DEPARTMENT OF ECONOMICS

DISCUSSION PAPER SERIES

Regulatory Benchmarking with Panel Data

Necmiddin Bagdadioglu

and

Thomas Weyman-Jones

WP 2007 - 03

Dept Economics
Loughborough University
Loughborough
LE11 3TU United Kingdom
Tel: + 44 (0) 1509 222701
Fax: + 44 (0) 1509 223910
http://www.lboro.ac.uk/departments/ec

Loughborough University

1

REGULATORY BENCHMARKING WITH PANEL DATA[1]

Necmiddin Bagdadioglu

necbag@hacettepe.edu.tr

Department of Public Finance, Hacettepe University, 06532, Turkey, and
ESRC Centre for Competition Policy, University of East Anglia, NR4 7TJ, UK

Thomas Weyman-Jones[*]

t.g.weyman-jones@lboro.ac.uk

Department of Economics, Loughborough University, LE11 3TU, UK

Abstract: This paper considers panel data procedures for regulatory benchmarking that allow for both latent heterogeneity and inefficiency, encapsulating the regulatory dilemma in comparative efficiency analysis for incentive regulation. It applies a distance function model with appropriate concavity properties for econometric estimation to a panel of electricity distribution utilities in Turkey, since electricity industry reform is a major policy issue there. The results confirm the importance of allowing simultaneously for heterogeneity and inefficiency and emphasise the need for specific time-invariant heterogeneity information, such as geographical data, on regulated utilities in different regions.

JEL number: L51, D24, C23,

Keywords: efficiency and productivity analysis, regulation, electricity distribution

---

REGULATORY BENCHMARKING WITH PANEL DATA

1. INTRODUCTION

In many developed economies the electricity utility industry has been liberalised, de-regulated and privatised with the wide adoption of forward looking incentive regulation often based on price-capping or revenue-capping. Comparative efficiency and productivity analysis, more commonly 'benchmarking', has become widely used by network regulators as part of these regulatory regimes, see Jamasb and Pollitt (2003) for a wide-ranging survey. The European Union Electricity Directive of 2003 requires that ex ante regulation will become the norm throughout the European Union, leading to wider use of efficiency and productivity analysis as noted by Filippini, et al (2005). However, productivity comparison requires careful consideration of the relative importance of inter-firm heterogeneity and inefficiency in contributing to firm performance. Distinguishing these two features is essential to the credibility of liberalisation and regulatory proposals. Panel data methods offer regulatory authorities a potential means of achieving this distinction between latent heterogeneity and inefficiency in a credible and consistent manner. However, the specification of the error terms in panel data analysis is critical to interpreting how inter-firm heterogeneity and inefficiency combine to impact on measured firm performance, as shown by Farsi et al (2006).

In this paper, we use stochastic frontier analysis to investigate the panel data modelling of heterogeneity and inefficiency for regulatory benchmarking. We apply several different approaches including true-SFA models, Greene (2005), to a sample of electricity distribution utilities in Turkey, where the industry is being liberalised as

it emerges from a period of extensive state ownership in preparation for EU accession; see Atiyas and Dutz (2005) and Erdogdu (2006) for the policy background on this issue. We demonstrate the sensitivity of the performance measures to the stochastic specification, and suggest a procedure based on satisfaction of second order concavity conditions for choosing between models. We investigate different models of the technology and find support for production relationships in which geographical characteristics are non-separable from other inputs in the electricity distribution industry. The paper commences by reviewing models for distinguishing heterogeneity and inefficiency emphasising the interpretation of time invariant effects in panel data. Specifications of the technology using second order approximations to the input distance function are then derived and these are used to measure inefficiency. The paper concludes with the regulatory policy implications of the findings.

2. PANEL DATA MODELS FOR REGULATORY BENCHMARKING

A general panel data framework, e.g., as suggested by Greene (2005), is:

$$y_{it} = f(\mathbf{x}_{it}, \mathbf{z}_{it}; \alpha, \boldsymbol{\beta}) + v_{it} - u_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\pi}'\mathbf{z}_{it} + v_{it} - u_{it}; \ i = 1 \dots N, t = 1 \dots T \qquad [1]$$

In this model, $\alpha + \boldsymbol{\beta}'\mathbf{x}_{it}$ contains the information about the production structure, and $\boldsymbol{\pi}'\mathbf{z}_{it}$ represents observable heterogeneity not related to the production structure but capturing firm specific effects; the composed error term comprises idiosyncratic error (v) and non-negative inefficiency (u). The alternative statements in [1] allow for the observable heterogeneity to be non-separable from the production function variables, [$\partial^2 y_{it} / \partial x_{kit} \partial z_{lit} \neq 0$], or separable from them, [$\partial y_{it} / \partial z_{lit} = \pi_l; \partial^2 y_{it} / \partial x_{kit} \partial z_{lit} = 0$].

Equation [1] is a general statement, and includes the pooled model as well as a number of multi-layered and interdependent panel data approaches. In regulatory benchmarking a key issue concerns the presence of time-invariant effects arising partly because the number of firms in the sample is likely to be large relative to the available number of time periods[2]. Time-invariant effects (abbreviated to TIE) could arise for two principal reasons. First, there may be significant inter-firm heterogeneity; this will be particularly important when geographical features affect the production relationships observed in a sample of regionally based firms. This is a characteristic of the electricity distribution industry. Second, there may be a wide variation in economic performance which does not change over time, if the regulated or state-owned firms have poor incentives to reduce costs. This is a characteristic of utilities making the transition from a period of cost of service based state-ownership or municipal ownership. We can classify these two causes of TIE as time-invariant latent heterogeneity (TIH) and time-invariant inefficiency (TIU). Consequently we need to specify the general model in [1] in a more restricted manner to capture the regulatory dilemma of whether TIE = TIH or TIE = TIU, or both, TIE = TIH + TIU.

