Electricity Distribution in Italy: Microeconomic Efficiency Analysis of Local Distributing Units with Methodological Cross-Checking

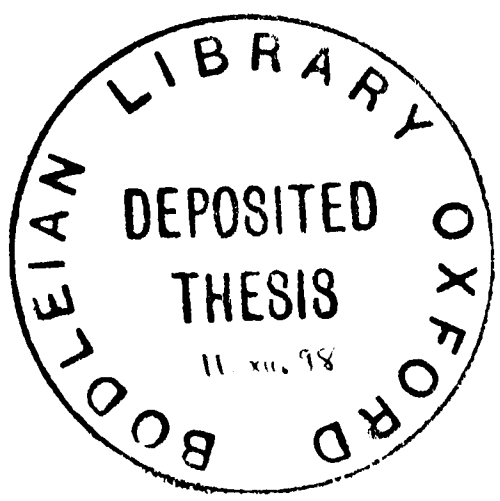
(81,000 Words)

Gian Carlo Scarsi

St Antony's College

University of Oxford

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To My Family

To Anna

To Their Love, Patience, and Support

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Together with Simon Cowan, my academic supervisor at Oxford University, there are a number of people who paved the way to the writing-up of this thesis. They are Christopher Gilbert, who encouraged my postgraduate studies; Carlo Scarpa, whose help with data collection in Italy was invaluable; John Vickers, who acted as my academic interviewer in Oxford; Sverre Kittelsen, who helped me understand the (fundamental) Scandinavian experience with electric utilities; Bill Macmillan, who promoted the purchase of some crucial PC software; Giuseppe Mazzarino, who helped me understand how to cope with Oxford's computing facilities; and - finally - all supportive relatives and friends from both Italy and the United Kingdom.

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Gian Carlo Scarsi

St Antony's College

University of Oxford

Abstract

This thesis 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 was examined with respect to

(*a*) ENEL - the Italian electricity monopolist whose restructuring and privatisation is now under way - and its local distribution branches (Chapters 2, 3, and 5);

(*b*) municipal authorities (MUNIs), i.e. town-based electric utilities which sometimes hold franchises for electricity distribution within city limits (Chapters 4 and 5).

Estimation results from Chapters 2 and 3 highlighted non-exhaustion of scale economies at sample-mean values. Scope economies between medium and low-voltage distribution were also detected (Ch. 2). Efficiency score series stemming from both econometric and linear programming techniques in Chapters 3 and 5 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 from Chapter 4 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) from Chapter 5 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 found out 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.

Apart from the main empirical work, this thesis also features institutional and theoretical overviews (Chapters 2 to 5) with relevant literature surveys, a DEA Numerical Appendix (Chapter 5), and a regional map of the Italian territory (end of thesis).

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CHAPTER 1

AN INTRODUCTION TO ELECTRICITY DISTRIBUTION IN ITALY

1. Introduction

This Chapter is aimed at describing the economic characteristics of electricity distribution in Italy. A brief digression will be made first, in order to present the global (technical-economic) environment in which electricity distribution takes place. Then, the Italian scenario will be introduced, with special reference to both the national monopolist's (ENEL) distributing arm and those municipally-owned local distributors which hold governmental franchises within some Italian districts. Section 2 is a general treatment of the Electricity Supply Industry's (ESI) economic features; Section 3 describes electricity distribution in particular; Section 4 discusses the Italian situation with ENEL as of November 1997; Section 5 is on municipally-based electricity distribution; Section 6 summarises some significant foreign experiences from both European countries and California (US); finally, Section 7 concludes and introduces the main topics being discussed in the following Chapters.

2. Technical and Economic Features of the Electricity Supply Industry (ESI)

The electricity industry presents several technical-economic subsets. Electricity supply to final customers - both domestic and industrial - is the final step of a complex process which is often based upon scale (and possibly scope) economies. Moreover, some basic differences exist between the electricity sector and other network-based industries which are generally

included in the public utility set (e.g., telecommunications, water, and gas). Oligopolistic competition possibilities in the electricity industry cannot be compared to those being currently envisaged for telecommunications[1]. One should - however - notice that the electricity industry is characterised by some (moderately) competitive production subsets. Of course, such 'core' subsets as high voltage transmission and local distribution are structured in such a way that competition will be infeasible as a result of peculiar cost characteristics making asset duplication inefficient on technical, economic, and environmental grounds.

The electricity industry splits up into five different production subsets, namely:

- input acquisition;
- generation;
- network transmission (high voltage);
- energy distribution (medium-to-low voltage);
- retail supply to final consumers (residential and industrial customers).

Input acquisition directly relates to the way electricity is produced. Some traditional fuels used in electricity generation are coal and oil. The most used non-polluting resource is water, whereas newer inputs include both nuclear power and natural gas. Such nuclear-free European regions as (parts of) Scandinavia and Italy need alternative energy inputs, which are sometimes imported. Differently from those Nordic regions (e.g., Norway) which chose to give up nuclear energy as a result of the Chernobyl accident (1986), Italy has no real alternatives to nuclear generation (apart from gas turbines). Its traditional generating resource, i.e. hydro-electric power, is no more a satisfactory option to meet the needs of an

[1] See Baumol and Sidak (1994), and the references therein, for an interesting overview of developments in US telephony.

industrialised country, as it only provides Northern regions with limited amounts of electricity. As a result, Italy is now one of Europe's biggest energy importers (it withdraws energy from France, Switzerland, Austria, Germany, and Eastern Europe). Moreover, it runs its own power stations by importing crude oil from several countries and natural gas from both Algeria and Russia.

Electricity generation is now a potentially competitive subset. The United Kingdom started in 1990-91 its competitive 'Pool' experiment[2], followed by Norway and Sweden, which have recently created a common spot market for bulk electricity. Similar experiments are now under way in California, too. With respect to our work, one should notice that generation *per se* is not particularly relevant to the economics of electricity distribution. However, whether generators are allowed to sell their power directly to customers is a question which may be of great interest for distribution mechanisms as well. This will be clarified later on, with special respect to the Italian electricity market.

Electricity transmission is responsible for transferring high voltage electricity from the generators' access points to distribution network nodes, which are generally structured on a regional basis. Even though some high-voltage power is directly conveyed to distribution networks, the bulk of transmitted energy is scaled down to medium voltage before being re-routed to distribution lines. Differently from generation, the economic characteristics of network transmission are such that any asset duplication would turn out to be inefficient. Strict cost sub-additivity is generally expected to be present in high voltage transmission within medium-sized countries such as the United Kingdom and Italy[3]. As pointed out by Vickers and Yarrow (1988) and Armstrong et al. (1994), competition in generation depends on *ex ante* capacity choices made by the network operator, which might put some generators

[2] Regarding the Pool's efficiency records, founded doubts were expressed by Green and Newbery (1991). See also Vickers and Yarrow (1991).

at an unfair advantage over others as a result of mere locational discrimination (obtained via the imposition of capacity constraints on the transmission grid). Nonetheless, it should also be noted that such 'bottleneck' concerns are limited to the issue of effective competition chances in generation, but do not influence the distribution scenario.

Distributing operators pave the way to final retail supply by withdrawing high voltage electricity from the 'motorway' system (i.e., the transmission network) and reducing its voltage by means of substations, transformers, and capacitors. Once voltage has been scaled down to such levels that are compatible with final supply[4], the distributing unit will have the possibility to either transfer electricity directly to final customers (whenever the regulatory environment allows it to do so) or sell it to electricity retailers.

Even though their voltage is lower and their spread is rarely more than regional, distribution networks - which are characterised by less sophisticated plants, too - enjoy natural monopoly conditions within certain areas[5]. The basic difference in contrast with huge, widespread national transmission networks is that distribution plants are confined to regional areas and - therefore - their monopoly power can be viewed as a local one. Natural monopoly conditions resulting from high fixed costs - most of which sunk - are still present, but inter-regional comparisons should be - at least theoretically - feasible.

The regulator could then try to extract more information for its needs by comparing different local monopolies and creating the right incentives for allocative - as well as internal - efficiency. A link between every firm's allowed price and the industry's average of marginal costs might be established. 'Yardstick' competition[6] is a theoretical model working for

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[3] See Eden (1981).

[4] Domestic levels generally lie in the 115-250V interval, 230V being the standard in Britain and 220V its counterpart in Italy.

