Observed and unobserved heterogeneity in stochastic frontier models

Maria Kopsakangas-Savolainen* and Rauli Svento**

10.3.08

Abstract

Stochastic frontier modeling has proceeded rapidly recently. Heterogeneity modeling internalized into frontier estimation has opened up new promising possibilities. In this paper we study different ways of considering heterogeneity in stochastic frontier models. It is possible to take heterogeneity into account by including of those effects in the mean and/or variance of the distribution of inefficiency (observed heterogeneity) or by randomizing some parameters of the stochastic frontier model (unobserved heterogeneity). We compare the advantages of heterogeneity including models over the conventional random effects models for measuring the cost efficiency of electricity distribution utilities. Our results indicate that in all heterogeneity accounting models mean inefficiency decreases significantly compared to the basic random effects model. According to our results randomizing some of the parameters seems to help to capture the unobserved heterogeneity and hence this kind of firm specific heterogeneity does not appear as inefficiency in our estimation results. Notable is that the model which accounts observed heterogeneity and the models which account unobserved heterogeneity produce clearly different rank orders.

Keywords: Cost efficiency, heterogeneity, electricity distribution, benchmarking, random parameter

JEL Classifications: C13, C23, D24, L51, L94

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* Department of Economics, University of Oulu, Finland. email:maria.kopsakangas@oulu.fi

** Department of Economics, University of Oulu, Finland. e-mail: rauli.svento@oulu.fi

1. Introduction

In many countries the electricity supply industry has been deregulated and restructured during the last decade. Restructuring has included introduction of competition to the supply of electricity but due to the natural monopoly characteristics distribution of electricity has remained in regional monopolies. Many countries have carried out regulatory reforms in the power distribution sector in order to achieve efficiency improvements. Benchmarking analysis has been seen as a very important tool for the regulator in comparing costs of the individual companies. Hattori, Jamasb and Pollitt (2005) have studied the performance of electricity distribution in the UK and Japan by using both of the main benchmarking methods, namely the data envelopment analysis (DEA) and stochastic frontier analysis (SFA).[1]

Electricity distribution networks are characterized by network-specific features from which some are observable while the others can be seen as unobservable heterogeneity. Heterogeneity depends on different shapes of network, on woodiness of the network area, on the snow load in network area etc. This kind of heterogeneity clearly affects the costs which are beyond the control of the managers.

If that kind of heterogeneity is not accounted for it can create considerable bias in the inefficiency estimates. There have been, however, rapid developments in various forms of econometric methods during the past two decades which can, especially if we have panel data, identify the unobserved heterogeneity. The literature of panel data models in stochastic frontier analysis starts form Pitt and Lee (1981) and is followed by Schmidt and Sickles (1984) among others. During the last few years many authors (see e.g. Jha and Singh (2001), and Dalen and Gomez-Lobo (2003)) have included also exogenous variables in the model to explain better the inefficiency component in the model.[2]

In these conventional fixed and random effect panel data models firm-specific heterogeneity can be taken into account but it is still more or less considered as inefficiency. Farsi and Filippini (2004) studied cost-efficiency with panel data models in the Swiss electricity distribution utilities. In that paper, they utilised original random effects and fixed effects models and reported that different model specifications could lead to different individual efficiency estimates.

[1] DEA and SFA methods have been used also in various ways of measuring productivity efficiency (see e.g. Hjalmarsson et al. (1996), Lee (2005), Odeck (2007)).
[2] See Kumbhakar and Lovell (2000) for an extensive survey of stochastic frontier models.

Kopsakangas-Savolainen and Svento (2008) utilised the variations of conventional random effects models in measuring cost-effectiveness of Finnish electricity distribution utilities. According to their results it seems that even though part or the heterogeneity can be explained by network characteristic variables the unobserved heterogeneity still appears as inefficiency in the conventional random effects models. We study the question of observable heterogeneity by including heterogeneity explaining covariates in the mean and of the inefficiency distribution.