If we are dealing with a sample in which TIH is not likely to be an important issue, then most or all time invariant effects can be attributed to inefficiency of firm performance: TIE = TIU. This reflects the application of classical panel data methods to stochastic frontier analysis, as suggested by Schmidt and Sickles (1984), see Kumbhakar and Lovell (2000) for a wide survey:

$$y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\pi}'\mathbf{z}_{it} + v_{it} - u_i \qquad [2]$$

---

[2] In this paper for example, $N = 82$, while $T = 6$

Time-invariant effects are restricted to the inefficiency component of the error term, and may be estimated by a range of methods. Fixed effects with firm dummy variables, FE-LSDV, or random effects with feasible generalised least squares, RE-FGLS, make minimal assumptions about the density function of the error components. The FE-LSDV model has the additional advantage that the inefficiency component can be correlated with the explanatory variables, but time-invariant observed heterogeneity, TIH, however, is not feasible. Pitt and Lee (1981) extended the RE version of the model by specifying additional properties for the inefficiency and idiosyncratic components of the error term: $u_i \sim N^+\left(\mu, \sigma_u^2\right)$, $v_{it} \sim N\left(0, \sigma_v^2\right)$, and used maximum likelihood estimation, RE-MLE, while Battese and Coelli (1992), and Kumbahakar (1990) further allowed the inefficiency component to be time persistent with a common structure across firms: $u_{it} = u_i h(t)$. We refer to this group of specifications as the *classical SFA-panel model*.

Greene (2001, 2005) argues strongly in favour of accounting carefully for inter-firm heterogeneity in applying SFA-panel methods. He first raised the ideas in connection with inter-country environmental and cultural differences in health service provision, but the geographical dispersion factor is also relevant. Therefore the assumption is now that time-invariant heterogeneity is the critically important time-invariant effect: TIE = TIH. Greene (2005) suggests a *True-SFA-panel* approach in which all time-invariant effects are treated as inter-firm heterogeneity, and inefficiency is treated as an unstructured time-varying effect.

$$y_{it} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\pi}'\mathbf{z}_{it} + v_{it} - u_{it} \qquad [3]$$

There are FE and RE approaches in this TIH model. The FE approach uses firm dummy variables in a MLE model with specified density functions for the error

components, while in the random effects approach the intercept is treated as random variable in a random parameters framework.

This True SFA-panel approach could, however, overcompensate for heterogeneity since inefficiency may also to be time-invariant in short panels of firms which have only been subject to state-ownership or non-incentive-based regulation. Consequently, in such panels of regionally dispersed firms, where geographical features impact on the production technology, and where pressures to improve efficiency may be absent, it is essential to measure time-invariant effects as both time-invariant inefficiency and time-invariant heterogeneity: TIE = TIU + TIH. The ability to do this is sample dependent, and requires the availability of time-invariant observed heterogeneity information, as Greene (2005) shows. In addition, the inclusion of both TIH and TIU in the model rules out a fixed effects approach, so that only versions of the random effects Classical RE-MLE method can be used. The consequence is that we can no longer permit the assumption that inefficiency can be correlated with the explanatory variables, which is available for FE approaches. This third approach could be referred to as *Classical Random Effects SFA with observable heterogeneity*,

$$y_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x}_{it} + \boldsymbol{\pi}'\mathbf{z}_i + v_{it} - u_i \qquad\qquad [4]$$

This model may have several different inefficiency specifications including time-invariant inefficiency, $u_i \sim N^+\!\left(\mu,\sigma_u^2\right)$, time-persistent inefficiency with a common structure across firms, $u_i h(t)$, or, even pooled or non-specific time-varying inefficiency, u_{it}, but the key feature is that it includes both TIH and TIU as possibilities. While the models in this third category are clearly richer formulations

and allow for time-invariant inter-firm heterogeneity and time-invariant or time-persistent inefficiency, as well as non-specific time-varying inefficiency, their applicability depends on the availability of sample-specific information. Maximum likelihood estimation is used for all of the models. The ability to capture both heterogeneity and inefficiency *when both may be time-invariant* is critical in investigating firms which may have been devoid of incentives for some, or all, of the sample. This is likely to be the outstanding feature of state-owned firms subject to several years of cost of service regulation. Such firms are found throughout the liberalising transition and accession countries, and they dominate the dataset used in this paper.

Farsi et al (2006) address this problem in a panel data study of electricity distribution utilities in Switzerland. Identifying the division between heterogeneity and inefficiency as crucial to regulatory benchmarking, they argue that inefficiency should be regarded as time varying because, even if managerial performance is constant, it interacts with time varying factors in a dynamic manner. They compare the Schmidt and Sickles GLS, Pitt and Lee MLE and Greene True RE-MLE models for error term specification in a Cobb-Douglas total cost regression. The parameter results are consistent across all three models but the inefficiency results are higher for the GLS and MLE models than the true RE-MLE model. This confirms the view that inefficiency and heterogeneity need carefully to be distinguished in regulatory benchmarking, and that the error term specification is critical. They argue that the assumptions of the true RE model are more consistent with the real world.

In the case of the sample of Turkey, it is more difficult to defend this argument because the industry, unlike the Swiss case, has had few if any regulatory incentives, and has instead experienced a policy of increasing nationalisation and expanded state-ownership, see Bagdadioglu et al (2007). In these circumstances, time invariant effects may include both heterogeneity and inefficiency. Consequently, we need an additional criterion to help distinguish between the time invariant heterogeneity and inefficiency in the sample. We suggest that a comparison be made of the economic properties, in particular the use of second order concavity tests, to discriminate amongst the different models; this allows us to compare the estimates of inefficiency from different models in a structured manner, and to note which specification has the stronger economic properties.

3. MODELLING THE TECHNOLOGY AND RELATIVE EFFICIENCY

The outputs are $\mathbf{y} \in R_+^R$ and the required inputs are $\mathbf{x} \in R_+^K$, and we represent the technology at time t by the input distance function, $D_I(\mathbf{y}, \mathbf{x}, t)$, see McFadden (1978)[3]. Since the value of the input distance function equals one if a producer is on the efficient production frontier, and exceeds one where the producer is inefficient, $D_I \geq 1$, we write

$$ln\, D_I(\mathbf{y}, \mathbf{x}, t) - u = 0, \quad u \geq 0 \tag{5}$$

The non-negative variable $u \geq 0$ corresponds to the inefficient slack in the use of inputs by each producer; it is the feasible contraction in inputs which will project an inefficient producer on to the efficient frontier of the input requirement set. In the econometric approach to inefficiency measurement u is treated as a random variable

---

[3] Coelli et al (2003) suggest reasons why the input distance function is a suitable model for regulatory benchmarking.