[5] See Chapters 2, 3, and 5 for an overview of previous quantitative studies on electricity distribution.

[6] Shleifer (1985).

symmetric, separate markets where both collusion and arbitrage are ruled out by initial assumptions. Of course, real situations are such that a strict yardstick regime will never be feasible. Nonetheless, at least some elements of yardstick competition could be applied to regulation of regional electricity distributors, especially if regional peculiarities are correctly accounted for by means of auxiliary regressions on costs.

The British approach to electricity distribution in the post-restructuring era gave rise to a set of twelve Regional Electricity Companies (RECs) in England and Wales, which were allowed to integrate upwards into generation to a limited extent (15% of their electricity requirements[7]) and buy electricity from the system, basically organised as a market of generators ('The Pool'). The national transmission network, also known as 'The National Grid Company' (NGC), acts as a common carrier and auctioneer of bulk electricity on the 'Pool' market, thus being excluded from the electricity business, except for nation-wide transport. Differently from what happened with respect to the Water Companies of England and Wales[8], no real yardstick regulation has been imposed - at least, not explicitly - on the British RECs so far[9].

Retail supply to final consumers is not a naturally monopolistic business. Such activities as installing and reading meters, or billing customers according to their consumption levels, do not show any persistent cost sub-additivity. Therefore, even though some economies of scope could certainly be envisaged between local distribution and supply, there is actually no strong economic reason for constraining retail supply to be exclusively run in conjunction with local distribution. On the contrary, final supply might be gradually liberalised, and - after allowing

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[7] A certain degree of vertical re-integration has recently been observed in the UK, even though the regulator keeps a cautious view on vertical mergers. However, the vertical economies issue is still an open one and must be mentioned here.

[8] See Cowan (1992, 1997); Armstrong, Cowan, and Vickers (1994).

[9] However, see the MMC (1997) report on Northern Ireland Electricity (NIE) for a discussion of comparative efficiency analysis with regard to RECs.

for any switching costs - independent retailers could be authorised to compete with existing (integrated) local distributors. This is already happening in several countries with special reference to industrial customers; England and Wales will completely liberalise even domestic supply to smaller customers during 1998[10].

As a conclusion, there are reasons to believe that final supply is potentially more competitive than generation itself because of generally lighter exit barriers (lower sunk costs). Broadly speaking, electricity production and supply may be viewed as a complex process whose ends are approximately competitive, whereas its 'core' features cost sub-additivity. What one should not think is that electricity is a monopolistic monolith to be sold and - as a consequence - heavily regulated without any previous restructuring.

3. Distribution Networks in Reality

The economic features of transmission systems have been analysed in depth by Scherer (1976), Bohn, Caramanis, and Schweppe (1984), Berrie (1983), and Green and Newbery (1991). Berrie (1983) also described the basic technical and economic characteristics of distribution networks. Although network economies are present in both distribution and transmission, it should be noted that the former's costs are basically independent of the location of generating plants. Moreover, system constraints which might alter the optimal choice of generators are not relevant to the distribution business. On the other hand, local monopoly characteristics will make distribution networks much more dependent on regional cost drivers. Peculiar features which are generally linked to local areas (e.g., new industrial plants to be served) will then turn out to be the most likely efficiency determinants of

[10] De-integration of retail supply, as well as generation, is now being experienced in Poland (although the restructuring process has begun only recently) and California (where the local Public Utility Commission has

electricity distribution. By the same token, distribution networks will tend to be less stable over time than transmission ones, as a consequence of their need to adapt to rapidly changing regional scenarios.

Following Berrie (1983), and Burns and Weyman-Jones (1994a), we now define a set of possible distribution networks, which will be examined in increasing order of complexity. First, the simplest form of electricity distribution system may be represented by a radial structure (see Figure 1), consisting of a single supply node, which is connected by a main to a number of separate nodes, where electricity is withdrawn and transferred to retail supply. Although every supply point will not depend on other ones - thus making cost disaggregation easily obtainable - a simple radial system is only a theoretical option because of its lack of reliability in the event of system failures. A possible alternative option would be to connect all the peripheral nodes in the radial system, so as to obtain a set of default lines which may be activated in case of failure of the main radial links. Radial schemes then evolve towards 'ring' systems. Since each node in a ring system is connected to the main access point (primary substation) from at least two other sources - rather than the single source as with the radial system - then the distribution company can exploit different loads on the system by shifting power between different nodes. Such an interconnected system also minimises the risk of supply interruption (see Figure 2).

Finally, as electricity loads increase, the ring system described by Figure 2 evolves towards a fully meshed system as shown in Figure 3, with high-voltage networks partially overlapping the lower voltage system. High-voltage reinforcement - which is actually present in some ENEL areas - is made necessary when loads in the system rise above the capacity of the lower voltage system, so as to jeopardise both the reliability and continuity of electricity supply. As

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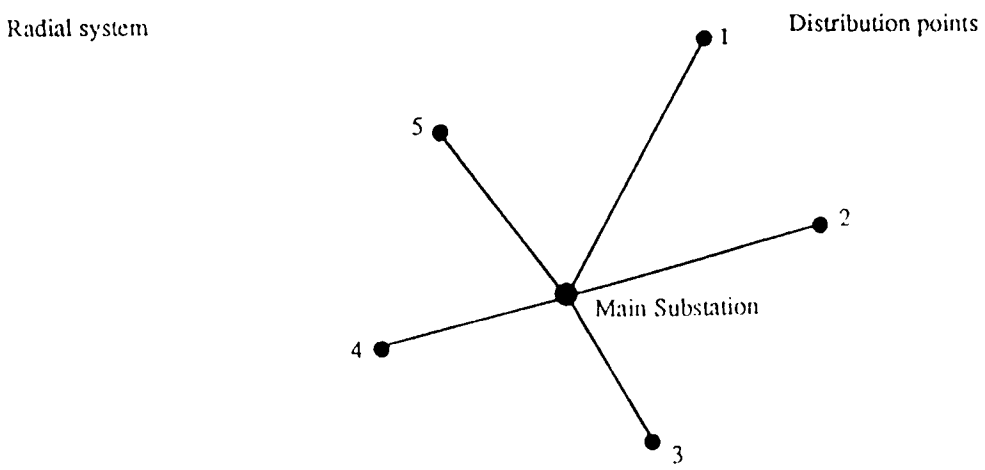
fostered market liberalisation to a laudable extent: see Section 6.5).

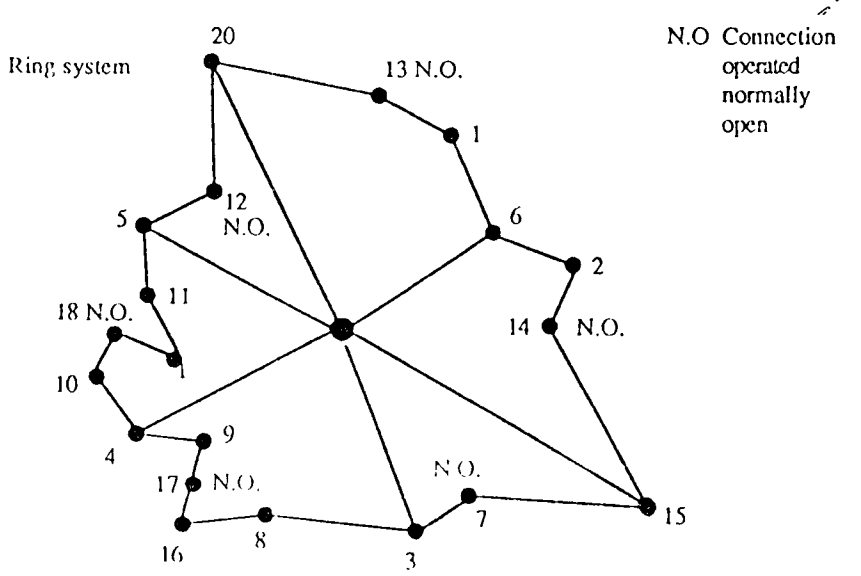
Burns and Weyman-Jones (1994a) notice, such high-voltage overlapping framework - aimed at reinforcing lower voltage lines - should be determined on an economic basis, so that the supplementary investment in high-voltage lines increases capacity both directly - through the installation of new mains and service lines - and also indirectly, by reducing capacity constraints at other points in the system.

