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Local Electricity Distribution in Italy: Comparative Efficiency Analysis and Methodological Cross-Checking[1]

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Non-Technical Summary

This paper analyses the efficiency of Italy s local electricity distributors according to two different measurement techniques. Distribution zones belonging to the national monopolist (ENEL) are compared with municipally-owned utilities (MUNIs) which serve individual towns and are usually owned by City Councils (with a few of them currently undergoing privatisation). ENEL-MUNI comparisons are displayed subject to a number of caveats, and statistical techniques are used in order to cross-check the results stemming from different methodologies.

The paper s main finding is that comparative efficiency analysis failed to spot any systematic efficiency superiority of ENEL s local units over municipal utilities. Overall efficiency comparison outcomes were mixed, thus suggesting that a case-by-case approach should be adopted by Italy s regulatory and governmental authorities when dealing with the territorial reform of electricity distribution. Similarly, any ownership transfers and/or mergers involving ENEL s units and MUNIs should depend on the varied efficiency records which were detected according to different regional and economic scenarios.

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1. Introduction

This paper analyses technical efficiency of local electricity distribution in Italy (1994, 1996) by using both econometric (deterministic frontier, stochastic frontier) and linear programming (Data Envelopment Analysis) tools. Cross-sectional data were examined with respect to

(*a*) ENEL - the Italian electricity monopolist whose restructuring and privatisation is now under way - and its local distribution branches;

(*b*) municipal authorities (MUNIs), i.e. town-based electric utilities which sometimes hold franchises for electricity distribution within city limits.

Estimation results highlighted non-exhaustion of scale economies at sample-mean values. Efficiency score series stemming from both econometric and linear programming techniques showed that Southern distributors were relatively under-represented among top units even after allowing for several exogenous environmental variables. The external effects which proved to influence technical efficiency in electricity distribution were consumer density, the percentage of industrial customers, the geographical nature of areas served (metropolitan areas, mountains, etc.), and the interaction between ENEL s units and municipal utilities in those towns featuring ENEL and MUNIs bordering each other.

Pooled ENEL-MUNI analysis failed to spot any systematic superiority of ENEL s units over municipalities. Generalisation on the ENEL-MUNI efficiency dispute was then discarded, in favour of case-by-case comparison. Paired-samples statistical testing (both parametric and non-parametric) showed limited agreement between Stochastic Frontier Estimation (SFE) and Data Envelopment Analysis (DEA) efficiency outcomes. Statistical concordance was more often found when comparing SFE and DEA models sharing the same input-output specification. Again, no apparent superiority of ENEL over MUNIs was detected by DEA linear programs. One-to-one comparisons confirmed that the outcomes were mixed, with ENEL s local branches outperforming MUNIs in metropolitan and (sometimes) rural areas, and MUNIs faring better in medium-sized, Po Valley towns (Northern Italy). Results were not clear-cut for Alpine and rural distributors. The latter - however - should be considered on a separate basis in that they will probably need permanent subsidies to meet universal service obligations, irrespective of the future structure of electricity distribution in Italy. Comparable (e.g., urban) units might - on the other hand - be subject to yardstick regulation based upon DEA s efficient peer outcomes.

2. Stochastic Frontier Estimation

This Section is concerned with the efficiency analysis of Italy s local distributors (ENEL) in 1996. As clarified later on, stochastic frontier methods are able to separate inefficiency effects from random noise/measurement error, by assuming specific statistical distribution functions for the random disturbance term. Modern computer packages are also able to calculate - in addition to standard numerical estimates - some interesting efficiency rankings of firms in the sample. Such rankings, albeit elegant and easy to use for policy-making purposes, strongly depend upon the variables which are chosen as cost determinants by the econometrician. We shall show how efficiency outcomes are sensitive to model specification issues by running alternative regressions featuring different environmental variables. In particular, the purpose of this Section is to highlight to what extent Southern local electricity units are really less efficient than their Northern counterparts. The analysis will allow for those external variables which are generally regarded as peculiar exogenous features , thus putting Southern ENEL distributing areas to a substantial disadvantage when compared to Northern distributors.

Deterministic frontier analyses have been most used in the Sixties and early Seventies[2]. The need for separating efficiency errors - i.e., those due to the firm erroneously shifting within its production possibilities set - from purely random noise led theoretical researchers in production econometrics to devise a brand-new framework which was capable of dealing with efficiency errors (one-sided), as separated from either noise or imperfect information[3].

The stochastic frontier production function was independently proposed by Aigner, Lovell, and Schmidt (1977), and Meeusen and van den Broeck (1977). The original specification involved a production function for cross-sectional analysis, featuring an error term which had two components, the first one to account for random effects (a traditional, two-sided disturbance term), with the second one accounting for technical inefficiency (a one-sided error). This model can be expressed in the following form:

$$
\begin{aligned}
&Y_i = X_i \beta + (v_i + u_i), \qquad i = 1,\dots,N,\\
&\textit{where}:\\
&Y_i = \text{production (possibly logged) of the } i\text{-th firm;}\\
&X_i = \text{a } k\times 1 \text{ vector of (transformations of the) input quantities of the } i\text{-th firm;}\\
&\beta = \text{a vector of unknown parameters;}\\
&v, u = \text{two separate random variables.}
\end{aligned}
$$

The two-sided random error (v) is assumed to be identically and independently distributed as a normal, with zero mean and constant variance. In particular, such a traditional two-sided random disturbance is independent of u, which is assumed to be a non-positive random variable accounting for technical inefficiency in production. The efficiency u is often assumed to have a truncated normal, half-normal, gamma, or exponential distribution[4]. If a cost function is used instead of a production relationship, the one-sided error will be non-negative, thus reflecting efficiency errors leading the firm to shift above its cost-minimising contour.

The original stochastic frontier specification has been used in a vast number of empirical applications over the past two decades. The above, standard specification has also been altered and extended in a number of ways. These extensions include the specification of more general distributional assumptions for the efficiency error (u), such as the two-parameter gamma distribution; the consideration of panel data and time-varying technical efficiencies; the extension of the methodology to cost functions and also to the estimation of equation systems. A number of comprehensive reviews of this literature are available, such as those proposed by Forsund, Lovell, and Schmidt (1980), Schmidt (1986), Bauer (1990), and Greene (1993).

Battese and Coelli (1995) proposed the Technical Efficiency Effects (TEE) model, which will be used here. Their stochastic frontier specification is equivalent to the Kumbhakar,

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[2] Nerlove (1963); Christensen and Greene (1976).

[3] Hebden (1983); McElroy (1987).

[4] See also Greene (1990).

Ghosh, and McGuckin (1991) proposal, with the exceptions that allocative efficiency is imposed *ex ante* - so that all firms in the sample may only be technically inefficient - and that panel data estimation is permitted. The Battese and Coelli (1995) model specification may be expressed as follows:

$$Y_{it} = X_{it}\beta + (v_{it} + u_{it}), \quad i = 1,...,N; \; t = 1,...,T,$$

where

Y_{it}, X_{it}, β are as defined earlier (with a time subscript to accommodate panel data);

v_{it} = a random disturbance, which is i.i.d. as a $N(0,\sigma^2)$, independent of

u_{it} = a non - positive efficiency error, which is distributed as a truncated normal (N_T).

The novelty of this model is that the non-positive (non-negative) efficiency errors are intended to account for technical inefficiency in production (cost), while being assumed to be distributed according to a particular truncated normal. The truncated normal distribution for the efficiency errors is intended to incorporate external effects (cost drivers) which might influence a firm s efficiency, even though they are not controllable by the DMU. In other words, such external effects coincide with the second-stage variables outlined by Lovell (1993). Technically, the incorporation of environmental variables in the stochastic frontier model - which allows the investigator to skip a second-stage (censored) regression of efficiency scores, thus gaining in terms of estimation efficiency - takes place by devising the following normal distribution (to be truncated at zero) for the efficiency error *u*:

$u_{it} \sim N(m_{it}, \sigma_u^2)$, where $m_{it} = Z_{it}\delta$ is a contemporaneous auxiliary regression such that

Z_{it} = a $p \times 1$ vector of variables which may externally influence the efficiency of a firm;

δ = a $p \times 1$ vector of unknown parameters to be estimated simultaneously with (albeit separately from) β.

Therefore, the efficiency error s distribution is truncated at zero, but its mean is neither a constant nor zero itself. On the contrary, environmental effects are internalised in the efficiency error s distribution by centring the truncated normal function on a value which results from the contemporaneous, auxiliary regression of the distribution s mean (*m*) on those external effects (socio-economic variables) which are not directly controllable by the decision-making unit. A single-stage estimation procedure featuring an auxiliary regression on environmental effects being nested in the efficiency error s distribution function will (ceteris paribus) deliver more reliable parameter/efficiency estimates than those that would have been obtained by using a two-stage estimation procedure. The above model, then, allows for the dependence of the inefficiency effects in the two estimation steps.