distributed across producers with a known asymmetrical probability density function. McFadden (1978:26) and Kumbhakar and Lovell (2000:32) state that properties of the input distance function include:

(i)   non-decreasing in **x,** $\partial \ln D_I / \partial \ln x_k \equiv ex_k \geq 0, k = 1 \ldots K$

(ii)   homogeneity of degree one in **x,** $D_I(\mathbf{y}, \mathbf{x}/x_K, t) = D_I(\mathbf{y}, \mathbf{x}, t)/x_K$

(iii)   concave in **x**

(iv)   non-increasing in **y,** $\partial \ln D_I / \partial \ln y_r \equiv ey_r \leq 0, r = 1 \ldots R$

(v)   scale elasticity of the production technology is measured by (see also Fare

and Primont (1995)): $E^t = -\left(\sum_{r=1}^{r=R} \partial \ln D_I / \partial \ln y_r \right)^{-1} \equiv -\left(\sum_{r=1}^{r=R} ey_r \right)^{-1}$

Applying the property in (ii), and using [5], provides an equation for estimation purposes:

$$- \ln x_K = \ln D_I(\mathbf{y}, \mathbf{x}/x_K, t) - u \qquad\qquad [6]$$

This paper proposes three elements to make [6] operational in a setting of panel data, $i = 1, \ldots, N; t = 1, \ldots, T$:

$$- \ln x_{Kit} \approx TL(\mathbf{y}, \mathbf{x}/x_K, t)_{it} + \pi' \mathbf{z}_{it} + v_{it} - u_{it} \qquad\qquad [7]$$

In this model $TL(\mathbf{y}, \mathbf{x}/x_K, t)_{it}$ represents the technology as the translog approximation to the log of the distance function containing the inputs normalised by the input on the left hand side of [6], $\pi' \mathbf{z}_{it}$ is the inter-firm heterogeneity that is separate from inefficiency and includes the exogenous operating characteristics, and v_{it} is the conventional idiosyncratic error term incorporating sampling error, measurement error and specification error. The remaining term in [7], i.e. ($- u_{it}$), is the inefficiency component of the disturbance error. The formulation in [7] is less general than it could be however since it imposes separability of the distance function in operating

characteristics. With non-separability, the exogenous characteristics can be modelled as if they enter the **y** vector directly so that they appear with second order and cross-product terms interacting with the other outputs, inputs and time to reflect the intrinsic nonlinearity of their impact on production technology

Making use of the notation: $\tilde{x}_k \equiv x_k / x_K$, $\mathbf{ly'} = (ln\, y_1 \quad \dots \quad ln\, y_R)$ and

$\mathbf{l\tilde{x}'} = (ln\, \tilde{x}_1 \quad \dots \quad ln\, \tilde{x}_{K-1})$, the translog input distance function $TL(\mathbf{y}, \tilde{\mathbf{x}}, t)$ in [7] is:

$$TL(\mathbf{y}, \tilde{\mathbf{x}}, t) = \alpha_0 + \boldsymbol{\alpha'} \mathbf{ly} + \boldsymbol{\beta'} \mathbf{l\tilde{x}} + \tfrac{1}{2} \mathbf{ly'} \mathbf{A} \mathbf{ly} + \tfrac{1}{2} \mathbf{l\tilde{x}'} \mathbf{B} \mathbf{l\tilde{x}} + \mathbf{ly'} \boldsymbol{\Gamma} \mathbf{l\tilde{x}} + \delta_1 t + \tfrac{1}{2} \delta_2 t^2 + \boldsymbol{\mu'} \mathbf{ly}\, t + \boldsymbol{\eta'} \mathbf{l\tilde{x}}\, t$$

[8]

The property of continuity of the function requires the symmetry restrictions on the elements of the matrices **A, B**: $\alpha_{rs} = \alpha_{sr}$ and $\beta_{jk} = \beta_{kj}$. The elasticities needed for the monotonicity properties are $ey_r = \partial\, ln\, D_I / \partial\, ln\, y_r$, $r = 1 \dots R$, and

$ex_k = \partial\, ln\, D_I / \partial\, ln\, \tilde{x}_k$, $k = 1 \dots K-1$, and $e_t = \partial\, ln\, D_I / \partial t$. These can be solved in terms of the coefficients of the fitted translog distance function as:

$$\begin{pmatrix} \mathbf{e}_y \\ \mathbf{e}_x \\ e_t \end{pmatrix} = \begin{pmatrix} \boldsymbol{\alpha} & \mathbf{A} & \boldsymbol{\Gamma} & \boldsymbol{\mu} \\ \boldsymbol{\beta} & \boldsymbol{\Gamma'} & \mathbf{B} & \boldsymbol{\eta} \\ \delta_1 & \boldsymbol{\mu'} & \boldsymbol{\eta'} & \delta_2 \end{pmatrix} \begin{pmatrix} 1 \\ \mathbf{ly} \\ \mathbf{l\tilde{x}} \\ t \end{pmatrix}$$

[9]

In [9] $\mathbf{e}_y$ is the column vector of output elasticities, $\mathbf{e}_x$ is the column vector of input elasticities. The normalising input in [7] and therefore the dependent variable in the regression analysis is $- ln\, x_K$; in the sample used here, this will be the (negative log of) the number of employees, so that an intuitive interpretation of the model in [7] is that it is (the negative of) a generalised labour input requirement function, but with the additional homogeneity properties of the input distance function imposed.

Kumbhakar and Hjalmarsson (1998) investigated the relative efficiency of electricity distribution in Sweden using a labour input requirement function, with a range of outputs and capital similar to those considered here[4]. The focus of that paper was on the impact of ownership type on relative efficiency. In this paper by contrast, where ownership type is not dispersed in the sample, the focus is on cross-unit heterogeneity. Returns to scale findings are mixed: Kumbhakar and Hjalmarsson, whose sample contained many small municipal utilities found evidence of increasing returns to scale, but many studies, such as Yatchew (2000) find that scale elasticity is not significantly different from one.