The heterogeneity variable we use is the load factor which is defined as the ratio of utility's average load on its peak load. It is clearly higher in urban areas than in rural areas. This is because Finland is sparsely inhabited (15 persons/km^2), with most of the population located in the south. In the sparsely inhabited areas the capacity requirement for the peak load is high compared to the average load of the network. In these areas capacity has to be sized according to high demand peaks which usually occur at the winter season when temperature fells occasionally very low (-50^{o}C). In these sparsely inhabited areas also the number of customers is clearly lower than in the urban areas (which causes extra costs to the distribution companies which are beyond the managerial effort). These sparsely inhabited areas are also highly forested with heavy winter snow-fall [3] which clearly affects the operational environment of the distribution utilities.

Greene (2005) proposed an approach that integrates an additional stochastic term in both fixed and random effects models in order to distinguish unobserved heterogeneities from cost inefficiencies. Farsi, Filippini and Greene (2005) applied stochastic frontier models in cost efficiency measuring to the electricity distribution sector. In that paper they focus on three panel data models: GLS model (Schmidt and Sickles), MLE model (Pitt and Lee (1981), and the true random effects (TRE) model (Greene (2005)). According to their results it is very important to model the heterogeneity and inefficiency separately. In their paper (2006) Farsi, Filippini and Greene compared different stochastic frontier models in very comprehensive and detailed manner. It seems that the true random effects model gives significantly lower inefficiency values than the other models they utilised. However, they point out a clear shortcoming of that model, namely that the firm-specific heterogeneity terms are assumed to be uncorrelated with the explanatory variables. Farsi, Filippini and Kuenzle (2006) have found similar results connected to different model specifications in measuring regional bus companies' cost efficiencies. According

[3] Heavy snow-fall causes frequent interruptions in electricity distribution.

to their results the true random effects model seems to give much more plausible results than the other model specifications. In their paper concerning the efficiency of Swiss gas distribution sector Farsi, Filippini and Keunzle pointed out the importance of taking into account the output characteristics (such as customer density and network size) in the cost efficiency measuring process.

To overcome the well known problems related to the basic fixed effect (FE) model (Schmidt and Sickles 1984), especially the fact that in the FE model any time invariant unobserved heterogeneity appears in the inefficiency component, Greene (2005) proposes an extended model which he called the “true fixed effects model” (TFE) to underline the difference with the FE framework commonly used. In the TFE model, fixed effects represent the unobserved heterogeneity, not the inefficiency as in the original FE model. The basic difference between the true fixed effects model and true random effects model is that in TFE model any correlation among the effects and explanatory variables are allowed.

The purpose of this paper is to study the potential advantages of the heterogeneity accounting stochastic frontier models over the conventional random effects models. We take heterogeneity into account both through the inclusion of those effects in the mean of the distribution of inefficiency (observed heterogeneity) and by randomizing some parameters of the stochastic frontier model (unobserved heterogeneity). We also estimate a combined model where we have randomized the frontier constant term and at the same time explained the mean of the inefficiency distribution by a covariate (load factor). As far as we know this kind of combined model has not been presented in the literature before. In addition we also estimate the “true fixed effects model” (see Greene 2005), where the unobserved heterogeneity is represented by the individual fixed effects. The models are estimated for 76 Finnish electricity distribution utilities. Our basic result is that random parameter estimation of stochastic cost frontiers is a more robust and concise way of modeling inefficiency than the one used in basic random effects modeling. That is why it can be recommended to the regulators to be included in their tool-kits. It is however notable that (especially) the true fixed effects model may be overspecified so that if there exists persistent inefficiency it is appearing completely in the firm specific constant term of this model. This means that if the earlier fixed effects form tends to overestimate the inefficiency component, it is possible that this form will underestimate it (see Greene 2004).

The rest of the paper is organized as follows: Section 2 gives an introduction of the heterogeneity in stochastic frontier models and in section 3 the data is presented. The estimated model specifications and the estimation technique is described in section 4. Section 5 gives the estimation results and provides brief discussion on their implications. Section 6 summarizes the findings.

2. Heterogeneity in stochastic frontier models

2.1. Observed heterogeneity

The first model that we use is the basic random effects (RE) specification proposed by Pitt and Lee (1981). In this model it is assumed that the firm specific inefficiency (in proportional terms) is the same every year

$$c_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it} + u_i \tag{1}$$

where u_i and v_{it} are independent and, moreover, u_i is independent of x_{it}. Equation (1) can be estimated by maximum likelihood.

