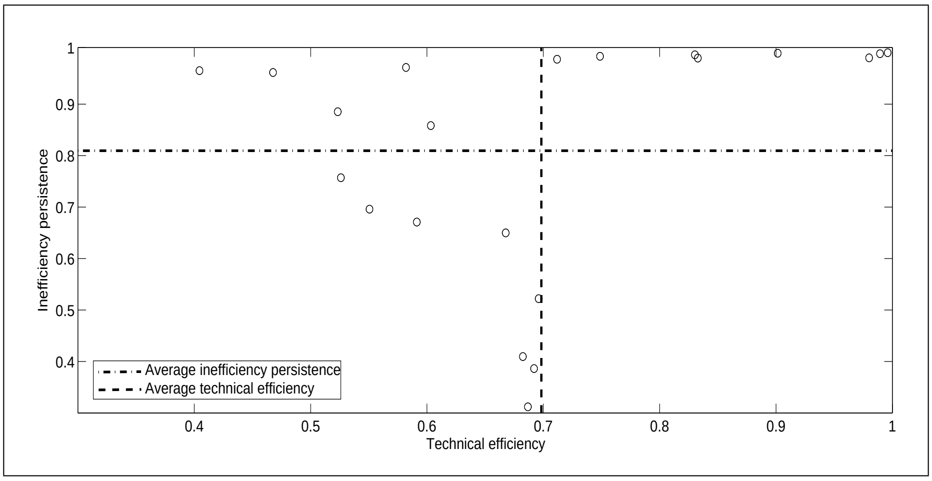
Differences between groups of Colombian utilities are also observed in the efficiency estimations and their evolution over time. Figure 10 exhibits the change in the average technical efficiency during the period by groups of firms. We observe that private distributors in Colombia are more efficient than public firms; however, both types of firms have presented increases in technical efficiency during the period. Something similar is observed in terms of the number of customers: large firms are more efficient than small companies but the efficiency gains are not very different between the two groups. Finally, firms operating mainly in rural markets and serving small customers are found to present large increases in technical efficiency while those in urban locations and serving large users have barely presented changes. These firms are also those exhibiting lower inefficiency persistence and higher scope for improvement. This has allowed rural companies and firms with more small customers to catch up with their counterparts in terms of efficiency.

Figure 10: Change in the average posterior mean efficiency by groups of firms during the period



Results on inefficiency persistence may also help the regulator to identify those firms where more attention is required. Figure 11 plots the posterior mean inefficiency persistence for every firm against their average posterior TE in the period 2010-2012. We observe not only that most of the firms present very high inefficiency persistence, but also that some of them are highly inefficient. This would imply that, in the absence of different incentives, these firms could become stuck at high inefficiency levels. In Table A.1 these results are presented for each firm along with other firm characteristics.

Figure 11: Inefficiency persistence and technical efficiency by firm



In general, efficiency in the Colombian distribution sector has been found to exhibit improvements. However, efficiency gains can only be clearly identified in the last five years. As previously described, this period coincides with the main reductions in the length of interruptions and energy losses, and the highest rates of increase in the number of customers. Although very preliminary, these results may favour the recent incentive regulation policies for improving quality of service and reducing energy losses. Nevertheless, the last five years have also been characterized by important increases in the electricity tariff for regulated users. As presented in Section 2 not only the tariff per kWh has presented important increases during the period, but also the proportion derived from distribution costs has increased relative to the other tariff components. This implies that Colombian users are now receiving a better service but that they are paying the costs of these improvements via higher tariffs. These results suggest that incorporating willingness to pay into the efficiency analysis of the Colombian distribution sector would be of interest. Certainly, in a recent study Yu et al. (2009) have found the social cost of outages to be considerably higher than the utilities' incentives in an efficiency analysis of UK distributors.

Finally, our findings may be helpful for the Colombian regulator and the Ministry of Mines and Energy, which have been recently working on the composition of groups of distribution firms that would share the same prices.[14] These groups have been formed following geographical criteria. However, our results suggest that the design of these groups should mainly consider the inefficiency persistence level of

[14]CREG resolution 058 of 2008 and Ministry of Mines and Energy resolutions: 182306 of 2009, 181347 of 2010, 180686 of 2011 and 180574 of 2012.

each firm and their characteristics in terms of customer density and consumption density.

6. Conclusions

The electricity reform in Colombia introduced the separation of activities in the electricity sector and set the conditions for privatization and competition. In general, the reform has had positive effects on the ability of the sector to overcome extreme weather conditions and meet demand requirements. However, for distribution companies, competition and privatization have been slow processes and the users did not benefit from improvements in service quality for the first ten years after the reform. In fact, previous studies measuring consequences of the reform on efficiency have not found evidence of improvements, although large differences in efficiency have been found among firms.

This may indicate the presence of high adjustment costs in the sector in Colombia and important heterogeneity factors among distributors. We include these conditions in a stochastic frontier model that accounts for dynamic effects and unobserved heterogeneity. Our findings suggest high inefficiency persistence in the sector that could be related to adjustment costs and inadequate incentive regulation. However, important differences are found among firms. In particular, firms operating mainly in rural markets and serving small customers present lower adjustment costs than firms with the opposite characteristics. This condition has allowed these firms to catch up urban firms and firms serving large users, which have exhibited higher technical efficiency during the whole period. In fact, customer density and consumption density are found to be important inefficiency drivers in the sector and unobserved heterogeneity sources to be relevant in distinguishing heterogeneity from inefficiency and identifying differences among firms.