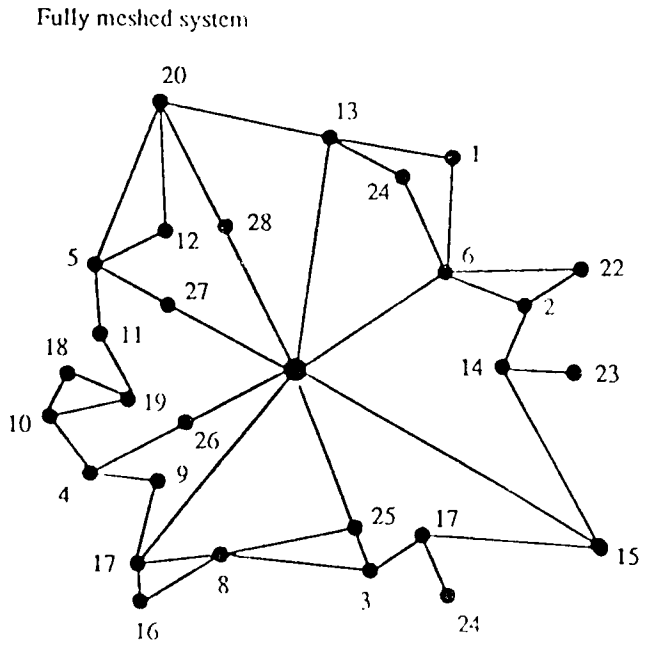
Fig. 1.1: Radial Distribution System[11].

Fig. 1.2: Ringed Distribution System.

Fig. 1.3: Fully Meshed Distribution System.







[11] Taken from Burns and Weyman-Jones (1994a), and eventually from Berrie (1983).

4. The Electricity Industry in Italy: Institutional and Political Background (ENEL)

The Italian energy market is characterised by a lack of indigenous resources, which makes Italy heavily dependent on imports. Oil is imported together with gas[12], whereas electricity is mainly auto-produced from fuel imports. Nonetheless, electricity itself is also imported for a fraction of the country's requirements, with France and Switzerland being the main sources. Ironically enough, imported electricity generally comes from massive foreign nuclear plants, which are sometimes located not far from the Italian border (Swiss sub-Alpine regions, Provence, and Marseille), thus making Italy's choice to give up nuclear power (1987) a curious issue.

Italy's energy policy has been centralised since 1962, when the government decided to take over the electricity industry and create a fully integrated monopolist, named ENEL (or *Ente Nazionale per l'Energia Elettrica, i.e.* National Electricity Board). Private generators were then *de jure* transferred to public ownership at symbolic prices, whereas the transmission/distribution network, which had enjoyed a mixed ownership structure with the State already being involved in high-voltage transmission, was almost completely transferred to the newly-created ENEL. Finally, town-based distribution and retail supply went public, too, with some exclusive franchises being granted to local authorities in some (especially Northern) middle-sized towns and large conurbations. Municipal distribution was also devised for several mountain villages located in South Tyrol[13].

ENEL was kept separated from ENI *(Ente Nazionale Idrocarburi,* or National Fuels Board), which mainly managed the processing of oil and gas. Some links were - however - established, since the two companies enjoyed some scope economies relating to the joint

[12] The main sources are Middle Eastern countries, as well as North African and East European ones with respect to natural gas.

production of refined oil, gas, and heat for power co-generation. The previously mixed structure of electricity generation and supply was reformed in such a way to leave industrial customers with their own generation and co-generation plants (FIAT in Turin, Breda/Ansaldo in Genoa, Italsider/ILVA in Naples and Taranto, and so on). Nonetheless, autogenerated electricity, as a by-product of industrial activities, was legally confined to self-consumption, thus preventing large industrial firms from entering the electricity market, which was then structured as a legal monopoly. *De jure* importing rights were also granted, so as to make ENEL the only Italian firm being entitled to trade electricity on an international basis. Both imports and exports were then conveyed through the national, publicly-owned monopolist.

On the other hand, retail supply was regulated according to a three-party licensing scheme among the government, ENEL, and some municipally-based authorities, ending up in a mixed structure where smaller towns, rural areas, and almost all territories in the South were served by ENEL itself as a final supplier, whereas separate local concerns were licensed as retailers - and often distributors - to operate within more advanced, especially Northern urban contexts.

Pricing policies for public utility services have traditionally been highly centralised in Italy. With special reference to electricity, the Interministerial Committee for Prices *(Comitato Interministeriale Prezzi,* or CIP) has directed prices and tariff structures according to a command-and-control criterion since energy nationalisation in 1962. CIP was abolished on 1 January 1994, when a presidential decree transferred responsibility for electricity tariff regulation to the Ministry of Industry and CIPE *(Comitato Interministeriale per la Programmazione Economica),* which is the main economic planning body in Italy. This was bound to be a provisional arrangement, since the government also decided to create some independent authorities for public utility regulation.

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[13] See Section 5 for further details on municipal distribution.

The first proposed option was to create a single regulatory body for all utilities. However, staggered divestiture plans for different utilities, as well as technical reasons, suggested to create separate regulators for each sector, to be similarly structured as those established in Britain over the past fifteen years. The electricity regulatory body (*Autorità per l'Energia ed il Gas*) was finally set up in September 1996, and is currently organised as a non-governmental department, being responsible towards the Parliament. It has an independent chairman and two deputies, who are in charge for seven years, and its full staff will be probably around eighty people. Its main task will be to examine the government's most recent proposals on ENEL's privatisation, which do not involve any prior break-up. Following decentralisation pressures, the regulatory agency for electricity has been based in Milan. ENEL's divestiture is now expected to start during 1998, and completion is planned by the decade's end. As regards the fuels industry, a first tranche of ENI's shares has been sold in November 1995. The semi-monopolistic position of the national gas utility did indeed appeal investors, so as to raise ITL 6,300 billion to the Italian Treasury. A second tranche has been marketed in early 1997, with similar outcomes. ENI's and ENEL's divestitures - when considered as a joint operation - may be regarded as one of the largest privatisations ever experienced in Western Europe.

The price formula which has been devised since 1994 is aimed at calculating annual tariff adjustments. Its first version dates back to 1991, when the electricity supply industry's tariff structure was still under CIP's control. According to such a rule, price changes on a yearly basis could not exceed the Retail Price Index (RPI) minus a productivity parameter, which should reflect expected technological improvements in the industry. This is clearly a RPI-X approach, whose incentives are stronger on technical grounds - as cost minimisation is incentive-compatibly fostered, except when the regulatory review approaches - as opposed to

traditional cost-plus regulation[14]. However, the future regulatory scheme will also include some indicators for service quality (which have not been specified so far), as well as fluctuations in exogenous costs (such as fuel input costs). This will probably entail some pass-through provisions for those costs which are regarded as exogenous to the industry. Notably, some input costs are not properly exogenous under the current circumstances, since the Italian government is entitled to alter them by means of several economic policy measures. Once the whole energy industry is privatised, exogeneity of fuel prices will probably be more plausible, even though ENEL's monopoly on foreign trade - which should be abolished - might still distort the market to a significant extent.

The government which came to power in 1996 clearly stated that geographic uniformity of electricity prices will be kept as part of universal service commitments. Therefore, cross-subsidisation among customers is likely to persist, unless a compensation fund is set up to smooth out differences in local supply costs. Quantity discounts to large customers are likely to be reduced, as a price discrimination ban is under way[15]. However, individual negotiation with large industrial customers will probably be maintained, provided that all negotiated terms are published by the utility. This should discourage undue preference, even though the real applicability of such a measure is highly jeopardised by asymmetric information problems. In any case, even when publication requirements are met with no cheating, no legal 'most favoured nation clause' will constrain the utility's pricing policies.

According to the government's plans, a transition period of no less than five years will be required for the gradual phasing out of cross-subsidies. The so-called 'social tariff' has also been abolished, thus pushing up Italian electricity prices to final customers considerably over

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[14] It should also be noticed that, as a result of the sort of information used by principals in revising the X parameter at each regulatory review, price-cap regulation will resemble traditional ROR (Rate-of-Return) regulation with a longer lag. This was first pointed out by Vickers and Yarrow (1988), and by other authors thereafter.

the last three years. Fixed rentals, which once had been set to purely symbolic levels, have experienced the most dramatic rise. The phasing out of cross-subsidies also increased prices at peak hours, as network congestion requirements induced the Italian authorities to adopt more severe time-of-day tariff schedules.