The above specifications have been expressed in terms of a production function, with the *u* efficiency errors being interpreted as technical (in)efficiency effects which cause the firm to erroneously shift below its stochastic production frontier. However, if we wish to specify a dual stochastic-frontier cost function, we should only alter the error term s specification by imposing that *u* is non-negative, thus meaning that the firm is now erroneously shifting *above* its total cost contour (or, alternatively, above its average cost curve). For example, such a change would give rise to a stochastic total cost function of the type defined below[5]:

[5] Recall Uzawa (1964), and Shephard (1970) on duality theory.

$$
\begin{aligned}
&TC_{it} = P_{it}\beta + Y_{it}\gamma + (v_{it} + u_{it}), \quad i = 1,\ldots,N; \;\; t = 1,\ldots,T, \\
&\textit{where}: \\
&TC_{it} = \text{Total Cost}; \\
&P_{it} = \text{a vector of input prices}; \\
&Y_{it} = \text{a vector of outputs}; \\
&\beta, \gamma = \text{vectors of unknown parameters to be estimated}; \\
&v, u = \text{the two components of } \varepsilon, \text{ with } v \sim N(0, \sigma_v^2) \text{ and } u \geq 0,\, u \sim N(m_{it}, \sigma_u^2).
\end{aligned}
$$

Of course, it is always $\varepsilon = v + u$, and all the assumptions about the peculiar nature of the efficiency error s statistical distribution are the same as those previously discussed for the Technical Efficiency Effects (TEE) model. Within a cost function framework, the u element obviously defines how far the firm operates above the cost frontier. If allocative efficiency is postulated *ex ante*, then the efficiency error will be closely related to the cost of technical inefficiency. On the other hand, if this assumption is not made, the interpretation of u in a cost function will be less clear, with both technical and input-allocative[6] inefficiencies being possibly involved. If one uses the TEE model - which assumes allocative efficiency as an *a priori* condition - then the interpretation of u within a cost analysis will always be in the sense of technical efficiency[7]. The stochastic cost frontier proposed above is identical to the one put forward by Schmidt and Lovell (1979), who also present a log-likelihood function for the cost model. These two authors note that the log-likelihood function for the cost frontier is the same as that of the production frontier, except for a few sign changes. The log-likelihood function for the cost-function analogue of the TEE (production) model was also found to differ from the production-based version for a few simple sign changes[8].

The TEE model being estimated here will instruct the computer program to follow a three-step procedure in recovering Maximum Likelihood (ML) estimates of a stochastic translog total cost function for ENEL s 147 local distribution zones. The three steps being taken to obtain final ML estimates of the translog parameters, leading to the computation of estimated efficiency scores (*EFFs*), are the following:

(*a*) Ordinary Least Squares (OLS) estimates of the translog total cost function are obtained. All β estimators, with the exception of the intercept, will be unbiased;

(*b*) a two-phase grid search over the γ parameter space is conducted, with the β parameters (except for the constant) being set to their OLS values, and both the constant and variance (σ–squared) terms being adjusted according to the Corrected Ordinary Least Squares (COLS) formula presented in Coelli (1995). Any other parameters - such as those relating to environmental effects, or *Zs* - are set to zero in this grid search;

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[6] Unless differently stated, throughout this paper we shall assume that allocative inefficiency relates to the optimal choice of inputs according to their relative prices. This input-allocative version of inefficiency is the one used in production theory (Koopmans, 1951; Farrell, 1957), and will also be employed in the DEA section.

[8] See Coelli (1996a).

(*c*) the values selected in the grid search sub (*b*) are used as starting values[9] in an iterative procedure (which makes use of the Davidon-Fletcher-Powell Quasi-Newton algorithm), so as to obtain final Maximum Likelihood (ML) estimates - and subsequent efficiency scores (*EFFs*) - for each firm in the sample. Productivity indices[10] might also be worked out by using efficiency ratios from one period to another. The model described above is capable of handling cross-sectional, time-series, and panel data analyses.

The main output of our analysis will be made up of standard ML parameter estimates - resulting from the three-step procedure outlined above plus scale economies statistics.

We worked on 147 ENEL local distribution zones (1996) and instrumented a translog total cost function within a stochastic frontier framework. The first, most general model was devised as follows:

$$\ln(\frac{TDC}{p_m}) = \beta_0 + \beta_1 \ln(\frac{p_l}{p_m}) + \beta_2[\ln(\frac{p_l}{p_m})]^2 + \beta_3 \ln(\frac{p_k}{p_m}) + \beta_4[\ln(\frac{p_k}{p_m})]^2 +$$

$$+ \beta_5 \ln Y + \beta_6 (\ln Y)^2 + \beta_7 \ln CUST + \beta_8 (\ln CUST)^2 + \beta_9[\ln(\frac{p_l}{p_m})\ln(\frac{p_k}{p_m})] +$$

$$+ \beta_{10} \ln Y \ln(\frac{p_k}{p_m}) + \beta_{11} \ln CUST \ln(\frac{p_k}{p_m}) + \beta_{12} \ln Y \ln(\frac{p_l}{p_m}) + \beta_{13} \ln CUST \ln(\frac{p_l}{p_m}) +$$

$$+ \beta_{14} \ln Y \ln CUST + v + u, \quad \text{where :}$$

$v \in \Re, v \sim N(0,\sigma_v^2)$ is a 2 - sided error, allowing for random noise
and/or measurement error;

$u \geq 0, u \sim N(\mu_i, \sigma_u^2)$, where $\mu_i = Z_i\delta$ is a contemporaneous auxiliary regression s.t.

$Z_i =$ a $p \times 1$ vector of variables which may externally influence
the efficiency of local units;

$\delta =$ a $p \times 1$ vector of unknown parameters to be estimated
simultaneously with (albeit separately from) β;

$$\mu_i = \delta_1 \ln DENS + \delta_2 \ln INDCUS + \delta_3 \ln INDLIN + \delta_4 \ln INDY + \delta_5 \ln THIRD +$$

$$+ \delta_6 \ln AIRMT + \delta_7 \ln AIRBT + \delta_8 \ln PTP + \delta_9 SOUD + \delta_{10} MOUNTD +$$

$$+ \delta_{11} METRD + \delta_{12} MUNID + \delta_{13} SEAD + \delta_{14} BORD + \delta_{15} INDUSD + \delta_{16} GEND.$$

Each zone within ENEL is concerned with both electricity distribution and supply. We gained access to distribution data as separated from supply figures. With respect to ENEL s sample of 147 local distribution zones for the financial year ending 31 December 1996, we were interested in computing the following values, to be inserted in our total cost model.

(*a*) total distribution cost (*TDC*), which is the dependent variable in the translog cost function; it is made up of capital and labour costs, plus materials (goods and services supplied by third parties), which are seen as residual cost components;

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[9] Of course, if starting values are specified *ex ante* by the econometrician, the computer program will automatically skip the first two steps of the above procedure.

[10] Cf. Törnqvist (1936), and Malmquist (1953).

(*b*) price of labour (p_l), being obtained as the ratio between labour cost (*LC*) and average number of employees (*N*) at 31 December 1996. Data on part-time employees are not released by ENEL. However, part-time jobs are not particularly common in the Italian electricity sector, so that one is led to suppose that such values would not have altered the labour price figure considerably. Therefore,

$$p_l = LC / N;$$

(*c*) price of capital (p_k), being computed as the ratio between capital costs and the length of distribution lines. This is clearly a proxy value for the user cost of capital. With ENEL s zones not being separately floated on the stock market, this was the only concrete possibility of calculating the unit cost of capital, given that financially-based measures such as those resulting from the CAPM method had to be ruled out. Within a cross-sectional analysis, no correction for either depreciation or real interest rates is needed. More generally, the (unit) user cost of capital should be calculated as

$$c_K = \frac{KCOST(i - \pi + \delta)}{K} = \frac{KCOST(r + \delta)}{K},$$

where :

$KCOST$ = historic cost of capital for each zone;

$i - \pi = r$ = real interest rate;

δ = depreciation charge for each period;

K = quantity of capital in physical terms.