There are some recognized problems connected to this model. One of them is that this model not only absorbs all unmeasured heterogeneity in u_i, but it also assumes that inefficiency is uncorrelated with included variables (Greene 2005). This problem can be reduced through the inclusion of those effects in the mean and/or variance of the distribution of u_i or to the variance of the distribution of v_i. Another problem connected to the basic RE model is that the inefficiency term is time invariant.

While in the true fixed effects model the unobserved heterogeneity is pushed into the cost function in the expanded random effect models the observed heterogeneity[4] is resided to the mean of the inefficiency distribution. The load factor (LF) is used as the observable heterogeneity variable. We have selected this variable because it accounts well the differences in the operational environments among distribution utilities. The variation of the load factor is quite significant

[4] See Greene (2004) for incorporating measured heterogeneity in the production function.

among different companies. This variation is due to the fact that in the sparsely inhabited areas (located mostly in the northern and eastern parts of Finland) requirement for the peak load network capacity is high compared to the capacity required for the average load. It is also a fact that these areas, where the load factor is relatively small, are the same areas where the land is highly forested[5] (and thus also the snow burden is much higher in the forested areas than in the not forested areas).

This model specification is called REH in the following. It can be written as

$$
\begin{aligned}
&c_{it} = \alpha + \boldsymbol{\beta}' \mathbf{x}_{\mathbf{it}} + v_{it} + u_{i,} \quad v_{it} = N(0, \sigma_v^2), \quad u_i = N^+\left(\mu_i, \sigma_u^2\right), \\
&\mu_i = \delta_0 + \delta_1 h_i ,
\end{aligned}
\tag{2}
$$

where h_i is heterogeneity summarising covariate (LF) explaining the mean of the inefficiency distribution and δ_0 and δ_1 are new parameters to be estimated. One problem connected to this specification is that even though the observed heterogeneity is now modelled out from the inefficiency distribution it does not recognise the unobserved heterogeneity which still remains in u_i. However, the second problem of the basic RE model is now reduced by allowing correlation between inefficiency explaining variables and frontier explaining variables through inclusion of the heterogeneity characterising covariate. Another positive feature related to this model is that it enables a more precise estimation of the frontier.

It is important to note that the REH model accounts only for the observed heterogeneity and it is difficult to evaluate beforehand any kind of superiority of these models in inefficiency measurements. One must also be careful in making interpretations, as the unobserved heterogeneity still remains in the inefficiency distributions.

2.2. Unobserved heterogeneity

Fixed effects model

To overcome the well known problems related to the basic fixed effect (FE) model (Schmidt and Sickles 1984), especially the fact that in the FE model any time invariant unobserved heterogeneity appears in the inefficiency component, Greene (2005) proposes the following model where firm specific constant terms are placed in the stochastic frontier

[5] The share of forested area in Finland is 68%. This means that Finland is the most forested nation/area in Europe.

$$c_{it} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it} + u_{it} \qquad i = 1,....n.\,; t = 1,....T.. \tag{3}$$

where c_{it} are the costs to be explained, x_{it} are the explaining variables, α and β are the parameters to be estimated, u_{it} is the inefficiency term and v_{it} is the error term capturing the effect of noise. Greene refers to this extended model as "true fixed effects model" (TFE) to underline the difference with the FE framework commonly used. In the TFE model, fixed effects represent the unobserved heterogeneity, not the inefficiency as in the original FE model. This approach will become impractical, however, as the number of firms in the sample, and the number of parameters in the model, becomes large (see Greene 2005). Greene shows, by using simulated samples, that although the fixed effects may be largely biased, as far as the structural parameters and inefficiency estimates are concerned, the model performs reasonably well. The model can be fit by maximum likelihood.