Tariff issues, as well as quality regulation, are being gradually transferred to the new regulatory body, which will also be responsible for resolving pricing disputes. Some co-ordination is also being sought between the industry regulator and the Italian Antitrust Authority (AGCM, or *Autorità Garante della Concorrenza e del Mercato).* As a first move, the Industry Minister is expected to set initial tariff levels for 'time zero regulation', on which future price adjustments will be calculated by the authority according to a RPI-X+Y scheme (Y being the cost pass-through element onto final customers for those input prices which will be deemed exogenous to the electricity industry).

The last move that CIP made before being liquidated was the rise in electricity marginal tariffs by an average 2% (December 1993), with connection charges going up by more than 40%. Cross-subsidies began to be phased out in August 1994, when an Industry Ministry decree revised social tariffs[16], as well as those applied to small-sized businesses. Since energy taxes still remain quite high in the country (fossil fuels being the most heavily taxed), Italy decided to say 'no' to a proposed EU energy/carbon tax. In this respect, it is worth noticing

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[15] Nonetheless, quantity discounts might well be justified by underlying costs.

[16] Residential tariffs were re-defined in such a way to levy surcharges for those households which are found consuming higher amounts of electricity than the standard quantities resulting from national averages (150 kWh/month for 1.5kW end-points, 220kWh/month for 3kW end-points, 1993). At the end of 1997, the electricity regulator (AEG) increased domestic tariffs for 1998 by 1% in real terms, roughly following inflation rates. The old 'thermo-surcharges' granted to ENEL so as to pass fuel costs partially on to final customers (fossil fuels being deemed too much price-erratic for ENEL to bear their risks in full) were implicitly inserted into the marginal price for electricity, thus simplifying electricity bills to a moderate extent. Two-part tariffs were confirmed for the vast majority of domestic users, and social benefits to poorer users were drastically reduced. Finally, municipal distributors were allowed to levy a small 'council tax' on electricity. Both ENEL and municipal units were also compelled to improve the quality of communication to final customers by means of clearer bills, bulletins, customer feed-back forms, partial funding of safety-improving devices (external meters, safety sockets/plugs), energy-saving schemes, and the like.

that heavy energy taxation in Italy is not due to any environmental or 'Pigouvian' concerns: on the contrary, it is just aimed at raising revenue by overtaxing inelastically demanded commodities such as oil and, albeit to a lesser extent, gas (in other words, it is a 'Ramsey' tax). General taxation pressures are then undermining Italy's energy intensity[17], whose value is still among the lowest ones when compared to the average of the industrial set of OECD countries which are periodically surveyed by the International Energy Agency (IEA).

4.1 The Electricity Industry in Italy: Structure

The Italian generating capacity in 1994 (OECD data) was based on:

- imports from Switzerland, France, and Germany (17.6% of total supplies);
- own generation, totalling 63.5 GW at end-1993, subdivided into oil-fired generation (51.8%), hydro power (18.9%), gas turbines (18%), coal generation (9.1%), plus some geothermal generation (no nuclear generation, as a result of 1987's referendum saying 'no' to nuclear power).

Total losses in the generating system are mainly due to the low efficiency of older plants, which are now being replaced by new CCGT generators (11.7 GW of new gas plant capacity is expected to be added over the period 1996-2000). The government is expecting gas-based generation to increase to 31% of total inland capacity by the year 2000. Gas/oil substitution will cause a massive switch from oil to natural gas (thanks to some new flexible multi-fired plants) in such a way that oil-based generation will fall to 36.5% of the total by 2000. Hydro-

[17] 'Energy intensity' is defined by the IEA (International Energy Agency) as the ratio between Total Primary Energy Supply (TPES) and GDP.

power should be retained, albeit with some restructuring, and coal-fired generation will be gradually reduced, although not phased out completely because of heavy labour-market pressures.

However, electricity imports are bound to go up in the foreseeable future because of the government's difficulties in reaching agreement with local authorities on the location of new multi-fired - and potentially polluting - stations. Nevertheless, some nuclear research is under way in order to convert old nuclear stations to a brand-new, cleaner technology which could make the nuclear option politically more appealing in the near future.

Except for auto-generation as a by-product of some big industrial firms, power generation has continuously been under ENEL's monopolistic control from 1962 to 1991. The first concrete moves aimed at tackling the liberalisation problem in electricity generation were made by Laws No. 9 and 10 in early 1991. Law no. 9/1991 partially deregulated independent generation, and - as a result of this - some 5,300 MW capacity were commissioned to independent producers over the period 1993-1998. Independent capacity (municipal utilities, industrial co-generators, and other industrial producers such as FIAT and Edison) rose by 240 MW to reach a total amount of 11,679 MW in 1994.

As a result of generating capacity being partially shifted to independent operators, ENEL is now expecting that its share in total generation will be reduced from more than 80% in 1993 to 71% by 2002. This is of course not enough for a real liberalisation of the generation subset, especially because no structure at all has been envisaged for the bulk electricity market so far. In other words, neither a 'Pool' market has been proposed, nor has a bidding system for generators been established by the government.

Therefore, new generators will only have the option of selling their electricity to the network, at such prices which will be unilaterally set by the network's owner, that is ENEL, albeit subject to a (highly imperfect and loose) regulatory constraint. The efficiency ranking of independent generators has also been left with ENEL itself - whose management could be subject to capture, as well as being clearly stimulated to unduly prefer (*ceteris paribus*) ENEL's own generating plants. The Treasury Ministry, which still is ENEL's majority shareholder, will only be required to formally approve such a ranking[18].

This once again calls not only for restructuring of the generation subset of production (according to the British, Chilean, Californian, and maybe Polish experiences[19]), but - above all - requires ENEL to be broken up in order to divest itself of non-monopolistic activities. In this respect, Law no. 10/1991 provides for grants for co-generation and renewable-based capacity, thus creating some incentives for new co-generation projects to be finalised.

Finally, one may notice with no surprise that partial liberalisation in Italian generation mostly favoured those industrial firms which were already generating power on their own (Edison, Sondel, FIAT, ILVA, plus some CCGT projects at API, ERG, and SARAS refineries). New generating projects were also hindered by some legal ambiguities on liberalisation of electricity sales, as well as on transport and exchanges of electricity among different generators prior to joining ENEL's network, which were subsequently sorted out by virtue of an Industry Ministry Decree dated August 1994.

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[18] However, the electricity regulator might impose that the 'interconnection' price should only cover ENEL's lost profits plus the opportunity cost stemming from the foregone business which would result from the alternative generators channelling their energy into ENEL's transmission network. Such a rule, known in the literature as the 'Efficient Component Pricing Rule' (ECPR), was first proposed for telecommunications (Baumol and Sidak, 1994), but its application to 'electrical interconnection' might also be useful in weakening ENEL's incentive to favour its own generating units when constructing the generators' ranking.

[19] See Galal et al. (1994) for a cost-benefit analysis of some public utility divestitures in three developing countries (Mexico, Chile, and Malaysia).

4.2 The Uneven Way to Privatisation

Changes of government during both 1994 and 1995 slowed down ENEL's privatisation process to a considerable extent, and especially jeopardised prospects for industry restructuring. However, under a plan approved by several Ministers in November 1994, ENEL has been obliged to divest itself of part of its generating capacity within three years of the first tranche sale.

Political pressures and revenue raising requirements are currently undermining electricity restructuring in Italy. Macroeconomic objectives are also interfering with the efficient shape that the Italian electricity industry should assume in the years to come. For the time being, restructuring will only be partial, as the following statements published by the Italian government clearly show:

- Competitive elements will be introduced in the power generation subset only, and should be based upon competitive bidding procedures for new generating capacity. However, no 'market for power' has been specified yet.
- Concession agreements will be negotiated for ENEL and other companies involved in transmission and local distribution.
- Geographic price uniformity will be retained, as part of general social policies.
- All companies will be required to unbundle their activities, in line with EU directives. Accounting separation will then be required, even though one can well suspect that information asymmetry will result in tricks being performed and transfer prices being widely used within ENEL's future balance sheets. Accounting separation is seldom a sound substitute for radical economic break-up of monopolistic firms.

- Universal service obligations will be generally retained, albeit such measures as the 'social tariff' for low users are going to be phased out to a full extent. Service obligations, as well as tariffs and quality levels, will be supervised by the new regulatory authority which has been set up in September 1996.