This formula is a simplified version of the Christensen and Jorgenson (1969) expression reported in Atkinson and Halvorsen (1980). It is intended to represent the rental price of capital, which includes an arbitrary depreciation charge. Whereas for power stations the expected economic life ranges from 20 to 30 years depending on technology, distribution networks have a longer expected life, due to slower technological progress. For example, it would be reasonable to suppose that the depreciation charge per year for electricity distribution is in the neighbourhood of 2.5%, thus reflecting the implicit assumption that a distribution network s expected economic life is around 40 years. Looking at Italy, the real interest rate from 1993 to 1996 has gradually fallen as a result of decreasing nominal rates and pretty stable inflation rates. If we had a time series to work on, it would not be unfair to assume a 7% nominal interest rate on risk-free assets (Italian Treasury Bonds) from 1992-93 to 1995 and 2.5% per-year inflation over the same period, leading to r = 4.5% on a yearly basis. This would imply

$$(r + \delta) = 7\% = 0.07.$$

Of course, within a cross-sectional analysis such a correction factor for the user cost of capital would simply re-scale the main figures. However, since we are preparing to receive further data from ENEL in the future, we applied the rental price of capital correction to our figures. If one considers the re-scaling factor, our actual expression for the user cost of capital - which will be regarded as the price of capital in our following econometric analysis - is given by

$$p_k =_{def} c_K = (0.07)\frac{COSTMTBT}{LINES},$$

where *COSTMTBT* is total cost of capital at each zone (constructed as the sum of costs relating to both medium-voltage and low-voltage plants) and *LINES* is the length of distribution networks (in kilometres), again including both medium-voltage and low-voltage lines, plus some high-voltage connections being used by local units in order to reinforce the network[11];

(*d*) price of materials (p_m), being computed as the ratio between total cost of third-party deliveries and the number of transformers. Such proxy variable is aimed at capturing the effect of external inputs on total distribution cost. Since materials are generally included in third-party works by ENEL, we used those costs as the numerator for our proxy price. Moreover, as materials are especially used in specific plants such as substations and capacitors, we expressed the materials price in terms of transforming units (substations). Therefore,

$$p_m = THIRDPT \,/\, TRANS.$$

Materials will be used as a residual input in the cost function. Total cost normalisation - to be imposed in order to deal with degree-one homogeneity in input prices has been usefully carried out by using materials as the numeraire input;

(*e*) traditional output (*Y*), being viewed as total GWh[12] delivered to final customers by each local distributor in 1996. It includes energy sold to industrial customers, to publicly-owned enterprises such as *Ferrovie dello Stato* (Italian Railways), and to residential users in both urban and rural contexts;

(*f*) following Neuberg (1977), it should be noticed that energy delivered to final customers is not always really exogenous. With special reference to non-regulated public utilities such as Italian ones, exogeneity of output might be dubious, in the light of considerable freedom being conferred upon ENEL in planning its output deliveries. In other words, differently from American-style utilities, ENEL is not compelled by the regulator to provide its customers with whatever quantities they desire at given (regulated) prices. Therefore, an alternative definition of output which should be really exogenous to the utility is the one considering total customers (*CUST*). Since total customers cannot be controlled by utilities as everybody has the statutory right to buy electricity from the national operator[13], the total customers variable has been successfully used in the recent literature[14] as a really exogenous proxy for output. We thus introduce total customers as a second definition of output within our multiple input-multiple output translog total cost function.

Apart from the standard input-price and output measures to be inserted in the translog cost function[15], a number of environmental variables were also specified, in order to capture

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[11] As for fully meshed distribution systems with overlapping peripheral high-voltage lines, see Berrie (1983), and Burns and Weyman-Jones (1994a).

[12] Recall that 1 MWh = 1,000 kWh, 1 GWh = 1,000 MWh, and 1 TWh = 1,000 GWh.

[13] Total customers are exogenously given by Nature at a certain moment in time.

[14] E.g., see Pollitt (1995).

[15] This provides for it to be a valid dual representation of a traditional production relationship.

external factors which might influence the efficiency performance of local ENEL zones, while being not directly controllable by the single decision-making unit (DMU). These environmental variables, or external cost drivers , are listed below:

(i) customer density (*DENS*), expressed as the ratio between total customers and areas served by each local distributor within ENEL. This should capture the effect of demographic features on electricity distribution costs;

(ii) percentage of energy delivered to industrial customers (*INDY*) on total energy deliveries: this aims at capturing the (positive) effect of more industrialised environments on local distribution costs;

(iii) percentage of third-party services - in terms of live costs incurred by the utility - on total distribution cost (*THIRD*): this is a way of testing the statement that buy might be better than make for some rural ENEL zones, and the expected effect of this variable is uncertain;

(iv) percentage of industrial customers on total customers (*INDCUS*), which is the counterpart of *INDY* when total customers is assumed to be a proxy for output, and should have a positive effect on efficiency;

(v) percentage of medium-voltage lines on total lines (*INDLIN*): this is a proxy for the percentage of lines being directed to industrial customers on total kilometres of line, and should also indicate that industrial areas exogenously boost efficiency performances;

(vi) percentage of overhead medium-voltage lines on total medium-voltage lines (*AIRMT*). This should capture the effect on costs of building overhead systems instead of underground cables, the *ex ante* assumption being that the former should be less costly;

(vii) percentage of overhead low-voltage lines on total low-voltage lines (*AIRBT*), where the *ex ante* assumption is reversed. That is, overhead cables for low-voltage deliveries to residential customers - especially within crowded urban contexts - should be more expensive than conventional underground low-voltage wires;

(viii) percentage of primary substations on total transforming substations (*PTP*). Primary substations are those carrying out the first and most important transformation task, by scaling down electricity voltage from high (transmission) to medium. More powerful primary substations tend to minimise electricity losses (ceteris paribus), even though such stations might have a negative effect upon short-run technical efficiency because they constitute an additional burden in terms of capital assets within a short-term setting;

(ix) a series of dummy variables capturing other environmental effects: landscape features (*MOUNTD* = 1 if the local zone is made up of more than 50% mountains higher than 700m, capturing the expected cost disadvantage of mountain distribution; *SEAD* = 1 if the zone includes coastal areas, capturing higher operating and maintenance costs stemming from the peculiar nature and weather of most Italian coastline districts), geographical peculiarities (*SOUD* = 1 if the distribution zone is located in Southern Italy, which is commonly perceived as an efficiency handicap; *METRD* = 1 if the zone is serving a metropolitan area , according to Italy s Law no. 142/1990[16], which might have either positive or negative effects on efficiency; *BORD* = 1 if the zone is on Italy s political borderline, which might capture either positive or negative externalities coming from interconnected neighbouring countries), and other technical-economic characteristics (*INDUSD* = 1 if the zone is located within an industrial district, which might show co-linearity with other variables introduced before, and have similar effects on efficiency; *MUNID* = 1 if the zone is either in the neighbourhood of, or perhaps surrounds, a municipal distributor to which expensive connection has to be granted, thus affecting the zone s technical performance in a negative fashion; finally, *GEND* = 1 if the zone also includes some generating plants, whose costs might be partially passed through by ENEL onto distributing branches, thus jeopardising their technical efficiency record due to mere accounting tricks).

The above variables should be carefully assessed until a final model - including a strict subset of them - is accepted as the closest approximation to the true model.

Before concluding this discussion, we would like to introduce some variables to be used in a following analysis featuring a pooled 1994-1996 sample of both ENEL s local zones and municipally-owned electricity distributors. Whereas the main sample was made up of 147 ENEL distribution zones for the financial year 1996, we only managed to get a 1994 cross-section of 37 municipal utilities running electricity distribution (as a separate business) among their activities. Moreover, we were not able to obtain data on costs. Differently from ENEL, municipally-owned distributors are not compelled to deliver their regulatory accounts to the electricity regulator (AEG, or *Autorit à per l Energia Elettrica ed il Gas*). Therefore, we only obtained production figures on municipalities. The input-output data which were collected are to be used within a dual production function setting.

We decided to pool the two samples, in spite of their different dates, because no significant technical progress seemed to have occurred for Italian electricity distribution from 1994 to 1996[17]. Furthermore, inflation issues are ruled out *a priori* since input-output data only will be used in the pooled regression, with no monetary values involved. Even though technical progress might have been present to some extent in distribution technology, this would simply increase the robustness of our results, which - as shown later on - are sometimes in strong agreement with the view that some municipal distributors, especially in medium-sized towns and in Lombardy, show higher efficiency levels than their surrounding ENEL-run electricity distribution zones do.

The production values which were collected for the 37 municipal distributors at 31 December 1994 are as follows:

(*a*) traditional output definition (*Y* = GWh delivered to final customers);

(*b*) alternative definition of output, as *CUST* (number of customers);

(*c*) capital values: kilometres of distribution line, all voltages (*LINES*); number of transforming plants (substations), both primary and secondary (*TRANS*);

(*d*) labour values: number of full-time equivalent employees at 31.12.1994 (*N* = end-year average);

[17] We ran a simple production regression for municipalities over the 1987-1994 interval, and found that the time trend coefficient was low and insignificant at 5%. This extrapolates low progress from 1994 onwards, too, provided that one excludes (unlikely) exogenous shocks over the 1994-1996 time period.

(*e*) a set of environmental variables, similarly defined as those employed within the ENEL analysis, except for those ones which could not be built up because of limited data de-aggregation (for example, *AIRMT*, *AIRBT*, and *PTP*). Among the dummy variables, for reasons which should be obvious, *MUNID* was redefined, being now equal to 1 for all municipalities in the pooled sample, and to 0 for all ENEL zones.

As previously noticed, the above values will not only be useful for (production-based) econometric analysis, but will also act as crucial inputs for the linear programming method (DEA) to be discussed at the end of the paper.