Random effects modelling

Greene (2005) proposes an extension also to the random effects model which is called the true random effects model (TRE). This model specification is

$$c_{it} = \alpha + \boldsymbol{\beta}'\mathrm{x}_{it} + w_i + v_{it} + u_{it}, \tag{4}$$

where w_i is the random firm specific effect and v_{it} and u_{it} are the symmetric and the one sided components specified earlier. At first, this would seem to be a regression model with three part disturbance, which raises questions of identification. However the model actually has a two part composed error:

$$c_{it} = \alpha + \boldsymbol{\beta}'\mathrm{x}_{it} + w_i + \varepsilon_{it} \tag{5}$$

where $\varepsilon_{it} = v_{it} + u_{it}$. This is an ordinary random effects model with one exception, now the time varying component has the asymmetric distribution. The conditional (on w_i) density is that of the compound disturbance in the stochastic frontier model

$$f(\varepsilon_{it}) = \frac{\Phi(-\varepsilon_{it}\lambda/\sigma)}{\Phi(0)}\frac{1}{\sigma}\phi(\frac{\varepsilon_{it}}{\sigma}) \tag{6}$$

where $\lambda = \sigma_u/\sigma_v$ and $\sigma = \sqrt{\sigma_v^2 + \sigma_u^2}$.

Thus this is actually a random effects model in which the time varying component does not have a normal distribution, though w_i may (Greene 2005).

This model can be estimated by maximum likelihood (though it is necessary to integrate the common term out of the likelihood function).[6] This model can also be rewritten as a stochastic frontier with a firm specific random constant term

$$c_{it} = (\alpha + w_i) + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it} + u_{it} \tag{7}$$

Now the additional firm specific random effect *(α+w_i)* is included to represent the unobserved heterogeneity among firms. It is thus assumed that the unobserved cost differences across firms that remain constant over time are driven by unobserved characteristics rather than by inefficiency.

2.3. Observed and unobserved heterogeneity combined

In the model TRE all time invariant inefficiency is interpreted as firm specific heterogeneity and this part is now captured to the frontier and thus it does not appear as inefficiency anymore. This part of "inefficiency" is assumed to be caused by such time invariant network characteristics (unobserved) which are beyond the firm's and its manager's control and hence it is seen that this part is rather firm specific heterogeneity than real inefficiency.

In the model REH all unobserved heterogeneity still appears as inefficiency. Now, however, the observed heterogeneity is taken into account through inclusion of some covariate to explain the mean of inefficiency distribution. It is possible to take both the unobserved and observed heterogeneity into account at the same time by combining the models TRE and REH. This model can be written as.

$$c_{it} = (\alpha + w_i) + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it} + u_{it} \tag{8}$$

$$v_{it} = N(0,\sigma_v^2), \quad u_i = N^+\left(\mu_i, \sigma_u^2\right),$$
$$\mu_i = \delta_0 + \delta_1 h_i,$$

Again we use the covariate load factor (LF) to explain the mean of the inefficiency distribution.

[6] There is no closed form for the density of the compound disturbance, but the integration can be done by quadrature or by simulation (see Greene 2005).

3. The data

The data used in this study consist of a panel of 76 electricity distribution utilities in Finland. It covers the 6-year period from 1997 to 2002. The data, which is unbalanced panel data, is collected from the statistics of the Finnish Electricity Market Authority.[7] Distribution utilities which are owned by industrial enterprises are excluded from this study. The relative size of the distribution utilities varies significantly which may explain part of the quite large variations in costs.

Table 1 gives the summary of descriptive statistics of the variables used in this paper. We have used constant Euro prices by converting all money values to the year 1997 by using the retail price index. Costs (c) are expressed as average costs calculated as total annual costs per kWh delivered. This includes the delivery to the final customers and the delivery to the networks. The costs of losses are excluded because of the lack of reliable data. Annual output (y) is measured in Gwh and as can be seen from Table 1 it varies quite significantly since the range runs from very small local utilities to the relative large utilities operating on urban areas. Total network length (TNL) is measured as the total length of the network in kilometres (including 0,4kV, 6-70kV and 110 kV networks). Annual labour price p_l is calculated by dividing total annual labour cost by the average number of employees. The capital price p_k is calculated by dividing the annual capital expenditures by the value of capital stock. Total capital expenditure is calculated as residual costs. We have approximated the capital stock by the present value of the network. The present value of the network is calculated using the information of annual inventories and replacement value of the network. The price of the input power p_p is in most cases computational.[8] This is particularly the case when the distribution utility receives part of its delivered energy directly from the local generator and purchases only part of its total delivered energy. Load Factor (LF) is the ratio of the average load supplied during a designated period to the peak load occurring in that period, in kilowatts. Simply, the load factor is the actual amount of kilowatt-hours delivered on a