- ENEL's monopoly rights on power imports and exports will be removed as a result of the restructuring programme being finalised.

- Law no. 10/1991 also established a new system of labelling and certification of appliances, so as to get along with EU's labelling and quality control requirements, to be met by 1995-96.

4.3 Environmental Issues, and Some Recent Developments in the Industry

Even though electricity is not as polluting *per se* as other kinds of energy[20], the choice among different generating technologies is crucial in determining the industry's contribution to global CO_2 emissions, which Italy has accepted to reduce to 1990 levels by 2000 (according to EU directives). For instance, oil and coal-based generation poses some problems in terms of air pollution, whereas even hydro power, which is the least polluting of all technologies, may result in earthquake - as well as landslide - risks being increased, let alone visual amenity problems.

In this respect, Law no. 61/1994 established a new national environmental protection agency, called ANPA *(Agenzia Nazionale per la Protezione Ambientale),* which will be charged with promoting and conducting environmental research, providing technical support

[20] However, electricity might be more polluting than gas for certain types of domestic usage, e.g. for cooking.

to regulators in formulating standards, and co-operating with the European Environment Agency (EEA).

As a general consideration, the Italian government should increase efforts to resolve conflicts of national, regional, and local jurisdiction in order to operate new environmentally friendly stations (CCGTs, renewables, and some new hydro power) to provide for greater flexibility in the choice of fuel inputs, within the constraints of both national and European CO_2 emission targets.

Changes of government, as well as quite slow legal reforms, postponed ENEL's privatisation during 1996-97. Partial divestiture of ENI took place in late 1995 and early 1997. The electricity regulator has now been set up, and the Minister of Industry signed a modified concession agreement with ENEL in December 1995.

No schemes have been adopted so far with respect to restructuring of electricity generation (except for limited rights being granted to independent generators), and - in particular - no criteria have been specified as regards a possible 'market for power'. ENEL still remains the market leader in the non-monopolistic generation subset (its market share still amounts to 78%), and no competition is currently being envisaged between independent generators and ENEL's generating arm. The only possibility which has been given to independents is a right of application for interconnection to ENEL's transmission network on the basis of 'generation proposals', to be ranked and selected by ENEL itself - with both the Industry and Treasury Ministers being generally expected to *ex post* subscribe to ENEL's decisions.

The creation of a 'Pool' market for power might be viewed as the main restructuring priority, and technical assistance can now be obtained thanks to the new regulatory body. The regulator should not be excluded from basic policy-making.

Moreover, market rules for generation should be specified by the agency, which is also expected to restructure the downstream market for electricity supply to final customers (both industrial and residential), in order to supervise ENEL's negotiations with retailers and open up the supply subset of production to competition (by extending the current municipal concessions to private retailers). Finally, the regulator is expected to set standards for investment in transmission and distribution, as well as quality and environmental[21] parameters.

On the other hand, the Italian government should make decisive moves towards a fair divestiture of ENEL's generating facilities and consider the possibility of breaking up the monopolist's local distribution network into several regional, or inter-regional, companies modelled upon the British Regional Electricity Companies of England and Wales (RECs). Finally, yardstick competition in distribution might be considered. This requires a sufficient number of comparable regional monopolies[22]: clearly, only three or four supra-regional distribution companies - as recently proposed by the government - would not suffice.

Following the latest regulations, the Italian Minister of Industry signed a 40-year concession agreement (effective from 1992) with ENEL in December 1995, specifying public service conditions, obligations to supply, geographic tariff uniformity, and a price discrimination ban towards customers belonging to every end-user category (both domestic and industrial). Agreements with municipal utilities will also be subject to regulation, and privatisation schemes are being proposed for some profitable local utilities in the Northern

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[21] The importance of environmental regulation should not be understated: for example, in his analysis of productivity growth in the American electricity generation industry, Gordon (1992) found that productivity growth was actually negative between 1968 and 1987, this being partially due to higher environmental costs imposed by energy regulators (electricity regulation in the USA is co-ordinated by the Federal Energy Regulatory Commission, or FERC).

[22] The MMC (1995) report on take-over of Northumbrian Water by Société Lyonnaise des Eaux discusses the issue of the value of the loss of a comparator firm following mergers and take-overs. It must be said that the accuracy of regulatory price controls may be reduced by the loss of comparators, which also introduces a clear trade-off between effectiveness of yardstick controls and possible exploitation of scale/scope economies.

regions of the country (Milan, Turin)[23]. The government has also drawn up 71 concession agreements with municipal authorities and intends to send them to the Antitrust Authority (AGCM) for approval.

As for ENEL's 'real' privatisation, gloomy prospects for future competition are the most likely option to date, following a new agreement reached by the Ministers of Treasury, Budget, and Industry in November 1995, which envisages a three-stage divestiture programme over two-to-three years[24], to be scheduled as follows:

- *Stage 1:* Minority stake (30%) to be floated by 1997, plus formal vertical unbundling of different production subsets (with no economic break-up), in line with European requirements about accounting separation within public utility firms. ENEL's *de jure* monopoly over import/export activities will be lifted according to EU and Italian antitrust regulations[25].

- *Stage 2:* ENEL's generating activities to be reorganised into a separate subsidiary, which will not be disembodied from its parent company. A second tranche of shares is to be sold with a governmental 'golden share' agreement. The transmission network should be ring-fenced and will be kept under public control by virtue of the golden share device. The government will also keep basic electricity policy under its direct control. Finally, no horizontal break-ups in electricity distribution are under way.

- *Stage 3:* Final flotation of ENEL, with the government giving up the majority of shares and, finally, its golden share rights. Strategic policies will remain centralised.

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[23] See the *Post Scriptum* for recent developments on municipal utilities.

[24] At the European Union (EU) level, an Electricity Directive was passed in January 1997 allowing for the phased liberalisation of the European electricity market from 1997 to 2006.

[25] This should halt legal proceedings started by the EU against Italy.

Neither the introduction of a market-based mechanism in generation is planned, nor is the establishment of a regional yardstick competition regime for distribution.

The break-up - as well as the 'common carrier' - option has been ruled out, thus showing the government's concern for revenue maximisation. Divestiture proceeds have been set as a top target, thus jeopardising the long-term success of electricity privatisation in terms of microeconomic efficiency. Macroeconomic constraints are probably undermining the effectiveness of divestiture from the viewpoint of efficient resource allocation and effective total cost minimisation (i.e., internal efficiency) within the industry. Senior management pressures also played a significant role in lobbying against ENEL's break-up: this resembles the British scenario with BT and BG at the early stages of their divestiture[26] (1984, 1986).

The Italian Antitrust Authority noticed that the government's plan is not sufficiently pro-competitive, and therefore suggested to submit it to the judgement of the new regulatory agency. Unfortunately, the government will not be bound to abide by the regulator's recommendations. An earlier, more pro-competitive plan had already been approved in November 1994, but was rejected in early 1995 after a change of government took place.

Finally, one would like to stress the environmental issue once more. First, the set-up of ANPA (the national environmental protection agency) has to be considered as a positive event, subject to the caveat that some form of co-ordination is now needed among ANPA and the other regulatory bodies at various levels, in order to implement a common environmental policy to be defended against external pressure groups. Some co-ordination would also be necessary between ANPA and ENEA, the Italian board for technological research in the energy sector.

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[26] See Yarrow (1989b) and Kay and Thompson (1986) on senior management as a constraint upon pre-privatisation restructuring.

In addition, the use of renewable fuels should be encouraged. ENEL has recently commissioned three experimental wind farms to be based in Central Italy's Apennines and in Sardinia, so as to increase Italy's alternative generation capacity, which now stands at a modest 45 MW of wind power capacity.

The last environmental prescription for the Italian government is to try curbing energy demand growth, with special reference to the road transport sector (motorways) - whose congestion has reached unacceptable levels - especially by stimulating freight demand on railways. As a concluding remark, one suspects that the formal commitment to reduce CO_2 emissions to 1990 levels by the year 2000 will hardly succeed in inducing the Italian government to tackle the road congestion issue effectively[27].

5. Municipal Electricity Distribution in Italy

Local utility services in Italy have traditionally been operated by municipally-owned concerns. Such firms, known as *Aziende Municipalizzate*, have been structured in such a way that almost all public utility services at city levels were transferred from national utility monopolists to City Councils, which were granted concessions from the government to run those services by using their own plants and personnel. Both price and quality levels, however, are set by Ministerial Decrees according to 'geographic uniformity' criteria, and generally equalise price/quality mixes to those which are imposed to national utilities. This clearly stimulates local utilities to cream-skim at ENEL's territorial borders when possible.