It should be noticed that the computer program which we used did not allow the analysis to include equation systems. Therefore, we excluded the two cost-share equations for capital and labour. We also have the total number of customers (*CUST*) as a different output indicator. Since, as Neuberg (1977) noticed, customers can be separately priced as a result of different tariff schemes being applied to different groups of customers (second-degree price discrimination - quantity discounts - and so on), we can consider both energy and customers as two distinct outputs in the total cost function. There are reasons to believe that, in the absence of effective regulation, customers are much more exogenous than GWh of energy delivered as a measure for output in electricity distribution. The translog total cost function was normalised in terms of the materials price p_m (degree-one homogeneity in input prices). Non-homotheticity was also guaranteed by full interaction terms.

We took advantage of the TEE model by separating traditional input-output variables from environmental effects. Therefore, we inserted input prices (capital, labour, and - implicitly - materials) and outputs only in the translog model, thus confining all environmental effects[18] to a simultaneous, auxiliary regression of m on Z (Z is the environmental effects vector). The latter regression defines the mean (m) of the truncated normal distribution $N(m, s^2)$ which is assumed for the one-sided efficiency error (u). Of course, u is non-negative, since it represents erroneous shifts of the i-th firm above its total cost contour (or AC curve), as a result of technical inefficiency. Input-allocative efficiency is imposed *ex ante*.

With no starting values being imposed, we estimated the above, general model and found that some environmental effects either had the wrong sign, were collinear with other variables, or were statistically insignificant. Therefore, we dropped the percentage of industrial customers (*INDCUS*) and lines (*INDLIN*), together with the percentage of overhead medium-voltage lines (*AIRMT*) and the generation dummy (*GEND*), which were severely insignificant at 5%. Then, we re-estimated the stochastic frontier model according to the three-step estimation procedure without inserting *INDCUS*, *INDLIN*, *AIRMT*, and *GEND* among our *Zs* (the environmental regressors). This gave rise to the following outcomes for a restricted, 12-environmental effects model (labelled Model 12TE):

Table 1: Model 12TE: Estimation Outcomes [Dependent Variable: $\ln(\frac{TDC}{p_m})$]

Coefficient Relating to ariable...	Parameter timate	Standard Error	*t*-statistic
(Constant)	34.89948	1.01000	34.60205
p_l	0.56502	0.28785	1.96287
p_l^2	-0.51774	0.19900	-2.59764
p_k	0.82507	0.39432	2.09387
p_k^2	-0.49249	0.17600	-2.79739
Y	3.01455	0.98800	3.05093
Y^2	0.10035	0.05278	1.90137
$CUST$	7.17963	0.61400	11.68960
$CUST^2$	0.33661	0.08100	4.15749
$p_l p_k$	0.97712	0.35500	2.75266
Yp_k	0.30703	0.20200	1.51675
$p_k\ (CUST)$	-0.44321	0.19100	-2.32533
Yp_l	-0.22636	0.20700	-1.09563
$p_l\ (CUST)$	0.39444	0.18800	2.09511
$Y(CUST)$	-0.13168	0.18800	-0.70018

EXTERNAL COST DRIVERS			
Coefficient Relating to ariable... **[Dependent Variable: m_u]**	**Parameter timate**	**Standard Error**	***t*-statistic**
DENS	-0.154229	0.039900	-3.866100
INDY	-0.184793	0.094196	-1.961780
THIRD	-0.284339	0.050200	-5.660420
AIRBT	0.094981	0.029200	3.253540
PTP	0.055148	0.022100	2.496420
SOUD	-0.074541	0.065700	-1.135150
MOUNTD	-0.003534	0.084300	-0.041950
METRD	0.193281	0.372000	0.519890
MUNID	0.172778	0.075800	2.280120
SEAD	-0.072725	0.069800	-1.041940
BORD	-0.189787	0.139000	-1.363830
INDUSD	0.023613	0.069400	0.340150

σ-squared	0.031803	0.00521	6.104223
Gamma (Grid Search)	0.0198	0.0103	1.9223301
Log-Likelihood Function	52.469		
LR Test of the One-Sided Error[19]	17.659		
No. of Iterations	55/100		
Sample Size	147		
Time Periods	1		

[19] Notice that this statistic has a mixed Chi-square distribution.

With respect to the above results, notice that all quadratic elements in the translog entered directly, i.e. with no 0.5 re-scaling (due to software restrictions). Of course, this will not influence estimation outcomes, since second-order effects will be computed as doubled quadratic-term coefficients. Secondly, iterations in the program were set at a maximum value of 100. The program managed to get converging ML estimates after 55 iterations out of the 100 which were technically available.

Standard checks for the total cost relationship to be well-behaved show that the function is actually non-decreasing in input prices and outputs. It is also quasi-concave in input prices. Output coefficients show that total cost is well-behaved in both energy delivered and the number of customers. Second-order effects also demonstrate that scale economies are decreasing in output size. Finally, degree-one homogeneity in input prices had been imposed prior to estimation, as a result of the p_m normalisation. A separate examination of environmental effects highlights the fact that, even after eliminating four badly-behaved variables, there are still some wrong (or 5%-insignificant) external effects left. Before looking at the efficiency scores which are implied by the above estimated stochastic cost frontier, we now compute some standard statistics of interest.

Scale economies for multi-output total cost functions are usually calculated following Panzar and Willig (1977), who introduced the concept of Overall Scale Economies (OSE). OSE are computed as the inverse of the sum of all partial log derivatives of total cost with respect to each relevant output, minus one. Thus, they are derived from the sum of partial cost-output scale elasticities. Partial scale economies are not relevant within those cost functions which split up output effects among several outputs. We then computed Global Returns To Scale (GRTS) as OSE + 1, and found that

$$GRTS = \left[\frac{\partial \ln(TDC/p_m)}{\partial \ln Y} + \frac{\partial \ln(TDC/p_m)}{\partial \ln CUST} \right]^{-1} = 1.50987 > 1 \text{ (sample - mean value)},$$

so that

$$OSE = GRTS - 1 = 0.50987 > 0 \text{ (s.m.v.)}.$$

Therefore, increasing returns to scale are detected at sample-mean values (the Taylor s series expansion points). This is more compatible with a U-shaped AC curve rather than with a L-shaped one. The second-order effect of output on total cost was computed as

$$SOE = \frac{\partial^2 \ln(TDC/p_m)}{\partial \ln Y^2} + \frac{\partial^2 \ln(TDC/p_m)}{\partial \ln CUST^2} = 2(0.10035 + 0.336612) = 0.873924 > 0.$$

The above (constant) value implies that global returns to scale are definitely decreasing as both outputs rise. Therefore, one might say that the extent of scale economies (Nerlove, 1963) is such that overall economies of scale are decreasing in output. Alternatively, it could be said that the second-order elasticity of normalised total cost with respect to outputs (*Y*, *CUST*) is significantly positive. This again suggests the idea of a U-shaped average cost relationship. In order to detect the Minimum Efficient Scale (MES), we solved the equation

$$\left[\frac{\partial \ln(TDC/p_m)}{\partial \ln Y}+\frac{\partial \ln(TDC/p_m)}{\partial \ln CUST}\right]^{-1}\Bigg|_{sample\ mean}=1$$

for both physical energy delivered and the number of customers, alternatively, at expansion point values. By taking anti-logs, we found that MES occurred at

$$Y_{MES}\big|_{\overline{CUST}}=403\,\text{GWh};\ CUST_{MES}\big|_{\overline{Y}}=364{,}687.9;\ Y_{mean}=1{,}107\,\text{GWh};\ CUST_{mean}=195{,}417.$$

We can see - by comparing MES with average values for energy and customers - that economies of scale are much more caused by customers than by *Y*. Once again, multiple-output cost functions are able to spot peculiar features which are overlooked by more traditional functional specifications. Not only physical output exhausts returns to scale at quite a low level, but also customers - which indeed show considerable scale economies - accommodate a region of decreasing returns for those local utilities featuring more than 365,000 customers (mainly, metropolitan zones). Therefore, even though scale economies are not in doubt, the AC relationship being suggested by the stochastic frontier analysis is a non-symmetric U-shaped 3D curve with a small region of decreasing returns in customers, and a large region of decreasing returns in physical output.

Consumer density should matter in lowering both total and average cost. By looking at our environmental effects , we can confirm that density is relevant to total cost minimisation. In particular, our estimate for the density effect is negative (–0.15423) and statistically significant. This is in agreement with the returns-to-scale finding on customers. Since density has not been considered to a second order in our linear TEE auxiliary regression, we are not able to say whether increasing density results in congestion of electricity distribution or not.