[7] The data is available in the address www.energiamarkkinavirasto.fi

[8] The input price is computed when distribution utility purchases only part of its delivered energy. The calculations are based on the market place payment, payment to the other companies' network and on the relative share of the received power and delivered power. It is important to correct the input price when only part of the delivered electricity is purchased. Otherwise it distorts the cost structure of these companies.

system in a designated period of time as opposed to the total possible kilowatt-hours that could be delivered on a system in a designated period of time.[9]

Table 1 Descriptive statistics (456 observations)

	Mean	Standard Deviation	Minimum	Maximum
Total annual costs (v)per kWh output (cents)	1.74	.40	.77	2.97
Annual output (y) in GWh	433.47	727.87	11.83	5825.90
Number of customers (CU)	27494	42784	1109	324197
Load Factor (LF)	0.499	.773E-01	.191	.866
Annual labour price (p_l) per employee (1000€)	28.39	7.75	8.14	53.00
Capital price (p_k) (1000€)	.103	.058	.020	.353
Price of input power (p_p) per kWh	.36	.14	.09	1.06

[9] Utilities are generally interested in increasing load factors on their systems. A high load factor indicates high usage of the system's equipment and is a measure of efficiency. High load factor customers are normally very desirable from a utility's point of view. Using a year as the designated period, the load factor is calculated by dividing the kilowatt-hours delivered during the year by the peak load for the year times the total number or hours during the year.

4. Estimated model specifications and description of the estimation

We estimate the four modifications of the models presented in chapter 3.2 by using Cobb-Douglas specifications. Assuming that the deterministic cost frontier takes the log-linear Cobb-Douglas form the stochastic cost frontier model can for the TFE and RE models be written as[10]

$$\ln c_i = \beta_0 + \beta_y \ln y_i + \beta_{LF} \ln LF_i + \beta_{CU} \ln CU_i + \beta_l \ln p_{li} + \beta_k \ln p_{ki} + \beta_T T + v_{it} + u_i , \qquad (9)$$

where T refers to time which is expected to capture possible technical change.

Linear homogeneity of cost frontier in input prices can be attained through the reformulation

$$\ln\left(\frac{c_i}{p_{pi}}\right) = \beta_0 + \beta_y \ln y_i + \beta_{LF} \ln LF_i + \beta_{CU} \ln CU_i + \beta_l \ln\left(\frac{p_{li}}{p_{pi}}\right) + \beta_k \ln\left(\frac{p_{ki}}{p_{pi}}\right) + \beta_t T + v_{it} + u_i \quad (10)$$

The total annual costs per kwh are explained by distributed kilowatts (y), load factor (LF) number of customers (CU) and labour and capital prices (p_L, p_K).

Our benchmark model is Model 16 which is the basic random effects (RE) model. In Model 16 the random terms v and u are expected to be normally and half normally distributed. The inefficiency term (u) is time invariant in this model specification. The first of the estimated models which accounts heterogeneity (observed) is the RE model extended by the inclusion of a heterogeneity component into the mean of the distribution of u_i. We call this model as REH model. Model TRE is the random parameter version of the RE model. Now, however, the inefficiency term (u) is time variant. In the TRE model a firm specific random constant term is used. This model specification is what Greene (2005) calls the true random effects model. Last model estimated is the True fixed effect model (TFE) proposed by Greene (2005).

The estimated model specifications are

[10] In TFE model also u_i is time dependent.

RE model

$$\ln c_{it} = \alpha + \beta_y \ln y_{it} + \beta_{LF} \ln LF_{it} + \beta_{CU} \ln CU_{it} + \beta_l \ln p_{Lit} + \beta_k \ln p_{Kit} + \beta_t T + v_{it} + u_i \qquad (11)$$

REH model

$$\begin{aligned} &\ln c_{it} = \alpha + \beta_y \ln y_{it} + \beta_{CU} \ln CU_{it} + \beta_l \ln p_{Lit} + \beta_k \ln p_{Kit} + \beta_t T + v_{it} + u_{it} \\ &v_{it} = N(0, \sigma_v^2), \quad u_i = N^+\left(\mu_i, \sigma_u^2\right), \\ &\mu_i = \delta_0 + \delta_1 \ln LF_{it}, \end{aligned} \qquad (12)$$