[27] The Convention on Climate Change was initiated at the UN Headquarters, New York City in May 1992; it was open for signature at Rio de Janeiro from 4 to 14 June 1992, and thereafter at the UN Headquarters themselves until 19 June 1993. By that date, the Convention had received 166 signatures. It entered into force on 21 March 1994. Ratification of the Convention went on until the Kyoto Conference on Climate Change (1997) and is still taking place. Italy ratified the Convention on 15 April 1994, after signing it on 5 June 1992. Following

They are also allowed to retain the profits stemming from urban services being priced at nationally-averaged levels. The rationalisation process which municipal utilities underwent during the past few years abated municipal electricity distribution to a considerable extent - from 12% in the Sixties to 7% in 1994. Local distributors are now serving around 2.4 million customers and distributing almost 14,000 GWh energy - around 7% of Italy's global electricity output in 1992. However, they generate only 8,500 GWh, the remainder being covered thanks to ENEL's medium-voltage deliveries. Electricity liberalisation in Italy has started by turning some of these municipal concerns into joint stock companies, thus establishing the basic condition for future stock market flotation.

Local authorities have their own dedicated personnel and are run by specialised managers, to be hired by City Councils - which own the concerns - by means of public calls for jobs (*concorsi pubblici*). Directors are charged with general management plus some technical tasks, whereas financial and long-term management is run by both internal bodies and City Councils themselves - which generally provide local authorities with funding and financial back-up, too. There are, however, some profitable local concerns - mainly located in provincial Northern towns - which actually *transfer* their profits to the City Councils they are owned by.

Industry concentration for local distributors in Italy is very high[28]: there are a few municipal firms serving highly populated areas, plus a substantial fringe of smaller, provincial units which hold concessions in the countryside and the mountains (mainly in the North-Eastern districts). In fact, only four municipal distributors own distribution plants and networks which exceed 100 MW capacity, with more than 100,000 customers and 100

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ratification, the agreement entered into force on 14 July 1994 on the Italian territory. Italy confirmed its emissions commitments (CO_2) for the year 2000 at the Kyoto Conference on Climate Change.

[28] See Kwoka (1996) on the limited amount of competition in electricity distribution which exists in the US. With respect to the US case, the author finds that competition in distribution does reduce costs.

employees: these are Milan (AEM Milan), Turin (AEM Turin), Rome (ACEA), and Brescia (ASM). Nonetheless, it is worth noticing that only Rome and the Northern industrial district of Brescia enjoy a complete territorial coverage over their municipal jurisdictions, whereas Milan and Turin currently feature a 'double' distribution system, with their municipal operators serving the city centre, and ENEL doing the remainder of the job in the outskirts. The Italian government should now decide whether Milan and Turin may have a 'global' and independent electricity distributor ('Milan Electricity', 'Turin Electricity'), to be devised by merging ENEL's local activities with their respective municipal operators (AEMs).

Furthermore, a recent parliamentary bill (L. no. 142/1990) introduced the concept of 'metropolitan area', and granted such a status to nine Italian towns (Turin, Milan, Venice, Genoa, Bologna, Florence, Rome, Bari, and Naples), which now have the right and duty - among other things - to distribute and supply both water and energy services to all kinds of customers throughout their cities and outskirts. Unfortunately, due to the fact that some of these towns had never run a proper local utility company before, electricity - as well as gas - distribution is currently being delegated to ENEL and SNAM (a subsidiary of ENI). However - as previously noticed - Turin, Milan, and Rome already control their own local electricity distributors, even though the only municipal concern to be granted a global concession over its whole metropolitan territory is the one based in the capital. Finally, metropolitan councils should also run local railways, and operate sewage and sewerage services as well. Whereas the latter are now provided locally by virtually every metropolitan council, railway services keep on being managed by the national railway operator (*FS*), with the only exception of Milan, Genoa, Naples, and Palermo, whose metropolitan train management has recently

shifted from *FS* to local concerns, in order to set up proper 'underground' services in the future[29]. We now turn to local electricity distribution in particular.

Municipal electricity distributors are traditionally present in Italy, being mostly concentrated in the Northern regions of the country. There are thirty-seven local utilities to date, running basic services and - sometimes - public transport as well. Except for a couple of distributors in the Centre and just one in the South-East, all remaining municipal firms are concentrated in Northern towns. They are regarded to be efficiently run overall, even though it is not always easy to separate their electricity business from other public utility services. Internal cross-subsidisation has traditionally been widespread, with special regard to those firms operating local bus and underground services, as well as basic public utility ones.

ENEL suggested that local distributors are too small in terms of efficient production scale, and should then be either shut down or merged into ENEL's departments themselves. As it will be shown by our local analysis, sub-additivity of cost is likely to hold for ENEL's zones; nevertheless, this does not necessarily mean that municipalities should be shut down in favour of ENEL's exclusive distribution. On the contrary, the most efficient distributors ought to be allowed to expand beyond municipal borders - in order to fully exploit scale economies - and yardstick competition might be envisaged with reference to both municipalities themselves and ENEL's local branches - especially if they are to be restructured according to the measures which will be proposed in the following Chapters.

We are going to examine a sample of thirty-seven municipal utilities. As previously noticed, the four largest local distributors in Italy are those located in Milan, Rome, Turin, and Brescia. Municipal distributors in Northern Italy were set up between the end of last century and the First World War. They obtained governmental concessions with regard to the

[29] As regards Milan specifically, metropolitan trains are now being integrated with underground lines, in order to reach for a unified public transport system, which the town had never enjoyed so far (April 1997).

management and supply of public utility services within city - and sometimes provincial - limits.

The most advanced local utilities enjoy substantial scale and scope economies by operating electricity, water, sewage and sewerage, gas, networked heating via co-generation, public lighting, public transport, and the processing of urban waste at the same time. They may be regarded as full multi-utility companies, albeit their scale of operations is strongly constrained by the presence of national suppliers managing public utility services throughout the country. Nevertheless, the Italian government is now planning to transfer local utilities from City Councils to private investors. Even though national monopolists such as ENI and ENEL would like local distributors to be either absorbed or shut down, the debate is open with reference to the optimal scale of production at which such concerns should be allowed to operate. Some provincial expansion is being observed at the moment for Northern utilities. This is broadly consistent with the outcomes of our study[30].

Local utilities usually co-generate electricity and heat, which is carried through (underground) heating pipelines and conveyed to the customer's premises[31]. Their distribution networks and substations are connected to ENEL's national grid, as well as to the micro-systems of neighbouring municipal concerns. Similarly, natural gas, which was introduced in Italy during the 1950s to replace coal-based gas, is distributed to both households and industrial customers by means of micro-grids being connected to SNAM's (ENI's gas subsidiary) main pipelines. Electricity voltage is scaled down thanks to municipally-owned substations and capacitors, whereas SNAM's raw natural gas - mainly imported from Algeria and now from Eastern Europe - is de-pressurised in order to be compatible with household

[30] See Chapters 4 and 5.

[31] The first Italian operator to introduce networked heating in Italy was the Northern industrial centre of Brescia, which started to 'distribute' heat to households in 1972, and implemented electricity and heat co-generation from waste in 1978.

usage. On the other hand, industrial customers are directly provided with medium or high-pressure gas. Finally, water is 'produced' and distributed on an independent basis, since Italy has never had a proper national system of interconnected networks for water and sewage. Basically, every municipal utility owns its plants - which complete the whole 'cycle' of water, from ground acquisition to purification, distribution, final supply, sewage, and sewerage. Pumping businesses are also active for both storing water and producing hydro-electricity to a limited extent. Generally, local concerns co-generate partial amounts of electricity either from waste - in which case, heat is by-produced as well - or from water, thanks to some pumping stations based on the Northern mountains[32]. Other generating units are now being bought, with CCGTs (Combined Cycle Gas Turbines) being the favourite technology in terms of both cost-efficiency and environmental considerations.