We conclude this Section by briefly commenting on the environmental effects estimates being computed by means of the TEE model. As previously discussed, such external variables neither were inserted in the main translog cost function, nor were they excluded from the estimation. Instead of performing a second-stage Tobit regression of efficiency scores on environmental factors, we preferred to run an auxiliary, internal regression to give the efficiency errors (u) a plausible mean on which their statistical distribution function could be suitably centred. Truncation of such a function was imposed at zero, in order to comply with the non-negativity constraint binding on u (which is a one-sided efficiency error). The auxiliary (internal) regression of the efficiency errors mean on external effects gave origin to the ML estimates which are discussed below:

(a) as previously noticed, consumer density was found to be beneficial in terms of total cost minimisation, at least to a first order (the model was not able to compute any second-order effects for environmental variables);

(b) industrial output (as a percentage of total energy delivered) also contributed to lower distribution costs; the industrial district dummy (*INDUSD*), however, turned out to be insignificant;

(c) third-party works were also beneficial to cost: this is perhaps a suggestion to ENEL s zones in favour of buying external services rather than making them internally[20];

(d) overhead cables in low-voltage distribution are more expensive than standard underground connections;

(e) primary (PTP) substations raise distribution cost, but are needed in large numbers for system security reasons, and for minimisation of electricity losses throughout the distribution system;

(f) the territorial North-South dummy (*SOUD*) was not statistically significant, and its coefficient had the wrong sign. Therefore, no systematic Southern effects were spotted by the stochastic frontier model;

(g) both landscape effects (*MOUNTD*) and metropolitan areas (*METRD*) were found to be statistically insignificant with respect to total cost minimisation;

(h) the presence of municipal distributors at zonal borders was discovered to rise distribution cost. This is probably due to urban cream-skimming [21] being performed by those municipalities which serve city centres, by connecting to ENEL s access points at city outskirts. This obviously involves connection costs to ENEL, which are probably reflected by the positive sign of *MUNID* s coefficient;

(i) finally, all coefficients for *SEAD*, *BORD*, and *INDUSD* turned out to be insignificant, meaning that the presence of either the sea or national borders as geographical limits to ENEL s zones did not significantly influence distribution cost. Industrial districts were found to be irrelevant as well; however, industrial output showed the right sign with statistical significance. It should also be recalled that the *GEND* dummy for generation had been excluded from the model at the outset, after showing severe insignificance in a preliminary run. This confirms the view according to which location of generating units may perhaps influence transmission and vice versa - with distribution being left unaffected, though.

Efficiency rankings for ENEL s 147 local zones are available by writing to the author[22].

[20] See Williamson (1975) on transaction cost economics.

[21] We say cream-skimming in the sense that municipalities take the best from city centres, with ENEL being confined to outskirts and surrounding rural areas. We do *not* mean that ENEL and local municipalities are allowed to compete on the same territories. Therefore, cream-skimming is here meant in a non-traditional sense.

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3. Stochastic Frontier Analysis of ENEL s Zones and MUNIs: Comparative Rankings From a Pooled Cross-Sectional Sample (1994-1996)

We built up a 1994-1996 pooled sample made up of 39 ENEL s zones (peers) and 37 MUNIs. When analysing the pooled sample, we chose to keep the translog production function s specification as parsimonious as possible, in view of the following considerations:

(*a*) by construction, the pooled sample showed strong similarity between MUNIs and ENEL s peers, which allowed us to save on environmental effects, thus gaining several degrees of freedom for estimation. Peculiar cost drivers are in fact useful whenever structurally different firms (for example, those belonging to Northern and Southern regions) make up the sample. However, if the sample is intentionally calibrated so as to include similar firms only, the number of environmental (*Z*) effects may be substantially cut down, in order to estimate a lighter specification;

(*b*) data homogenisation problems forced us to drop some environmental effects for which we had no complete figures (e.g., simultaneous maximum demand, industrial lines, industrial customers, percentage of PTP transformers, and so on);

(*c*) smoothing of rankings is also an issue to be worth investigating: by considering relevant external effects only, we limited overlapping rankings, while keeping model specification parsimonious enough according to a general-to-simple methodology;

(*d*) insignificance of most environmental effects when examining the homogeneous pooled sample (instead of the slightly inconsistent ENEL or MUNI one) pushed us to refine the model from a purely *statistical* point of view, so as to reach for a very light specification, including three environmental variables only[23].

We estimated a 3-effects stochastic translog production model being based on a sample of 76 pooled observations for 37 municipal utilities (business year 1994) and 39 ENEL s peers (business year 1996), which were selected according to both geographical and economic criteria. As a rule, all twins - i.e., ENEL zones relating to the same town as MUNIs - were inserted as peers, plus proxy twins being chosen among the nearest ENEL units and/or those provincial units which most resembled - in both economic and environmental terms - the MUNI they were coupled with. We also tried to run the same stochastic regression on a non-restricted, 184-observation sample (made up of all the 147 zones from ENEL, plus 37 MUNIs), with negligible outcomes. These were attributed to heterogeneity of most ENEL zones as opposed to the 37 MUNIs, which originated considerable interference with the relevant comparisons to be made. After realising that the MUNIs should have been compared to some twins (or peers) only, we non-randomly selected 39 ENEL units, so as to go for the calibrated pooled sample mentioned above. Such a sample is obviously homogeneous by construction.

To sum up, after excluding irrelevant external effects and selecting the 76-observation pooled sample as the right one, we fitted the following stochastic translog TEE production model (named SFM3, three effects):

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[23] Notice that this strictly relates to the homogeneity issue, as a result of ENEL s peers being chosen by construction. Consequently, sample selection itself tends to invalidate statistical significance of most initial external effects, thus confirming the basic argument sub (*a*).

$$\ln Y = \gamma_0 + \gamma_1 \ln K + \gamma_2 (\ln K)^2 + \gamma_3 \ln L + \gamma_4 (\ln L)^2 + \gamma_5 \ln K \ln L + v + u, \quad \text{where:}$$

Y = total energy delivered to final customers (GWh);

K = kilometres of distribution line;

L = number of full - time employees (end - year average);

$v \sim N(0, \sigma^2)$ is a two - sided stochastic disturbance;

$u \sim N(\mu_i, \sigma^2)$ is a one - sided efficiency error ($u \leq 0$) with truncated - N distribution s.t.

$\mu_i = \delta_1 \ln DENS + \delta_2 GEND + \delta_3 MUNID.$

Note the extreme simplification imposed on the model as a consequence of the calibrated pooled sample adopted. As regards external effects, it is worth noticing that both *DENS* and *GEND* are as defined before, whereas the municipal dummy (*MUNID*) has now a new meaning, following the direct introduction of MUNIs in the analysis. In this Section, define *MUNID* as a dummy variable assuming the value one for all MUNIs (37 units), and the value zero for all ENEL peers (39 zones). We would like to recall this here because it will help the reader interpret *MUNID* s effect on total energy delivered - as outlined by the analysis below. Estimated coefficients from the pooled translog stochastic frontier regression are reported in the following Table.

Table 2: Pooled Sample (37 MUNIs, 39 ENEL): SFM3 Estimation Outcomes [Dependent Variable: lnY]

Coefficient Relating to ariable...	**Parameter Estimate**	**Standard Error**	***t*-statistic**
(Constant)	6.14266	0.55300	11.10440
Labour	0.24248	0.12190	1.98941
(Labour)²	-0.10112	0.06520	-1.56516
Capital	0.61358	0.29200	2.10298
(Capital)²	-0.10551	0.05290	-1.99557
L· K	0.21803	0.11100	1.97300

EXTERNAL EFFECTS *[Dep. Var.: m_u]*			
Coefficient Relating to Var.	**Parameter Estimate**	**Standard Error**	***t*-statistic**
DENS	0.146050	0.049400	2.959490
GEND	0.437790	0.134000	3.267220
MUNID	1.181000	0.251000	4.700580
s-***squared***	0.116000	0.032200	3.612626
g***(Grid Search)***	0.824000	0.113000	7.265297
Log-L. Function	8.83E+06		
LR Test of the One-Sided Error	0.54414E+02		
Number of Iterations	25		
Max. Number of Iterations	100		
Number of Cross-Sections	76		

First, from estimation outcomes one notices that the stochastic production function is well-behaved in both capital and labour, with capital (expressed in kilometres of distribution line) showing a stronger first-order effect on output (GWh). As regards second-order coefficients, decreasing marginal returns are shown by both inputs. Given the sample s self-imposed homogeneity, we were able to restrict our environmental analysis to three *Z*s only (customer density, presence of generating plants within MUNIs/zones, and the *MUNID* dummy), whose coefficients all showed a positive and significant relationship with output. Customer density had a positive effect on *Y* - meaning that, as the number of customers per square kilometre rises (ceteris paribus), energy delivered will consequently go up.