TRE model

$$\ln c_{it} = (\alpha + w_i) + \beta_y \ln y_{it} + \beta_{LF} \ln LF_{it} + \beta_{CU} \ln CU_{it} + \beta_l \ln p_{Lit} + \beta_k \ln p_{Kit} + \beta_t T + v_{it} + u_{it} \qquad (13)$$

TFE model

$$c_{it} = \alpha_i + \beta_y \ln y_{it} + \beta_{LF} \ln LF_{it} + \beta_{CU} \ln CU_{it} + \beta_l \ln p_{Lit} + \beta_k \ln p_{Kit} + \beta_t T + v_{it} + u_{it} \qquad (14)$$

TRE&REH model

$$c_{it} = \alpha_i + \beta_y \ln y_{it} + \beta_{LF} \ln LF_{it} + \beta_{CU} \ln CU_{it} + \beta_l \ln p_{Lit} + \beta_k \ln p_{Kit} + \beta_t T + v_{it} + u_{it} \qquad (15)$$

$$\begin{aligned} &u_i = N^+\left(\mu_i, \sigma_u^2\right), \\ &\mu_i = \delta_0 + \delta_1 \ln LF_{it}, \end{aligned}$$

5. Results

In Table 2 results for these estimations are presented.[11] The endogenous explained variable is total annual costs per kWh in 1997 cents. The normalising price divider is the input power price p_P.

[11] We have used LIMDEP 8.0 in all estimations (see Greene 2002).

The first observation on the estimation results is that all coefficients of the frontier are highly significant[12] and have expected signs. Both price effects have positive signs in the all model specifications and the capital price effect is larger in absolute terms in all other models than in the TFE model. The high capital price estimates are understandable due to capital intensity of distribution networks. The sign of output (y) estimator is negative in all specifications which is expected since the explained variable is total costs per kWh. As the distributed quantity increases the unit costs decrease up to the point of minimum efficient scale. Also the sign of the time estimate is negative. This indicates that there has been technological development which has decreased the total unit costs.

It is also notable that in the basic random effects model (RE) the constant term is considerably smaller than the corresponding averages from the REH specification. This being the case the basic RE model estimates the frontier to be down to the left compared to the extended RE model. The estimate of LF is significantly smaller in REH model than in other specifications. The other parameter estimates are relatively close to each other.

The variance parameter of the underlying distribution of u_i, $\sigma_{u,}$ is estimated as .353 (see Table 3) in basic random effects model (RE). In the extended version of RE (REH!) as well as in the randomized version TRE and TFE and in the combined model TRE&REH counterparts are .150, .096, .101 and .106. These point out that some of the variation in the inefficiency in the original RE model can be explained as heterogeneity. Based on this notification we can expect the estimated inefficiencies to diminish. According to BIC-criteria it seems that the model which accounts both the observed and unobserved heterogeneity at the same time i.e. the combined model TRE&REH fits the data best.

[12] Except LF in the RE model.

Tble 2. Cost frontier parameters of models 1 – 5

	RE		REH		TRE		TFE		TRE&REH	
	Coeff.	Std.er	Coeff	Std.er	Coeff.	Std.er	Coeff.	Std.er	Coeff.	Std.er
Constant	-1.614	.272	-2.326	.126+07	-1.484	.049			-1.079	.069
lny	-.647	.053	-.657	.050	-.703	.010	-.595	.018	-.670	.013
LnCU	.584	.054	.603	.052	.644	.010	.569	.016	.582	.014
LnLF[13]	-057	.050	-2.550	.675	-.032	.014	-.352	.033	.034	.019
$\ln p_l$	.297	.008	.288	.007	.300	.004	.445	.014	.321	.006
$\ln p_k$	.386	.009	.394	.009	.402	.003	.277	.012	.397	.005
T	-.014	.002	-.014	.002	.015	.001	-.017	.005	-.016	.001
Scale par. for distr.[14]					.193	.003			.151	.003
Log likelihood	389.40		413.52		416.79		302.60		421.73	
N	419		419		419		419		419	
BIC-criteria[15]	-736		-779		-791		-569		-801	

[13] In the model REH this is refers to the third equation in model (17).
[14] Scale parameter for distributions of random parameters.
[15] BIC=-2*logL+Q*logN, where Q is the number of parameters.