With special reference to electricity distribution, local utilities started obtaining governmental concessions during the first decade of the twentieth century, following popular referenda. Local distributing companies were first created and then incorporated into municipal concerns, to be managed by City Councils as separate entities. Electricity distribution networks are owned by the local companies themselves, together with some substations and capacitors, whereas several access points to ENEL's grid exist in order for electricity to be transferred and swapped between the networks. Although local concerns generally own some small generating assets, they are basically 'net importers' of electricity at such wholesale prices which are set by ENEL and forwarded to either the Interministerial Committee for Economic Planning (CIPE), or - more recently - the electricity regulator (Energy Authority), for official approval.

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[32] This is particularly true of North-Eastern utilities situated in the East of Lombardy and in the Northern provinces of the Venetian macroregion (Veneto's highlands and Trentino-Südtirol).

Local utilities are currently protesting against administrative prices for wholesale electricity or 'Tariffe Uniche Nazionali' (TUN) - which were devised as a sort of 'Bulk Supply Tariff' (BST, defined by the British Energy Act 1983[33]). Apart from buying ENEL's high-voltage electricity and producing some by themselves, local distributors are also interconnected to neighbouring networks owned by bordering municipal utilities[34]. Then, Italy is currently experiencing a sort of 'double' distribution network across some of its provinces, whereas the national grid for high voltage transmission is obviously not duplicated and still firmly owned by ENEL itself.

From a technical point of view, local municipalities own medium-voltage distribution networks - as well as supply facilities, such as micro-transformers and meters - and several transforming substations. These are interconnected to each other, and used to scale down electricity voltage from 23-25,000V to 15,000V. Then, hundreds and - sometimes - thousands of medium-to-low voltage transformers are run at the end of the scaling process, in order to distribute electricity to firms and households at 380V and 220V, respectively. Very large users - such as steel plants - either auto-generate their own electricity or are connected to medium-voltage lines directly. Even though some 'consumer charters' are present to establish and enforce customer rights with respect to low-voltage (domestic) electricity supply, it is worth noticing that local distributors are still 100% monopolists in supply services as well. No

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[33] See Yarrow (1986).

[34] Municipal distributors are connected to both ENEL and other municipal networks. This stems from the past, municipal structure of electricity distribution in the North of Italy prior to nationalisation (1962). For instance, the Northern and North-Eastern municipal utilities based in Milan, Brescia, Verona, Rovereto, and Vicenza (located in Lombardy, Veneto, and Trentino) jointly own a co-ordinating centre managing electricity transfers and swaps on both their distribution and transmission networks. Of course, ENEL also takes part in this process, but the municipal links are older and generally prioritised by MUNIs, which turn to ENEL's supply as a last resort option only (demand peaks). On ENEL's centralised prices to MUNIs, see the above discussion with regard to the 'Tariffe Uniche Nazionali'. Gas pipelines are run by municipalities according to similar criteria. Gas, as well as electricity, might be distributed on a regional basis by some municipalities in the near future. MUNIs already provide several provincial centres with networked heating and water, and sometimes with gas. On the other hand, electricity distribution is generally restricted to main towns only, and to their immediate outskirts.

liberalisation in supply is under way at the moment in Italy, contrary to the 'new electricity experiment' which is going to take place in the United Kingdom in the very near future (1998).

When one tries to compare ENEL's performance with that of local concerns, several problems are encountered:

(*a*) municipal authorities sometimes co-generate electricity and heat, which is distributed to final customers along with electricity itself, with possible scope economies and (in some cases) no accounting separation;

(*b*) several public utility services are provided by local concerns. This - once again - gives rise to scope effects, together with non-trivial common cost allocation problems;

(*c*) even though municipal concerns serve industrial demand as well, their customer structure is generally biased in favour of domestic users (with the noticeable exception of some medium-sized industrial districts in Northern Italy);

(*d*) ENEL's capital structure is significantly 'heavier' than that of municipal firms, even after adjusting for size, as the national monopolist is legally required to operate below its real plant capacity because of obvious security reasons. In other words, ENEL is compelled to maintain excess capacity to some extent, whereas local distributors are not[35].

In spite of the above-mentioned caveats, we shall be able to provide a comparative analysis of ENEL and municipal distributors by working on disaggregated production data involving physical measures, which - differently from costs - are not subject to either disaggregation or indexation problems. Cost functions will be replaced by dually-equivalent production

[35] In other words, ENEL can be regarded as a last-resort distributor to all municipally-served customers.

relationships[36] within a stochastic production frontier framework[37]. Moreover, methodological cross-checking will be provided by means of non-parametric efficiency measurement methods[38], which cater for both price-dependent and price-independent efficiency measures[39].

6. Some Lessons from Europe and the US

This Section is broadly based on the OECD/IEA's 1996 Report regarding the 'Energy Policies of IEA Countries'. Its function is to draw some useful lessons from the experience of a small set of European countries (Sweden, Norway, France, and the United Kingdom) and the state of California (USA).

6.1 Sweden

Sweden has restructured its electricity sector to allow for competition in generation and choice for consumers at all levels. The revised system was initiated in January 1996 and includes a common market for power with Norway. Finland should step in this unified generation market in a short time. Both fair and sufficient competition will be important to the success of this reform. In this regard, the opening up of the market with other Scandinavian countries may provide competition for the few generators that dominate the Swedish electricity system today.

As for generation sources, a Parliamentary Energy Commission set up in 1994 has been considering the issues of the nuclear phase-out and the transformation of the energy system in

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[36] Shephard (1970).
[37] See Aigner, Lovell, and Schmidt (1977), and Chapter 3.
[38] See Charnes, Cooper, and Rhodes (1978), and Chapter 5.
[39] See Fare, Grosskopf, and Lovell (1985, 1994); Fried, Lovell, and Schmidt (1993).

the context of meeting the stated energy policy objectives. In addition, the Energy Commission recommended to increase the use of renewable resources for electricity generation.

The nuclear phase-out issue is of paramount importance in Sweden, since nuclear generation jumped from 2.7% of the total in 1973 to 51.3% in 1994, thus reducing more traditional hydro-power generation to 41.4% of total generation in 1994 from 76.7% in 1973. Public concern about nuclear waste, as well as the inherent risk of nuclear plants, are pushing the Government to reconsider the whole generation strategy very carefully, also following antitrust recommendations with respect to the generators' market. Such a market should now become more competitive as a result of the new 'Scandinavian Pool' (Sweden, Norway, with Finland stepping in shortly) being created in 1996. What the Swedish government should try to promote for the foreseeable future is a wider market for electricity trade in the Nordic regions, where energy intensity is high but competition is bleak. Furthermore, very low population density within a wild landscape does not help make the market thicker.

6.2 Norway

Policy developments over the last three years have continued to strengthen Norway's role as a significant oil and natural gas producer. In the restructured electricity market, competition is increasing as regulatory clarification encourages more participants and the Nordic power market has now started with Sweden (January 1996). In addition, a climate change action plan was announced, including new voluntary measures with industry participants.

The electricity market, reformed in 1991, is characterised by competition in production and trading, and by monopoly control of the transmission and distribution companies under a

relatively tight regulatory regime, complemented by 'Third-Party Access' (TPA) arrangements at all levels[40].

There are three organised markets for electricity trade in Norway: spot, a regulated market to balance supply and demand, and a 'weekly' market. Both the daily and the weekly markets have been gaining in importance over time. Continuous trade in the weekly market was introduced in 1995, to transform the old forward market with 'physical' deliveries into a futures market with only financial transactions. Trade in the organised markets is continuously increasing, and now accounts for about 30% of total electricity trade in Norway.

In December 1995, a White Paper was approved on electricity trade with Sweden. In anticipation of the opening up of the Nordic electricity market with Sweden in January 1996, quantitative restrictions on electricity trade and duties on cross-border trade were eliminated. The Swedish electricity sector itself has been restructured along the lines of the Norwegian market. According to the most recent agreements, the Norwegian and Swedish national grid companies, Statnett SF and Svenska Kraftnat, will jointly own the Power Market exchange. In July and September 1995, new long-term contracts for power provision were signed with Danish and German generators, which completed a previous governmental programme according to which a total of four long-term power exchange links had to be established among Norway, Denmark, Germany, and the Netherlands.

Pro-competitive measures have then been adopted in the generation subset, even though something more might be done at the retail supply level, where smaller customers are still incurring huge switching costs in transferring their consumption from one supplier to another. Industrial customers, on the other hand, are still taking advantage of old long-term contracts at favourable rates, which the government is now expected to dismantle gradually. Finally, one

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[40] See Forsund and Kittelsen (1992, 1997), and Kittelsen (1993, 1996), which will be reviewed later on in this thesis.

should notice that Norway gave up nuclear generation at the outset and therefore, differently from Sweden, its generation capacity has always been virtually 100% made up of traditional hydro-electric power.