The *GEND* dummy also indicated a positive relationship between generating plants and delivered output. Since *GEND* s coefficient was deemed insignificant in the previous total cost analysis, a special comment must be made on this outcome. First, power stations are generally located by ENEL where demand for electricity is stronger. This obviously creates a positive correlation between the presence of generating plants in the area and the amount of delivered output, which was not spotted within a total cost framework, as ENEL always separates generation, transmission, and distribution in its internal accounts. Moreover, one expects that transmission costs - and not distribution costs - are influenced by the location of generators, whereas delivered output - directly stemming from transmitted energy - has a more direct relationship with maximum demand in each area, and - therefore - with ENEL s locational choices concerning generating units. Finally, as regards MUNIs, the generation/output relationship is even deeper, because several municipal distributors own their dedicated power stations in order to minimise dependence on ENEL s supplies[24] and maximise system security. Since both metropolitan distributors and those holding franchises for medium-sized Northern towns are the biggest auto-generators, the positive effect of *GEND* upon *Y* is further explained, and *GEND* s coefficient turns out to be fully justified.

With reference to the *MUNID* dummy, it must be noticed that its positive relationship with delivered output should be interpreted in the light of *MUNID* s new definition within the current, pooled analysis. Because of the presence of MUNIs together with ENEL zones in the sample, *MUNID* has been redefined in such a way to be worth one for each MUNI, and zero otherwise. Positive correlation between the new *MUNID* and delivered output might then be simply due to the fact that some municipal utilities are very large (metropolitan distributors, and urban ones).

An appropriate analysis would entail direct comparisons between MUNIs and their peers. The following Table accomplishes this task by displaying the winner (MUNI/ENEL) for each single comparison.

Table 3: MUNIs and their ENEL Peers (SFM3): Winners/Losers

MUNIs	Peers (ENEL)	Winner
Roma	ROMA	ENEL
Milano	MILANO	ENEL
Torino	TORINO	ENEL
Brescia	BRESCIA	ENEL
Bolzano	BOLZANO	ENEL
Verona	VERONA NORD, VERONA SUD	ENEL
Vicenza	VICENZA	ENEL
Rovereto	SALO', TRENTO	ENEL
Tolentino	MACERATA	ENEL
Primiero	TRENTO	ENEL

[24] These are unilaterally priced by ENEL itself.

Brunico	BOLZANO	**MUNI**
Tione	SALO', TRENTO	ENEL
Laces	BOLZANO	ENEL
Silandro	BOLZANO	ENEL
Modena	MODENA	ENEL
Trieste	TRIESTE	**MUNI**
Parma	PARMA	**MUNI**
Imola	BOLOGNA, RIMINI	ENEL
Terni	TERNI	**MUNI**
Cremona	CREMONA	**MUNI**
Sanremo	IMPERIA	ENEL
Voghera	VIGEVANO, LODI	ENEL
Bressanone	BOLZANO	ENEL
Trani	MONOPOLI	**MUNI**
Seregno	BOVISIO, CORSICO, MELZO, MILANO EXT., LODI, BUSTO A., ONZA	ENEL
Vercelli	VERCELLI	**MUNI**
Rep.S.Mar.	RIMINI, PESARO	ENEL
Riva d/G	SALO', TRENTO	ENEL
Osimo	ANCONA	ENEL
Sondrio	SONDRIO	**MUNI**
Levico T.	TRENTO	ENEL
Soresina	CREMONA, LODI	**MUNI**
Tirano	SONDRIO, LECCO	**MUNI**
Gattinara	VERCELLI, BIELLA, VERBANIA	**MUNI**
Mezzolomb.	TRENTO	ENEL
Selvino	BERGAMO EXT., BRENO	**MUNI**
Vigo d/C	BELLUNO, BASSANO	**MUNI**

It is clear from the Table above that 13 out of 37 MUNIs outperformed their ENEL comparators. This entails that more than 35% of MUNIs were relatively more efficient - in technical terms - than their surrounding/neighbouring ENEL zones. This may not seem to be an exciting outcome for MUNIs in general, thus crediting the view according to which ENEL s zones are, on average, more efficient than municipalities. However, if urban areas only are allowed for - thus excluding mountain villages in the Trentino/South Tyrol region - the percentage of municipalities which were found to be relatively more efficient jumps to 46.15%. Apart from metropolitan areas - where ENEL turned out to outperform MUNIs dramatically (Rome, Milan, Turin) - smaller towns in the North and Centre of Italy had their MUNI as the relative efficiency winner against the surrounding ENEL zone (Trieste, Parma, Terni, Cremona, Vercelli, Sondrio). Moreover, when one restricts the efficiency comparison to Lombardy s MUNIs only, the percentage of winner MUNIs reaches 55.6%. In particular, several urban and suburban distributors in the Milanese region outperformed their ENEL peers (Cremona, Sondrio, Soresina, Tirano, Selvino).

A final word should be spent on ENEL s dominance over MUNIs in the main metropolitan contexts, and on Trani s successful comparison its closest ENEL peer (Monopoli). As regards metropolitan comparisons, the insertion of only three environmental effects does not suffice to claim excessive punishment for city centres (which are served by MUNIs). Since our pooled analysis is almost a naked one (when it comes to external variables), comparisons are crude. Therefore, MUNIs in Milan, Turin, and Rome were simply outperformed by surrounding ENEL zones. This may be partially due to the fact that efficiency was measured in production (not in cost) terms. Since medium-sized towns in the North and Centre of Italy were better managed by MUNIs, one suspects that municipal distribution technology satisfactorily suits provincial towns, although it is defeated in metropolitan areas. This consideration is strengthened by the fact that some smaller MUNIs (Brunico, Trani, Soresina, Tirano, Gattinara, Selvino, Vigo di Cadore) managed to outscore their ENEL peers within either rural or mountain contexts.

It then appears that, as Pollitt (1995) suggested, different companies enjoy different technologies, which cannot be constrained within any particular functional form, because they are tailored to different environmental contexts. For instance, according to our results, it seems that municipal distributing technology does better in smaller towns - despite the scale economies issue - whereas ENEL s performance is definitely higher within metropolitan areas. However, because of small sample problems, one cannot seriously make authoritative inference on this. Furthermore, if one believed that ENEL zones and MUNIs have different technologies in electricity distribution, constraining their production functions to be the same across the whole pooled sample would simply be wrong in the first place. It would be much wiser to suspend our judgement on relative efficiency in metropolitan contexts until a non-parametric technique is introduced, in order to cross-check our comparative results against a distribution-free approach[25] which does not force production relationships to have a particular functional form (even though as general as the translog).

To conclude, it is worth noticing that the only Southern MUNI in the sample (Trani, Apulia) outperformed its ENEL peer (Monopoli). This is obviously not enough to predict any municipal superiority over ENEL in the South, simply because electric municipalities from Southern Italy are non-existent. However, this outcome *per se* is interesting, as it shows that

[25] Data Envelopment Analysis (DEA) computes efficiency scores - instead of estimating them - and eliminates model specification problems (at some cost).

the only Southern municipality[26] not only fared better than its ENEL comparator (66.4% against 66.3% technical efficiency, a negligible difference) but - what s more important - also managed to join the first efficiency group (1–38), thus locating its efficiency score at a higher level than the average one (66.4% vs. 61.9%). In ranking terms, Trani s MUNI stands at number 31 (out of 76), which is a respectable result for a non-urban unit. In practice, however, future prospects for municipal electricity distribution in the South are bleak, due to traditional ENEL incumbency resulting from Southern electrification being completed, upgraded, and co-ordinated by ENEL itself in the early 1960s. On the contrary, non-urban Northern electrification had already been provided by local firms during the first decades of this century, prior to electricity nationalisation under ENEL (1962). To sum up, no one really believes that a municipal electricity system could really develop in the *Mezzogiorno*, so as to follow the pattern of those local structures which are traditionally present in the North and - albeit to a lesser extent - Centre of Italy.

Finally, the relevant percentages of winning units are displayed in the following Table.

Table 4: MUNI/ENEL Efficiency Comparison (SFM3): Statistics of Interest

Percentage of MUNI winners	35.13%
Percentage of MUNI winners if no mountain villages in rentino/South Tyrol are considered	46.15%
Percentage of MUNI winners if Lombardy only is onsidered	55.56%
Largest Winner Towns (MUNIs)	Parma, Terni, Vercelli, Cremona, Trieste, ondrio
Winner in Metropolitan Areas (Rome, Milan, Turin)	ENEL

4. DEA Outcomes from a MUNI-ENEL Pooled Sample (1994-1996)

This Section provides a cross-check of the Stochastic Frontier outcomes by means of the increasingly used Data Envelopment Analysis (DEA) technique, a linear-programming tool described at length by Charnes, Cooper, and Rhodes (1978), by Banker, Charnes, and Cooper (1984), and more recently by Fried, Lovell, and Schmidt (eds., 1993).

The basic, American-style assumption regarding exogeneity of output does not hold for Italy s distributing units, which are not strictly compelled to provide customers with whatever electricity amounts they need. Moreover, inputs can be reasonably thought of as moderately fixed in the short run because of both stickiness in labour management and political interference in capital investment. Therefore, output maximisation with fixed inputs seemed to be the best starting option for our DEA computations. This gave rise to model DEA22(OUT), featuring two outputs (electricity, customers) plus two inputs (labour,

[26] Note that Apulia is one of the most developed regions in the *Mezzogiorno*.

capital/lines). Generally speaking, the comments made on stochastic-frontier results are still valid after DEA. The Table in the Appendix clearly shows that the efficient ENEL-MUNI units under SFE had their results confirmed in the vast majority of cases.