Concavity of the input distance function in **x** can be expressed in terms of the Hessian, by applying the arguments used by Diewert and Wales (1987) for the cost function. The Hessian of the input distance function with respect to **x** is derived as:

$$H(\mathbf{x}) = \mathbf{B} - \hat{\mathbf{e}}_x + \mathbf{e}_x \mathbf{e}_x' \qquad [10]$$

In [10], $\hat{\mathbf{e}}_x$ is a diagonal matrix with the input elasticities $ex_k, k = 1...K-1$ on the leading diagonal, and zeros elsewhere, and **B** is the matrix of second order coefficients on the input terms in the translog function. Concavity requires that $H(\mathbf{x})$ be negative semi-definite[5]. At the sample means with mean corrected data, these first and second order derivatives in [9] and [10] simplify to:

$$\begin{pmatrix} \mathbf{e}_y \\ \mathbf{e}_x \\ e_t \end{pmatrix} = \begin{pmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\beta} \\ \delta_1 \end{pmatrix} \qquad [11]$$

$$H(\bar{\mathbf{x}}) = \mathbf{B} - \hat{\boldsymbol{\beta}} + \boldsymbol{\beta}\boldsymbol{\beta}' \qquad [12]$$

---

[4] Kumbhakar and Hjalmarsson (1998) found that a hedonic composite of energy, customers and network length performed successfully in their labour input requirement function.
[5] Negative semi-definiteness is checked from the sign pattern of the principal minors of the Hessian.

4. DATA AND MODEL SPECIFICATION

The data used comprise a panel of 82 regional electricity distribution utilities in Turkey from 1999-2004, i.e. 492 observations in total. The source of the data is the Ministry of Energy and Natural Resources of the Government of Turkey.

The variables describing the technology of the electricity utilities are:

y_1: numbers of customers

y_2: electricity consumed (MWh)

x_1: transformer capacity (MVA)

x_2: network length (kilometres)

x_3: network losses (MWh)

x_4: numbers of employees

x_5: numbers of transformers

z_1: service area (squared kilometres)

z_2: customer dispersion, i.e. the reciprocal of customers relative to service area (1/numbers per squared kilometre).

Output variables are designated as y_r, input variables as x_k, and operating characteristics as z_m. An input orientation is adopted because it is recognised that utilities will be constrained to minimise input usage subject to meeting exogenous output targets. The outputs are customer services, which are proxied by the numbers of customers served in each area by each distribution utility, and electricity distributed. Both of these outputs have price signals in the customer tariff components of the utilities. Service area in the case of these utilities is a time invariant exogenous

13

operating characteristic variable. However it could be regarded in this context also as a non-priced output since it represents an additional target for service level coverage. If this assumption is adopted, then, in the input orientation used here, service area (in log form) will appear as indistinguishable from the other outputs, and it will enter the translog function with first and second order cross product terms. It will also directly

impact on the scale elasticity: $-\left(\sum_{r=1}^{r=3} ey_r\right)^{-1}$

A second way to treat service area is to model it as an exogenous firm characteristic (also in log form), which captures inter-firm heterogeneity, and which appears linearly in the regression model as part of the $\pi'\mathbf{z}_{it}$ component: the estimated scale

elasticity is: $-\left(\sum_{r=1}^{r=2} ey_r + \pi_1\right)^{-1}$. A third way to incorporate service area in the model is to embed it in the ratio variable: customer dispersion, and to incorporate this (not in log form) as an exogenous operating characteristic, with no scale elasticity impact.

The capital infrastructure to supply this range of services consists of transformers and network length, and this is supplemented by labour input. In all of the initial estimation work, the number of transformers and transformer capacity were found to be highly collinear (as will be expected when network reinforcement is accomplished by simply adding transformers of a given capacity rating), and consequently the number of transformers (x_5) was eventually excluded (after considerable initial experimentation with both variables) in order to achieve meaningful estimation. In reinforcing a network, electricity losses will rise as service area expands unless additional physical capital is used. Consequently, electrical losses can be used as another form of input to proxy the direct capital requirements of improving the quality

of the network. The model is similar in concept to Bagdadioglu et al (2007). Summary statistics are shown in table 1.

TABLE 1 HERE

In computing the estimates, all data were expressed in terms of ratios of the panel mean for each variable, so that the first order terms in the translog estimates measure the elasticities at the sample mean[6]. The normalising input and therefore the dependent variable in the regression analysis is $-ln\,x_4$, the negative log of the number of employees, as described earlier.

5. EMPIRICAL RESULTS FOR THE EFFICIENCY COMPARISONS

The three broad categories of panel data model outlined earlier are: 1. *Classical SFA-panel models,* which assumes that all time invariant effects are inefficiency, TIE = TIU, 2. *True SFA-panel* which assumes that all time invariant effects are latent heterogeneity, TIE = TIH, and 3. *Classical Random Effects SFA with observable heterogeneity*, which permits time invariant effects to be both heterogeneity and inefficiency, TIE = TIH + TIU. Within this group we can choose between separable (S) and non-separable (N) time-invariant heterogeneity. In all of the fitted models, time-varying customer dispersion consistently failed to demonstrate any statistical significance, and this is in line with other studies which have found that customer dispersion performs badly in panel data applications to regulated electricity industries, Burns and Weyman-Jones (1996).

---

[6] All of the estimations and the computation of the productivity indexes were done in the LIMDEP 8 and STATA 9 software applications.

The spread of technical efficiency scores can be large or small depending on the model fitted, which serves to demonstrate the fundamental regulatory dilemma. This is shown in figure 1, which illustrates the kernel density distributions of Technical Efficiency for models 1 and 2. In model 1, all time invariant effects are inefficiency; this is the standard SFA approach, represented here by the random effects Pitt and Lee(1981) time-invariant inefficiency model. In model 2, by contrast, represented here by the *True FE-SFA-panel*, all time invariant effects are treated as heterogeneity, and inefficiency is found in the time varying residual which is equivalent to the non-specific Aigner, Lovell and Schmidt (1977) model of the composed error term.

FIGURE 1 HERE

It is clear from figure 1 that assuming that all time invariant effects are heterogeneity has driven out all of the measured inefficiency from the model, since the distribution of technical efficiency for model 2 is clustered close to the value of 1. A regulator choosing model 1 over model 2 would run into severe challenge from regulated firms for failing to account for latent heterogeneity. This is a stark illustration of the regulatory dilemma which has been played out in many western European jurisdictions. Farsi et al (2006) found exactly this effect in their study of Swiss electricity utilities. In that case, they were able to argue that the assumptions of the true-SFA model are more consistent with the real world.