In particular, firms exhibiting high inefficiency persistence and low technical efficiency should draw the attention of the regulator because they could be stuck at high inefficiency levels. Overall, our findings may be helpful for the regulator and the Ministry of Mines and Energy in Colombia in their current composition of pricing groups. Although, a geographical criterion has been followed, our results suggest that inefficiency persistence, customer density and consumption density should be considered as the main criteria when identifying groups of distribution firms for regulatory purposes.

The evolution of efficiency in the sector is found to be very stable and no major changes can be identified until 2008. Since then, gains in technical efficiency are observed, suggesting that net benefits have been derived from recent incentive regulations introduced for reducing length of interruptions and energy losses. However, the tariff paid by users also evidenced high growth during the last five years and the proportion of the tariff assigned to the distribution component showed important increases from 2010. This suggests that incorporating customer willingness to pay into the efficiency analysis of Colombian utilities would be an interesting area for future research.

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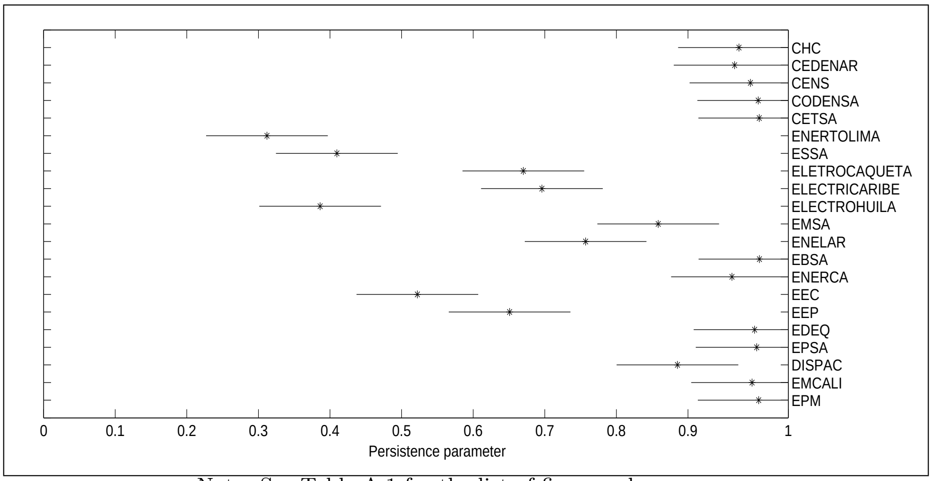
Appendix

Figure A.1: 95% probability intervals for firm specific persistence parameters under Model DPH



Note: See Table A.1 for the list of firms and acronyms

Table A.1: Posterior mean estimations of TE and persistence under model DPUH, customer density and consumption density by firm

Firm	**Average TE 1998-2012**	**Inefficiency persistence**	**Cust. Dens. (users/km)**	**Cons. Dens. (kWh/user)**
Central Hidroeléctrica de Caldas S.A. E.S.P. (CHC)	0.5520	0.9713	31199	341
Centrales Eléctricas de Nariño S.A. E.S.P. (CEDENAR)	0.3045	0.9651	23072	474
Centrales Eléctricas del Norte de Santander S.A. E.S.P. (CENSA)	0.6118	0.9872	13996	94
CODENSA S.A. E.S.P. (CODENSA)	0.9894	0.9981	47207	830
Compañía de Electricidad de Tuluá S.A. E.S.P. (CETSA)	0.9892	0.9996	47355	2116
Compañía Energética del Tolima S.A E.S.P (ENERTOLIMA)	0.4667	0.3120	13205	77
Electrificadora de Santander S.A. E.S.P. (ESSA)	0.4624	0.4096	33639	152
Electrificadora del Caquetá S.A. E.S.P. (ELECTROCAQUETA)	0.4977	0.6700	20120	209
Electrificadora del Caribe S.A. E.S.P. (ELECTRICARIBE)	0.4506	0.6960	40553	336
Electrificadora del Huila S.A. E.S.P. (ELECTROHUILA)	0.4720	0.3862	16663	94
Electrificadora del Meta S.A. E.S.P. (EMSA)	0.5033	0.8584	39699	261
Empresa de Energía de Arauca E.S.P (ENELAR)	0.4260	0.7571	21334	981
Empresa de Energía de Boyacá S.A. E.S.P. (EBSA)	0.9960	0.9999	21356	237
Empresa de Energía de Casanare S.A. E.S.P. (ENERCA)	0.3677	0.9615	13352	110
Empresa de Energía de Cundinamarca S.A. ESP (EEC)	0.4760	0.5221	42579	153
Empresa de Energía de Pereira S.A. E.S.P. (EEP)	0.4913	0.6509	21193	299
Empresa de Energía del Quindío S.A.E.S.P. (EDEQ)	0.6487	0.9930	33337	452
Empresa de Energía del Pacífico S.A. E.S.P. (EPSA)	0.7303	0.9959	50925	269
Empresa Distribuidora del Pacífico S.A. E.S.P (DISPAC)	0.4233	0.8853	22464	475
Empresas Municipales de Cali E.I.C.E E.S.P (EMCALI)	0.7328	0.9895	61707	2331
Empresas Públicas de Medellín E.S.P. (EPM)	0.9015	0.9988	82735	389