Output orientation was selected in the pooled analysis so as be consistent with stochastic-frontier outcomes on the same mixed sample (model SFM3, a translog production frontier with energy delivered as output, and kilometres of line and employees as inputs). Moreover, variable returns to scale were assumed. The Table in the Appendix provides usual comparisons of scores for three DEA models[27] and model SFM3, developed in Section 3 and featuring three environmental variables only.

In terms of notation, recall that the reported Table features ENEL s units - chosen on the basis of both geographic and economic proximity to their municipal counterparts - in block capitals, whereas municipal utilities are in small letters (with a final M indicating municipality). If one looks at the comparative table of efficiency scores, it once again seems that DEA and SFE outcomes are not dramatically different. Among 100% efficient units, DEA often spotted municipalities that had been deemed efficient by the SFM3 model, too. It is useful to recall from Section 3 that, even though a minority (slightly more than 35%) of municipalities were found to be more efficient than their ENEL peers, the picture became much less unbalanced (46%) after excluding non-significant mountain distributors in the Trentino-South Tyrol region. After considering Lombardy only, the percentage of MUNIs outscoring their ENEL comparators jumped from 46.15% to 55.6%. It would be interesting to know whether such mixed conclusions are also confirmed by the DEA models being applied to the 1994-1996 pooled sample. The most elegant way to possibly confirm that the national monopolist is actually wrong when claiming that all municipalities are less efficient than ENEL s own local units is simply to test whether efficiency scores from model SFM3 are statistically in agreement with at least one of the three DEA series presented in this Section. At a first glance, the towns that even in DEA had their municipality outscoring ENEL are Brunico (South Tyrol), Cremona (Lombardy), Gattinara (Piedmont), Parma (Emilia), Selvino (Lombardy), Sondrio (Lombardy), Soresina (Lombardy), Terni (Umbria), Tirano (Lombardy), Trieste (Venezia Giulia), Vercelli (Piedmont), and Vigo di Cadore (Veneto).

Obviously, such similarities between DEA and SFE should be statistically confirmed. The Tables below provide batteries of descriptive statistics and comparison tests, which will be commented on in detail throughout the following paragraphs.

[27] The three DEA models used are: DEA22OUT (two outputs and two inputs, output orientation), DEA1C (total customers as the only output, plus two inputs), and DEA1Y (energy delivered as the only output, plus two inputs).

Table 5: Pooled Sample: Non-Parametric and Parametric Tests

Descriptive Statistics

Models	N	Mean	Std. Deviation	Minimum	Maximum
DEA1C	76	0.676018	0.226345	0.2296	1
DEA1Y	76	0.602	0.274529	0.1662	1
DEA22	76	0.713093	0.22532	0.261	1
SFM3	76	0.618842	0.205177	0.226	0.99

One-Sample Kolmogorov-Smirnov Test

	DEA1C	DEA1Y	DEA22	SFM3
K-S Z (Normal)	0.803	1.027	1.12	0.588
Z Prob (2-tailed)	0.539	0.242	0.162	0.88
K-S Z (Uniform)	1.376	1.467	1.902	0.895
Z Prob (2-tailed)	0.045	0.027	0.001	0.399

Parametric Paired-Samples *t*-tests

Pairs/Values	DEA1C-SFM3	DEA1Y-SFM3	DEA22-SFM3
t-value	5.304	-0.649	6.405
Deg. Freed.	75	75	75
t-prob	0.000	0.518	0.000

Non-Parametric Tests

Not appropriate.

Additional Cross-Checking (Paired-Samples Parametric *t*-tests)

Not needed.

K Related-Samples Tests

Tests	Friedman	Kendall's W	Cochrane
Chi-Sq. Value	107.368	107.368	n/a
Deg. Freed.	3	3	n/a
Chi-Sq. Prob	0.000	0.000	n/a

From the one-sample Kolmogorov-Smirnov tests, it appears that normality failed to be rejected for all series, with uniformity being also accepted for SFM3. This allowed us to perform standard parametric *t*-tests on paired samples, with no need for rank-order procedures. The *t*-tests strongly rejected the null hypothesis of zero mean for the series of differences between matched pairs of samples DEA1C-SFM3 and DEA22OUT-SFM3. On the contrary, statistical agreement between DEA1Y and SFM3 s efficiency series strongly failed to be rejected, with *t* s probability standing at almost 52%. This basically confirms the conclusions reached in Section 4 with regard to the relative efficiency of some Northern (especially Lombard) MUNIs as compared to their ENEL counterparts. Therefore, the most similar DEA model to SFM3 - which, once again, is the one featuring energy delivered as the only output, in line with SFM3 s translog production equation corroborates our previous results. Even the remaining DEA models, however, confirmed that such town-based municipal units as Terni, Parma, Vercelli, Cremona, Trieste, and semi-urban ones as Soresina, Tirano, and Brunico managed to outperform their ENEL peers. Once more, the conclusion to be drawn is that no generalisation is possible when comparing MUNIs to ENEL s zones. It is probably true that ENEL does better than small rural and mountain municipal utilities, but sometimes in towns - and especially in the Milanese region - municipalities take the lead. ENEL claims that all MUNIs are less efficient than its distributing local zones. Such generalisation should be rejected, as all comparisons must be carried out on a strict case-by-case basis.

Finally, we emphasise the fact that related-samples tests being performed on all series from pooled sample analysis rejected any similarity, thus crediting the alternative hypothesis that at least two of the examined samples were actually telling the investigator different things. As we saw, however, one out of three matches was actually successful in delivering the same statistical information, and this was - not by chance - the pair which coupled the two most similar specifications, i.e. one-output DEA (with energy as Y) vs. one-output SFE.

5. Policy-Making Suggestions and Regulatory Perspectives

The policy-making suggestions which might be put forward as a result of the work carried out so far stem from the following couple of considerations:

(a) ENEL's econometric analysis showed that (1) non-exhausted economies of scale were found at sample-mean values, and that (2) Northern dominance in efficiency terms persisted even after allowing for exogenous handicaps (with some noticeable exceptions of Southern non-default efficient units);

(b) statistical paired-samples testing and direct rank comparisons found no systematic ENEL dominance over MUNIs: the case-by-case comparison approach was then proposed. DEA comparisons failed to spot any statistically significant superiority of ENEL's units.

As regards point (*a*), given the results on scale economies it seems that town-based electricity distribution is not optimal, as it does not allow firms to work at efficient scale. In fact, ENEL is not organised as a series of local distributors. Its distributing compartments are actually in the number of eight, and operate on an inter-regional basis. The distribution branches of ENEL generally cover much larger areas than the British RECs do, and there are reasons to believe that their size is incompatible with efficiency maximisation. Something intermediate might be sought by the electricity regulator when reforming Italy's electricity distribution sector. For instance, those municipalities which were found to be comparatively more efficient might be granted permission to expand beyond city limits so as to reach for optimal scale, while retaining - at the same time - their local nature[28]. As regards scope economies, it would be probably a good policy choice to keep medium and low-voltage distribution together. Moreover, sub-additivity of cost at local levels should be assumed as a default condition, unless the reverse is proven.

Again on point (*a*), Northern dominance on efficiency grounds was robust to the insertion of pro-Southern environmental variables. Even though some Southern branches managed to feature among the first 50 most efficient units, the majority of them failed to deliver satisfactory results. In policy-making terms, this could lead the regulator to seriously re-consider the cross-subsidy issue between Northern and Southern ENEL distributing units. In order to sustain national price uniformity in the energy industries, the Italian Government - formerly, ENEL's only shareholder - has traditionally allowed massive cross-subsidies to be directed towards ENEL's Southern branches over the years (either transferring profits from Northern units, or raising funds out of general taxation schemes). The present analysis shows that, apart from rural Southern units, there is no strong reason to believe that such North-South cross-subsidies should be maintained. Of course, countryside and mountain units - both from the North and South of Italy - should continue being subsidised in order for universal service to be provided; yet, standard urban branches from the South should be (yardstick) regulated in a similar fashion as should Northern areas. On yardstick competition, as Bogetoft (1994) notices, DEA techniques in particular might be viewed within a principal-

[28] Local distributors proved to be a sensible economic choice in some other European contexts, e.g. Scandinavia and Switzerland.

agent (regulator-regulatee) perspective, since DEA's output provides the investigator with peer firms, i.e. those frontier-efficient units whose input-output mix is closest to that of the relatively inefficient unit under examination. By linking the DMU's performance target to the input-output values which DEA reports for its 100% efficient peers, the energy regulator might implement yardstick competition even in the absence of input price figures.