On the other hand it should be expected that, in a transition economy emerging from years of state-ownership, there will be a legacy of time-invariant inefficiency which has not yet been subject to direct high-powered incentive regulation. If inefficiency is

indeed time-invariant, then the True SFA-panel model may have over compensated for heterogeneity and failed to reveal the time-invariant inefficiency. In applying the True SFA-panel model with fixed effects to UK water regulation, Saal et al (2007) were able to argue that in a sample with a long time span, and where the firms had for several years been the subject of incentive based regulation, the true-SFA model was an appropriate procedure. In that context, it was inappropriate to expect extensive time-invariant inefficiency. The opposite argument could apply in the case of state-owned companies in transition economies where incentive regulation has not yet replaced extensive public ownership. This is likely to be especially the case with a short time-span panel data set such as we have here. Consequently it is necessary to investigate a model which allows time-invariant effects to represent both inefficiency and heterogeneity. A fixed effects model is not appropriate here, because it excludes direct measures of time-invariant heterogeneity which are needed to allow room for measuring time-invariant inefficiency.

In this sample we have a geographical variable which can represent time-invariant heterogeneity: the service area of each utility. Although we already know that time-varying customer dispersion does not add to explanatory power, it is likely that utilities with very different service areas will have different production characteristics. We are able to allow this characteristic to be non-separable in the production function variables in model 3(N) and separable in model 3(S). Figure 2 shows the effect on the technical efficiency distribution from model 1 of including time-invariant heterogeneity in the form of service area data in model 3(N). Any of the random effects models can be used for the comparison, and the one shown here is the time-

invariant inefficiency model of Pitt and Lee (1981) with first order, second order and cross product terms in service area included in the regression.

FIGURE 2 HERE

Two conclusions can be drawn from the kernel distributions shown in figure 2. The distribution of technical efficiency in model 3(N) is shifted further towards the 100 percent efficiency standard compared with model 1, but the effect is much less marked than that from model 2's comparison with model 1. Using the time-invariant heterogeneity implicit in the geography of service area produces a statistically significant but much lower compensation for heterogeneity than the full fixed effects model. Heterogeneity is allowed for without driving out the measured inefficiency. The use of separable time-invariant heterogeneity in model 3(S) is compared with model 3(N) in figure 3 and it can be seen that there is a significantly different effect from using the service area variable in a non-separable manner. The model with non-separability produces a technical efficiency distribution that is displaced further towards higher levels of efficiency than when separability is assumed.

FIGURE 3 HERE

The effect of non-separable time-invariant heterogeneity in model 3(N) has been treated as an additional output which interacts with the other outputs and inputs in the model. However, service area is not a priced output in the sense of affecting the level or structure of customer tariffs. Yet it does appear to affect the production relationship in electricity distribution in an important way, and appears to be a more statistically

18

successful means of modelling heterogeneity than the use of customer dispersion. In tables 2 and 3, we look in more detail at the properties of the models being compared.

TABLE 2 HERE

Summary statistics for representative examples of all four (1, 2, 3(N), 3(S)) of these model categories are presented in table 2. In comparing the two polar cases of models 1 and 2, the mean technical efficiency differs by over 34 percent in line with the impression from figure 1, and the true fixed effects model shows virtually zero variation in the technical efficiency scores. Both models 1 and 2 suggest that there are increasing returns to scale which does not reflect other findings in the literature on electricity utilities of this average size, and both models 1 and 2 fail the concavity test since neither set of parameters produces a negative definite Hessian, $H(\bar{\mathbf{x}})$ at the sample mean.

Consequently there are issues with the specification of these two models. Model 3(S) with separable time-invariant heterogeneity displays lower elasticity of scale but still in the range of increasing returns, and has a similar average and dispersion of technical efficiency to model 1. However, it too fails to satisfy concavity at the sample mean. Model 3(N) is the case of non-separable time-invariant heterogeneity in which service area is modelled as a non-priced output interacting with the other variables in the production technology. It does have an elasticity of scale closer to that found in other studies of distribution utilities of comparable size, and it displays a higher average technical efficiency than either of the other random effects models, 1 and 3(S). In addition, this random effects model with time-invariant heterogeneity is

the only category of model to satisfy the negative definite Hessian (concavity) conditions at the sample mean. Consequently, we investigate this model in more detail.

Table 3 reports two forms of hypothesis test between different random effects models; we use a likelihood ratio (LR) test on the log likelihood functions from the underlying regression to test for preferred specification, and we use a non-parametric Mann-Whitney test on the difference in the median technical efficiency scores. For the LR tests, we impose one restriction on comparing models 1 and 3(S), and impose 6 restrictions on comparing models 3(S) and 3(N). Model 3(N) is clearly the preferred specification and it yields higher average technical efficiency scores than the other two models, in addition to satisfying the economic property of concavity of the Hessian. It appears therefore that using time-invariant observed heterogeneity that is non-separable from the production function has allowed us to improve on model 1's failure to allow for heterogeneity, to improve on model 2's inability to permit time-invariant inefficiency, and to improve on the failure of model 3(S) to meet the concavity conditions[7].

TABLE 3 HERE

Although we have concentrated on the results for one form of model 3(N) here, there are several different versions of it that can be used. While a fixed effects approach is

---

[7] Some researchers have imposed concavity conditions as part of the estimation procedure. Jorgenson and Fraumeni (1981) use Cholesky decomposition to impose concavity at every sample point, but this results in a very highly restricted model with many coefficients constrained to zero. Ryan and Wales (2000) impose concavity at a single point and find that this resulted in satisfaction of the conditions at most other sample points; this study used a time series sample on US manufacturing with a relatively low number of observations. O'Donnell and Coelli (2005) use Bayesian estimation to impose concavity.

ruled out because of the presence of observed time-invariant heterogeneity, model 3(N) can be fitted as a standard RE-FGLS model with no distributional assumptions about the error terms other than constant variance, or it can be fitted as a time-invariant inefficiency model based on Pitt and Lee (1981), or it can be fitted as a common structure time-persistent model based on Battese and Coelli (1992), or even as a pooled sample time varying inefficiency model based on Aigner Lovell and Schmidt (1977). In other words the model permits but does not impose time-invariant inefficiency, and permits time persistent and time varying inefficiency as well. We use LR and asymptotic t-tests to choose between these candidates. The LR test clearly rejected the pooled time-varying inefficiency model against the Pitt and Lee model (LR test statistic: 949.04). The coefficients and log likelihood function values for Pitt and Lee and Battese and Coelli models are very close, except that the common time persistence parameter (eta) in the Battese and Coelli model is not significantly different from zero at the 5 per cent level. The coefficients and scale elasticities of the Pitt and Lee and RE-FGLS models are virtually identical at the first order and all of the versions of model 3(N) satisfy the concavity conditions at around 88 percent of the sample points, and give virtually identical technical efficiency distributions.