In Table 3 we present statistics of inefficiency scores. The scores represent the percentage deviation from a minimum level that would have been incurred if the company had operated as best-practice (or cost efficient) based on our data.

These basic statistics clearly show that all heterogeneity (either observed, unobserved or both) accounting models capture the firm specific heterogeneity into the cost frontier allowing the inefficiency distribution move to the left and become more concise. Also the distribution of the frontier in randomized specifications is more concise. Another clear observation is that TFE produces clearly different inefficiency scores than either the basic RE model or the random parameterized versions of the RE model. The difference among basic RE model inefficiency scores and those which TFE model produces can be explained by the clearly different model assumptions. First difference is the assumption of time varying inefficiency over time. Both RE and REH models assume constant inefficiency over time. The second difference is that in TFE correlation between firm specific effects and explanatory variables is allowed. This is not the case for the basic RE model. Third clear difference is that in the basic RE model any unobserved firm-specific differences are interpreted as inefficiency. Given that in electricity distribution a considerable part of the unobserved heterogeneity is related to network characteristics and is very likely beyond the firm's own control, the inefficiency estimates can be overestimated in RE models. All these three distinguishing assumptions among TFE and RE models can be observed from our inefficiency estimates. It is notable that the variance of the frontier in TFE model is rather big (.165) which shows that the model does not produce robust estimates for the frontier. This can be due to the rather short panel of the data or insufficient number of observations

When we compare the basic random effect model to the random parameterized versions of RE model one observation to note is that mean inefficiency estimates clearly diminish. This can be explained by the fact that in the random parameterized models unobserved heterogeneity is not appearing as inefficiency. However, taking into account the fact that the firms in question are local monopolies it is possible that they do not operate as efficiently as possible and consequently part of the time invariant inefficiency (now assumed to be due to firm specific unobserved heterogeneity) may be due to inefficient management and hence the model TRE may underestimate the inefficiency scores.

Also the inefficiency scores among TFE and random parameterized versions of the RE model differs somewhat. Even thought the maximum inefficiency score is clearly smaller in TFE model the mean of inefficiency is higher in TFE model than in model TRE. However, the mean of inefficiency is clearly closer each other among the TFE model and the random parameterized version of the RE model than among the basic RE model and its parameterized versions.

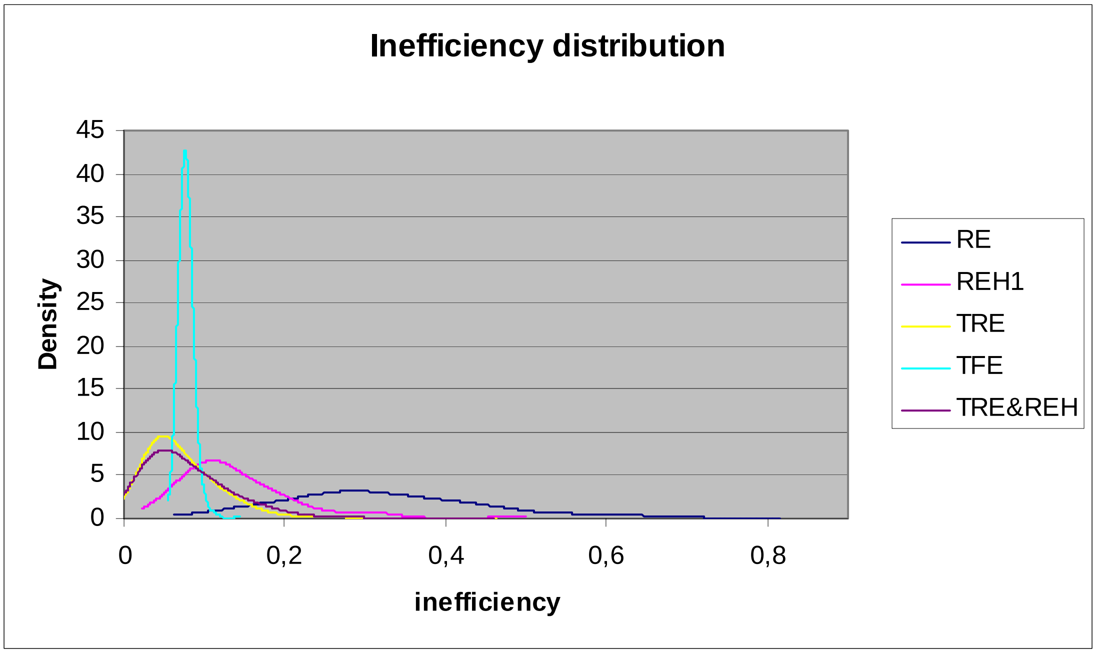
Table 3. Statistics of inefficiency scores[16]