Furthermore, linear combinations of peers (so-called 'projected points' on the efficient isoquant) might be constructed in order to compare the inefficient unit to its 'virtual' efficient twin, thus linking regulatory targets to 'optimal' production mixes. Of course, DEA's purely deterministic nature is a major obstacle to plain yardstick regulation of the kind shown above. However, after adjusting for peculiar features and allowing for measurement error - which new stochastic-DEA models might do in the future - DEA will naturally lend itself to practical yardstick regulation of geographically-separated local monopolies lying within the public utility realm[29].

As regards point (*b*), neither the econometric nor the linear programming analyses managed to spot any statistically significant superiority of ENEL's local units over municipal distributors (MUNIs) located in the North and Centre of Italy. Lombard municipalities even proved to fare better than ENEL local branches in five out of nine direct comparisons. Paired-samples statistical tests and DEA runs again spotted no significant efficiency differences between ENEL units and MUNIs, thus failing to support ENEL's claims according to which MUNIs should either be shut down, or be incorporated with the national monopolist's distributing arm. With reference to the ENEL-MUNI dispute (shut down MUNIs vs. allow them to survive and - possibly - expand beyond municipal limits), case-by-case analysis is called for, as no generalisation was suggested by the work carried out in this paper. We immediately put this into practice by sketching a tentative, crude table reporting those MUNIs which could be granted expansion. Also notice that the MUNIs which systematically outscored their ENEL comparators - according to all methodologies - are mainly from the Northern plains (Po Valley) and, more precisely, from the Milanese region of Lombardy.

[29] Yardstick regulation typically applies to electricity, water, and gas distribution.

Table 6. Relatively Efficient MUNIs (Candidate for Expansion).

MUNI > ENEL	Region	ENEL Comparators
Brunico	Trentino-A.A.	BOLZANO
Trieste	Friuli-V.G.	TRIESTE
Parma	Emilia-R.	PARMA
Terni	Umbria	TERNI
Cremona	Lombardia	CREMONA
Trani	Puglia	MONOPOLI
Vercelli	Piemonte	VERCELLI
Sondrio	Lombardia	SONDRIO
Soresina	Lombardia	CREMONA, LODI
Tirano	Lombardia	SONDRIO, LECCO
Gattinara	Piemonte	VERCELLI, BIELLA, VERBANIA
Selvino	Lombardia	BERGAMO EXT., BRENO
Vigo di Cadore	Veneto	BELLUNO, BASSANO d/G

As regards ENEL-MUNI comparisons, metropolitan areas cannot be unambiguously classified. Moreover, because of self-evident environmental reasons, Alpine MUNIs from North-Eastern districts should not be included in the comparison altogether. We preferred not to express any judgement on metropolitan areas either, because MUNIs and ENEL units operating there (e.g., in Milan and Rome) are not fruitfully comparable. Differently from medium-sized towns, metropolitan areas are very heterogeneous in that they feature separate residential (often managed by MUNIs) and industrial (often operated by ENEL) districts, which are much more integrated with each other - and usually served by the local MUNI - in medium-sized towns. Therefore, whereas MUNI-ENEL comparisons were - albeit imperfectly - possible for the average city, their feasibility was seriously jeopardised with respect to metropolitan areas due to the above-mentioned heterogeneity reasons. Of course, limited homogeneity is also encountered for smaller towns' MUNIs and surrounding ENEL zones (which sometimes serve rural provincial districts), but the magnitude of this drawback is probably more acceptable for small cities[30].

[30] In other words, higher uniformity between urban and peripheral territories is assumed for medium-sized towns as opposed to large conurbations, which seems to be a sensible hypothesis.

To conclude, the regulatory perspectives stemming from this paper point towards:

(*a*) fewer cross-subsidies among ENEL's local distributing branches - maybe leading to a revision of national price uniformity constraints on electricity distribution;

(*b*) feasible yardstick regulation as a consequence of DEA outcomes on efficient 'peers' for each inefficient DMU under examination;

(*c*) case-by-case analysis of which MUNIs should be authorised to survive future horizontal restructuring of electricity distribution, and which ones should - on the contrary - be merged into ENEL's surrounding distributing branches.

As regards point (*c*), the whole discussion being carried out in the previous Sections unambiguously rejected the feasibility of any generalisation with respect to the ongoing, comparative efficiency dispute between ENEL's distribution zones and local municipal administrations.

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Pooled Sample (1994-1996): DEA Efficiency Scores (DEA22OUT, DEA1C2, DEA1Y2) as Compared to SFE Results (Model POOL3TE)

Unit	SFM3	DEA22OUT	DEA1C	DEA1Y
ANCONA	0.712	0.7845	0.7845	0.6112
BASSANO	0.666	0.7725	0.731	0.752
BELLUNO	0.552	0.5825	0.5825	0.3639
BERGAMO EXT.	0.855	0.8987	0.8891	0.8375
BIELLA	0.56	0.7077	0.5692	0.7077
BOLOGNA	0.85	1	1	0.9939
BOLZANO	0.334	0.379	0.349	0.379
Bolzano (M)	0.241	0.261	0.261	0.2324
BOVISIO	0.899	0.9268	0.9268	0.8908
BRENO	0.533	0.5494	0.5494	0.5426
BRESCIA	0.706	1	0.7774	1
Brescia (M)	0.418	0.5643	0.523	0.5643
Bressanone (M)	0.295	0.2983	0.2983	0.2268
Brunico (M)	0.448	0.4412	0.4412	0.3174
BUSTO A.	0.855	0.9757	0.8942	0.9757
CORSICO	0.975	1	1	1
CREMONA	0.569	0.663	0.596	0.663
Cremona (M)	0.685	0.7112	0.7112	0.5181
Gattinara (M)	0.662	1	1	1
Imola (M)	0.44	0.4596	0.4505	0.4548
IMPERIA	0.717	0.7495	0.7495	0.3326

Laces (M)	0.226	0.2911	0.2296	0.2911
LECCO	0.797	0.8966	0.8045	0.8966
Levico Terme (M)	0.293	0.2905	0.2905	0.1662
LODI	0.721	0.7405	0.7405	0.5861
MACERATA	0.619	0.6523	0.6523	0.4043
MELZO	0.936	1	0.9715	1
Mezzolombardo (M)	0.412	0.962	0.4405	0.962
MILANO	0.977	1	1	1
MILANO EXT.	0.862	0.921	0.8839	0.921
Milano (M)	0.537	1	0.9595	1
MODENA	0.744	0.9906	0.834	0.9821
Modena (M)	0.432	0.455	0.455	0.4229
MONOPOLI	0.663	0.7207	0.7207	0.3746
MONZA	0.99	1	1	1
Osimo (M)	0.405	0.4102	0.4102	0.2264
PARMA	0.683	0.7556	0.7333	0.7428
Parma (M)	0.946	1	1	0.8767
PESARO	0.66	0.7225	0.7225	0.451
Primiero (M)	0.324	0.3606	0.3606	0.216
Rep. S. Marino (M)	0.297	0.3521	0.2994	0.3521
RIMINI	0.642	0.6537	0.6537	0.4706
Riva del Garda (M)	0.511	0.513	0.513	0.2997
ROMA	0.744	1	1	1
Roma (M)	0.495	1	1	1
Rovereto (M)	0.288	0.6323	0.3408	0.6323
SALO	0.687	0.7134	0.7134	0.6594
Sanremo (M)	0.468	0.4874	0.4874	0.2016
Selvino (M)	0.99	1	1	0.2362

Seregno (M)	0.61	0.6473	0.6473	0.5303
Silandro (M)	0.328	0.4026	0.3288	0.4026
SONDRIO	0.556	0.5593	0.5593	0.3873
Sondrio (M)	0.605	0.6923	0.6841	0.5877
Soresina (M)	0.99	1	1	0.4933
TERNI	0.433	0.4687	0.4687	0.3572
Terni (M)	0.976	1	1	1
Tione (M)	0.462	0.5358	0.4766	0.5166
Tirano (M)	0.599	0.591	0.591	0.2825
Tolentino (M)	0.471	0.462	0.462	0.3983
TORINO	0.886	0.9862	0.9862	0.9286
Torino (M)	0.476	0.8445	0.8445	0.7017
Trani (M)	0.664	0.7072	0.7072	0.2991
TRENTO	0.633	0.689	0.689	0.599
TRIESTE	0.481	0.5758	0.4844	0.5758
Trieste (M)	0.608	0.6118	0.6118	0.3045
VERBANIA	0.62	0.6357	0.6357	0.3607
VERCELLI	0.435	0.4695	0.4552	0.4675
Vercelli (M)	0.752	0.8519	0.8519	0.5307
Verona (M)	0.344	0.8126	0.4586	0.8126
VERONA NORD	0.692	0.7236	0.7236	0.5749
VERONA SUD	0.707	0.7884	0.7694	0.7639
VICENZA	0.693	1	0.7476	1
Vicenza (M)	0.547	0.6581	0.6581	0.4634
VIGEVANO	0.658	0.6771	0.6771	0.48
Vigo di Cadore (M)	0.937	1	1	1
Voghera (M)	0.548	0.5587	0.5587	0.1984