Table 4 displays the estimated parameters for the Pitt and Lee version of the model. We note that from the separate estimates of the underlying error variances: σ_u^2 and σ_v^2, we can infer that over 94 percent of the composed error variation remains attributable to time-invariant inefficiency, even when time-invariant heterogeneity is explicitly allowed for.

TABLE 4 HERE

Finally, in table 5 we summarize the economic properties of the estimated model at the sample mean and throughout the sample.

TABLE 5 HERE

Monotonicity properties are strongly satisfied in terms of statistical significance at the sample mean, as they are in virtually every model that has been fitted. In addition they are also satisfied at over 430 of the sample points. The same is true of the negative semi-definiteness property of the Hessian $H(\mathbf{x})$ which is satisfied not only at the sample mean but also at 88 percent of the individual sample points. Scale elasticity is not significantly different from one at the sample mean, confirming that utilities of this mean size have largely exhausted the available scale economies. Nevertheless a notable result for the scale property is that although scale elasticity, E, is not significantly different from one at the sample mean, it does exceed one at around 360 of the sample points. This indicates that the mean scale of the utilities is skewed upwards by the presence of a limited number of large utilities, and that there are many small utilities that individually display increasing returns to scale. This may explain why the Government of Turkey is keen to encourage mergers of electricity distribution utilities in the period prior to liberalisation, see Bagdadioglu et al (2007) for a non-parametric analysis of theses proposed mergers.

6. INTERPRETATION AND CONCLUSIONS

In this paper, our objective has been to examine the issue of regulatory benchmarking. We described panel data procedures that permitted two sources of time-invariant

effects, heterogeneity and inefficiency, which encapsulate the regulatory dilemma in benchmarking. Since the distinction between heterogeneity and inefficiency is critical for regulatory credibility, benchmarking exercises need to adopt a specification which can allow both effects to be measured. Typically, panel data samples will do this, especially if one of these factors (usually heterogeneity) can be assumed to be time-invariant while the other (usually inefficiency) can be assumed to be time-varying. Farsi et al (2006) were able to use this assumption effectively in modelling the regulated electricity distribution industry in Switzerland. This assumption is more difficult to sustain in the type of sample used here, involving centrally controlled state-owned firms whose inefficiency may be static. One solution therefore is to incorporate observed time-invariant heterogeneity into a classical RE-SFA model and to determine whether the economic properties (such as concavity) of this model are superior to those of the other models. This model permits but does not impose time-invariant inefficiency, and this can be tested, as we did in this paper. In addition, we found that treating the observed heterogeneity as non-separable from the other inputs and outputs was superior to a separable model. Overall, we found that a model with non-separable observed heterogeneity did have stronger economic properties (concavity in inputs) than the alternative specifications in this sample. The problem for regulators in such benchmarking cases is twofold: how to obtain good data on time-invariant heterogeneity, and how to specify the economic properties used to distinguish between models.

REFERENCES

Aigner, D.J., C.A.K. Lovell and P. Schmidt (1977) Formulation and Estimation of Stochastic Frontier Production Function Models, *Journal of Econometrics*, 6, 21-37

Atiyas, Izak and Mark Dutz (2005) Competition and Regulatory Reform in Turkey's Electricity Industry, in Bernard M. Hoekman and Subidey Togan (eds.) Turkey: Economic Reform and Accession to the European Union, a co-publication of the World Bank and CEPR, Washington, 187-208.

Bagdadioglu, Necmiddin, Catherine M. Waddams Price and Thomas G. Weyman-Jones (2007), "Measuring potential gains from mergers among electricity distribution companies in Turkey using a non-parametric model." *The Energy Journal* 28, (2): 83-110

Battese, George E. and Tim J. Coelli (1992) Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India*, Journal of Productivity Analysis*, 3, 153-169

Burns, P., and T.G. Weyman-Jones, (1996) 'Cost Functions and Cost Efficiency in Electricity Distribution: a stochastic frontier approach', *Bulletin of Economic Research* 48:1, March, pp.44-64

Coelli, Tim, Antonio Estache, Sergio Perelman and Lourdes Trujillo (2003*), A Primer on Efficiency Measurement for Utility and Transport Regulators*, Washington, World Bank, 2003

Diewert, W.E., and T.J. Wales (1987) Flexible Functional Forms and Global Curvature Conditions, *Econometrica*, 55, 1, Jan, 43-68

Erdogdu, Erkan (2006) Regulatory Reform in Turkish Energy Industry: An Analysis, *Energy Policy*, in press.

Färe, Rolf and Daniel Primont (1995) *Multi-Output Production and Duality: Theory and Applications*, Boston, Kluwer Academic Publishers.

Farsi, Medhi, Massimo Filippini, and William Greene (2006) Application of Panel Data Models in Benchmarking Analysis of the Electricity Distribution Sector, Centre for Energy Policy and Economics, *Annals of Public and Cooperative Economics,* 77 (3), 271-90

Filippini, Massimo, Medhi Farsi and Aurelio Fetz (2005) Benchmarking Analysis in Electricity Distribution, Centre for Energy Policy and Economics, Swiss Federal Institutes of Technology, *CEPE Report Nr.4,* May.