	RE	REH	TRE	TFE	TRE&REH
Minimum	.972-01	.419-01	.117-01	.575-01	.102-01
Maximum	.782	.481	.450	.142	.445
Mean	.327	.141	.737-01	.775-01	.808-01
Std.Dev. of $E[u_i$	.130	.738-01	.470-01	.948-02	.600-01
σ(v)	.068	.067	.032	.165	.023
σ(u)	.353	.150	.096	.101	.106

In Figure 1 the inefficiency distributions of all models are presented. The deviation of the distributions of different models is clear. One notification to make is also that the kurtosis of inefficiency distribution of the TFE model is clearly higher than the one in other model specifications.

[16] On the estimation of inefficiency in the stochastic frontier models see Jondrow et. al (1982)

Figure 1. Inefficiency distributions



In practice the regulators use different benchmarking methods to rank companies according to their inefficiencies. The correlation matrixes based on Spearman's correlation test between the ranks obtained by the inefficiency results from different models are presented in Table 4. One observation to note is that the inefficiency ranks between the basic RE model and all other models than model REH are negatively correlated. The correlation among RE model and its extended form REH are positive and close to 1 which indicates that these models rank the firms very similarly.

When we investigate the ranks firm by firm we notice that when the unobserved heterogeneity is taken into account the rank of the firms which are located in sparsely inhabited rural areas with long distribution distances increases and the ranks of the relatively big cities decreases. Based on this observation it seems that these models produces rank orders which take account such heterogeneity factors which are beyond the control of the firm or it managers and hence are such factors which should not be considered as inefficiency in regulatory benchmarking.

The problem associated with the Spearman test statistics is that it tests the monotonic relation among two variables. This relation exists when any increase in one variable is invariably associated with either an increase or a decrease in the other variable. This means that this test does not recognize the distance among two variables. This clearly distorts these results.

Table 4. The Spearman correlations of the inefficiency rankings.

	RE	REH	TRE	TFE	TRE&REH
RE	1				
REH	.962	1			
TRE	-.332	-.300	1		
TFE	.-085	-.057	.217	1	
TRE&REH	-.280	-.334	.309	.069	1

6. Conclusions

The main interest of this paper was to look at the potential advantages of heterogeneity extended stochastic frontier models over conventional random effects models in cost efficiency measurement. Especially we were interested in how the inefficiency estimates change when we use random parameter models instead of conventional random effects models. We have applied a basic random effects model, one version of extended random effects model where observed heterogeneity is captured by explaining the mean of the inefficiency with the load factor covariate, two random parameterized versions stochastic frontier models (these models are assumed to take the unobserved heterogeneity into account) from which the first one is the so called true random effects model and the second is the true fixed effects model and finally a model which combines the true random effect model with the model which explains the mean of the inefficiency distribution by some covariate.. Our data consists of 76 regional distribution utilities which vary significantly if measured by output as well as by the operative environment.

Our basic result is that random parameter estimation of stochastic cost frontiers produce clearly smaller inefficiency estimates than the basic random effects model or its extended version. The inefficiency estimates produced by the heterogeneity accounting version of the basic random effects model are also clearly smaller than the one resulting from basic random effects model. Notable is, however, that even though both ways of accounting heterogeneity (observed or unobserved) diminish the inefficiency estimates they end up with very different rank orders of firms.

The firm specific inefficiency scores based on the true fixed effects model are very close to each other and if we look at the variance of the frontier in this model we notice it to be rather big (.165) which shows that the model does not produce robust estimates for the frontier. This can be due to the rather short panel or insufficient number of observations. According to BIC criteria the model which combines the characteristics of unobserved and observed heterogeneity fits the data best.

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