Greene, William G. (2001) New Developments in the Estimation of Stochastic Frontier Models with Panel Data, *EWEPAVII, 7th European Workshop on Efficiency and Productivity Analysis*, University of Oviedo, September 25, 2001

Greene, William G. (2005) Fixed and Random Effects in Stochastic Frontier Models, *Journal of Productivity Analysis*, 23, 7-32

Jamasb, Tooraj and Michael Pollitt (2003) International benchmarking and regulation: an application to European electricity distribution utilities, *Energy Policy*, 31, 1609-22

Jorgenson, D.W., and B.M. Fraumeni (1981) Relative Prices and Technical Change in Berndt, E., and B. Field (eds) *Modeling and Measuring Natural Resource Substitution*, MIT Press, Cambridge, MA

Kumbhakar, Subal (1990) Production Frontiers, Panel Data and Time-Varying Technical Efficiency, *Journal of Econometrics*, 46, 1-2, 201-12

Kumbhakar, Subal, and C.A. Knox Lovell (2000) *Stochastic Frontier Analysis*, Cambridge, Cambridge University Press

Kumbhakar, Subal, and Lennart Hjalmarsson (1998) Relative Performance of public and private ownership under yardstick competition: electricity retail distribution, *European Economic Review*, 42, 97-122

McFadden, Daniel (1978) Cost Revenue and Profit Functions in Melvyn Fuss and Daniel McFadden (eds) *Production Economics: a dual approach to theory and applications*, Volume 1, Amsterdam, North Holland

Pitt, M.M., and L-F Lee (1981) Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry, *Journal of Development Economics*, 9, 43-64

O'Donnell, C.J. and T.J. Coelli (2005) A Bayesian Approach to Imposing Curvature on Distance Functions, *Journal of Econometrics* 126, 493-523

Ryan, D.L. and T.J. Wales (2000) Imposing Local Concavity in the Translog and Generalized Leontief Production Functions, *Economics Letters*, 27, 253-60

Saal , David, David Parker and Thomas Weyman-Jones, (2007) Determining the contribution of technical, efficiency and scale change to productivity growth in the privatized English and Welsh water and sewerage industry: 1985-2000, *Journal of Productivity Analysis*, (forthcoming)

Schmidt, P., and R.C. Sickles (1984) Production Frontiers and Panel Data, *Journal of Business and Economic Statistic*s, 2, 367-74

Yatchew, Adonis (2000) Scale Economies in Electricity Distribution: A Semiparametric Analysis, *Journal of Applied Econometrics*, 15:2, 187-210

Table 1: Summary data for electricity distribution utilities in Turkey

82 utilities, 1999-2004, Inputs and Outputs	Average	Standard Deviation	Minimum	Maximum
X1: Transformer capacity (MVA)	550	1052	35	8603
X2: Network length (km)	9014	7006	809	36280
X3: Network losses (MWh)	239818	472704	4507	3738892
X4: Employees	405	410	62	2547
X5: Number of transformers	1779	1273	176	6605
Y1: Customers	308380	441945	25775	3431596
Y2: Electricity (MWh)	956997	1709629	32827	13193349
Z1 = Y3: Service area (km2)	9450	6342	840	38257

Table 2: Comparative results from different treatments of time-invariant effects, TIE

model	1. classical SFA-panel (RE-MLE)	2. True Fixed Effects SFA-panel	3 (S). separable TIH in RE-MLE	3 (NS). non-separable TIH in RE-MLE
Property	All TIE are inefficiency	All TIE are heterogeneity	TIE can be inefficiency and heterogeneity	TIE can be inefficiency and heterogeneity
Scale elasticity	1.27	1.09	1.03	0.958
Median TE (%)	61.8	96.4	61.9	66.6
Quartile Range (%)	16.9	0.8	17.3	19.6
Negative definite Hessian, $H(\bar{\mathbf{x}})$	no	no	no	yes

Table 3: Differences between Technical Efficiency scores.

Comparison	H_0: no difference in the model specification underlying the efficiency score	H_0: no difference in the median technical efficiency scores
Test	LR value on H_0	Mann-Whitney p-value on H_0
Model 1 and 3(S)	30.64 (χ^2 5% critical value: 3.84)	0.0371
Model 3(N) and 3(S)	112.18 (χ^2 5% critical value: 12.59)	0.0368

Table 4: Translog input distance function with time-invariant inefficiency and non-separable time-invariant firm heterogeneity

Dependent Variable: -ln x_4, NT = 492

Variable	Coef.	asymptotic t value
ly1	-0.5164	-11.91
ly2	-0.1178	-4.61
ly3	-0.4093	-8.66
lxn1	0.19619	6.24
lxn2	0.27103	8.84
lxn3	0.03704	2.52
ly11	-0.1196	-2.41
ly22	0.03801	1.22
ly33	-0.1458	-4.09
ly12	-0.0285	-0.4
ly13	0.28397	5.32
ly23	-0.0772	-2.05
lxn11	-0.0296	-0.65
lxn22	-0.0194	-0.74
lxn33	-0.0095	-1.27
lxn12	-0.0256	-0.43
lxn13	-0.0367	-1.29
lxn23	-0.0051	-0.22
ly1lxn1	0.19916	2.68
ly1lxn2	-0.1484	-2.54
ly1lxn3	0.02898	0.94
ly2lxn1	-0.1261	-2.28
ly2lxn2	0.16416	3.62
ly2lxn3	0.014	0.67
ly3lxn1	-0.2499	-6.93
ly3lxn2	0.14319	4.42
ly3lxn3	-0.0755	-4.33
t	0.02765	10.37
tsq	0.00217	2.7
ly1t	0.00731	1.28
ly2t	0.00006	0.01
lxn1t	0.00027	0.05
lxn2t	0.00691	1.54
lxn3t	-0.0008	-0.38
intercept	0.47454	11.63
μ	0.37934	7.82
γ	0.95836	$= \sigma_u^2/\sigma_u^2+\sigma_v^2$
σ_u^2	0.0398	(inefficiency distribution)
σ_v^2	0.00173	(idiosyncratic distribution)

Table 5: Monotonicity, scale and concavity properties of the fitted input distance function with non-separable time-invariant heterogeneity at the sample mean and throughout the whole sample

MONOTONICITY property	Elasticity	Parameter	Standard error	Whole sample: % of sample points with function decreasing in outputs, increasing in inputs
at sample mean	ey1	-0.516	0.043	100
at sample mean	ey2	-0.118	0.026	94
at sample mean	ey3	-0.409	0.047	92
at sample mean	ex1	0.196	0.031	98
at sample mean	ex2	0.271	0.031	93
at sample mean	ex3	0.037	0.015	89
SCALE property	Scale Elasticity	Parameter	Standard error	Whole sample: % of sample points with increasing returns to scale
at sample mean	E	0.958	0.046	
			Fail to reject H_0: $E = 1$	72
CONCAVITY property	Function	Principal Minors	Values	Whole sample: % of sample points where $H(\mathbf{x})$ is negative definite
at sample mean	$H(\overline{\mathbf{x}})$	First order:	-0.217, -0.236, -0.055	
		Second order:	0.051, 0.011, 0.013	88
		Third order:	-0.003	

Figure 1: Technical Efficiency distribution for models 1 and 2
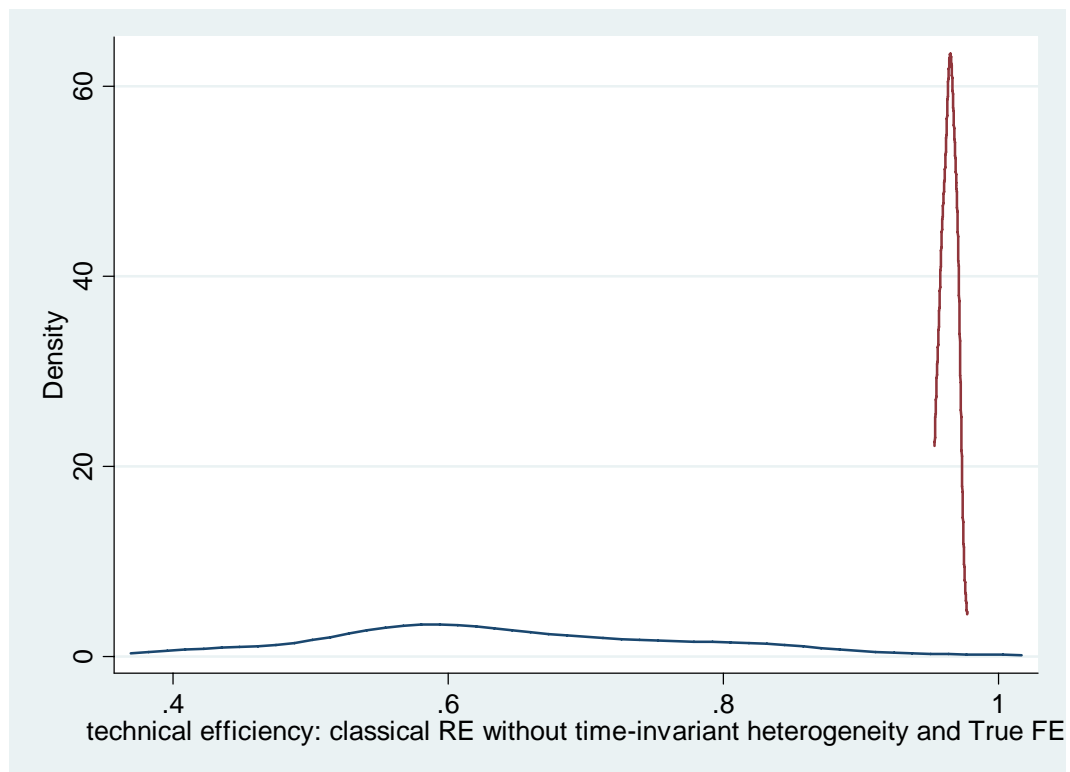*Classical RE without time invariant heterogeneity and True FE-SFA*

Figure 2: Technical Efficiency distribution for models 1 and 3 (N) (time invariant inefficiency and time-varying heterogeneity versus time-invariant inefficiency and time-invariant heterogeneity)
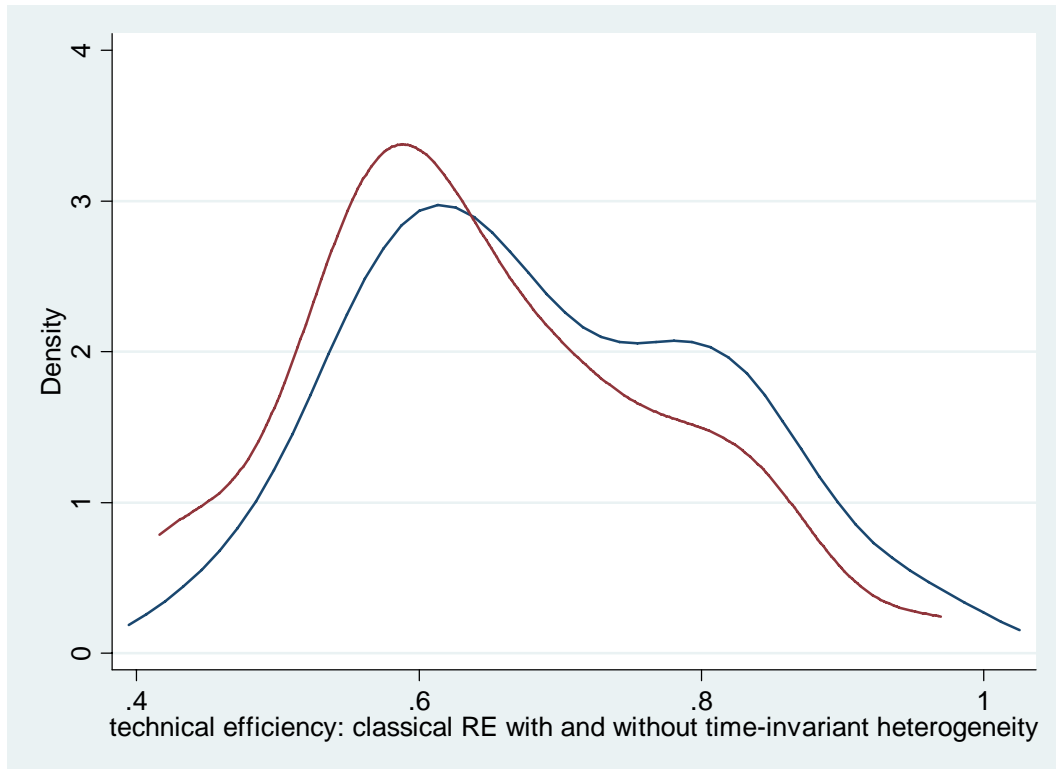
Figure 3: Technical Efficiency distribution for models 3 (N), and 3 (S) (time-invariant inefficiency and time-invariant heterogeneity) with and without separability