6.3 France

Restructuring of the electricity supply industry and discussions concerning the compatibility of French and EU proposals have dominated the energy policy debate in recent years. The government accepts that monopoly rights over imports/exports and transmission conferred on Electricité de France (EdF) are excessive, in view of the maturity of the industry and the need to encourage efficiency in electricity supply - let alone the matters concerning European economic integration. An agreement at EU level on some form of liberalisation of electricity markets may be in sight now. To the extent that the proposed system will open up generation to competition from non-EdF producers, it is to be welcomed. Nevertheless, further steps to liberalise electricity production and supply are also needed.

The French situation with EdF's integrated monopoly[41] cannot be taken as a prominent example of break-up to Italy. In order to catch up with European requirements, the French government ought to implement, according to EU pro-competitive Energy Directives, proposals to introduce competition in generation, ensuring that all generating options (traditional plus renewable) are allowed to compete on an equal basis. EdF's import/export monopoly rights might be removed, and an independent regulatory authority with clearly defined roles and responsibilities could be created. Furthermore, EdF's accounting separation should be enforced according to the generation, transmission, and distribution businesses, so

[41] EdF has also expanded abroad, by stepping in the British distribution market. As a huge electricity producer, it downloads some of its extra capacity abroad, mainly directing its exports to Britain and Italy.

as to ensure full transparency and fair competition in the context of electricity liberalisation, according to EU regulations. Sectoral cross-subsidies might be removed as well. Finally, greater attention should be paid to nuclear power issues, as France is perhaps the most nuclear-intensive country in the European Union.

6.4 The United Kingdom

The British electricity experiment has been widely studied[42]. We shall only provide a brief summary of the most recent events.

As for the complex way to competition in the restructured generation subset, one should notice that, finally, in late 1995 the two main fossil generators (National Power and PowerGen) agreed to sell 4,000 MW and 2,000 MW (respectively) of their coal-fired or oil-fired capacity by the following year. However, they are at the same time planning to switch to CCGT technology substantially. This will, quite ironically, make the fossil plants' divestiture a sort of well-conceived strategic management move.

In fact, even though 6,000 MW of plant account for about 10% of total capacity available in England and Wales today, the sale will still leave the two main generators with about 50% of total capacity. The Pool price will then be affected, but it is likely that base-load demand in England and Wales will still be met by National Power and PowerGen together.

As regards retail supply, at the time of the Electricity Supply Industry's privatisation in 1990, competition was introduced into final supply of electricity for those customers using more than 1 MW. In 1994, competition was extended to medium-sized consumers (using

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[42] See Vickers and Yarrow (1991) for a thorough analysis. Some interesting econometric evidence is in Green and Newbery (1991), and Pollitt (1995). A cost-benefit examination of the former Central Electricity Generating Board is provided by Newbery and Pollitt (1997).

more than 100 kW), and from 1998 all customers in England and Wales will be finally set free to choose their electricity retailer.

Distribution continues to work on a regional basis, and prices are regulated according to a RPI-X+Y scheme. Looking at market performances for the 12 Regional Electricity Companies, one would argue that the regulatory constraint imposed on them has been definitely generous during the first years at least (1990-1994). In particular, because of evident implications regarding vertical reintegration of the British electricity industry - as well as potential anti-competitive effects - an investigation was launched in 1996 by the Monopolies and Mergers Commission (MMC) into the take-over bids by National Power and PowerGen for two RECs. It is worth noticing that by early 1996, notwithstanding the fact that they mainly divested themselves of the stakes they once owned in the National Grid Company (NGC), seven out of the 12 RECs in England and Wales had been taken over. A proposed hostile take-over of one of the RECs was observed, too (the famous one by Trafalgar House, which subsequently led to an interim distribution price-cap review by the electricity regulator). It is then clear that substantial rents have been earned in the distribution subset of the British electricity industry. This calls for tighter regulation and strong antitrust policies, in order to face the danger of vertical re-integration.

However, apart from the above caveats, more and more multi-service companies are likely to emerge in the United Kingdom over the next few years. Companies will sell electricity, natural gas, and other energy products to end-users. A number of RECs now sell gas to industrial customers, and this will expand as the tariff gas market evolves[43]. Finally, a provision in the most recent Gas Act (1995) requires suppliers to publish tariffs, unless they relate to products which are part of an energy service package.

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[43] Recall that BG's monopoly in the tariff - i.e., residential - market is going to be eliminated by 1998, similarly to what will happen with respect to electricity supply.

As for British nuclear power, let us just recall that, according to the most recent privatisation moves, the ageing Magnox reactors and their liabilities are going to be retained under public ownership, whereas the seven advanced gas-cooled reactors and Sizewell B, the country's first pressurised water reactor, were sold during 1996. A holding company, called British Energy, has been created to own the parts of Nuclear Electric and Scottish Nuclear which were floated in 1996.

Last but not least, information and transparency have been boosted in Britain thanks to such publications as the Annual Energy Report.

6.5 California (United States)

Given the complexity of energy policies in such a giant as the United States, we shall limit to point out some interesting developments in the Californian electricity supply industry[44].

First, it is worth noticing that the Federal Energy Regulatory Commission (FERC) issued in April 1996 a final rule concerning open access to interstate transmission lines. The rule, known as *Order 888,* aims at introducing competition rapidly into the US wholesale power market, by providing for the following:

(*a*) functional unbundling of wholesale transmission from the remainder of utility services, and standardisation of transmission tariffs;

(*b*) establishment of standard charges for ancillary services (*e.g.*, scheduling, dispatching, voltage control, and system protection);

(*c*) definition of a mechanism for the recovery of 'stranded costs' caused by wholesale competition.

FERC has also announced its intention to require information disclosure via real-time information networks. An electronic information system is under way: it will be able to distribute data among all competitors on such things as transmission capacity availability, ancillary services, scheduling of power transfers, dispatches, current operating and economic conditions (and related responses by the utility), and - finally - system reliability.

Furthermore, following a two-year debate, the Californian Public Utility Commission (CPUC) agreed in December 1995 on the phased introduction of 'retail wheeling', whereby

[44] The interested reader may refer to Joskow (1997) for an analysis of US electricity reform.

end-users would be allowed to buy electricity from firms other than the utility that provides the wires to bring the service to them. This move is actually the first major step in the USA towards competition in electricity at retail levels. Under the plan, the largest industrial customers would be free to choose among different suppliers starting from 1998 and all other industrial, commercial, and household customers will be free to do so from 2003 onwards.

The three main Californian electricity utilities, which account for around 85% of the state's market, will be prohibited from shifting unrecoverable or 'stranded' costs from one class of customers to another: recovery of these costs and the incremental costs of renewables-based power is to be obtained through a transitional surcharge, which will be levied on all customers until 2005. Finally, all generators will be required to sell their power into a 'Pool', to be operated by an independent company. Spot prices will be fixed hourly, according to instantaneous supply and demand changes.

A Bill has also been introduced in Congress, aimed at encouraging all states to standardise their approaches to electricity and remove regulatory barriers to retail competition. As of March 1996, 41 states were actively considering to restructure their electricity supply industries, although no state other than California had taken a final decision at that date.

As a conclusion, one should notice that both the 'open access' rule, and the moves regarding information disclosure are really key-steps forward. However, the resolution of complex issues of state and federal jurisdiction with respect to retail activities remains an important element in broadening competition beyond the wholesale market. Nonetheless, Congressional moves aimed at removing regulatory barriers to retail competition may well help in this regard.

7. Conclusions

In this Chapter we outlined some basic features of the electricity supply industry, with special reference to the distribution subset of production, which will be the main topic of the thesis. First, we described some basic economics of electricity distribution[45]. Then, we focused on some important facts relating to the Italian electricity supply industry[46]. Finally, we considered a small sample of foreign countries (Norway, Sweden, France, the United Kingdom, and the state of California, US) whose lessons might be useful to the Italian policy-maker.

The following parts of this thesis will focus on the main efficiency issues which the Italian government is going to face as a consequence of ENEL's global restructuring programme. In particular, Chapter 2 will introduce a standard deterministic frontier approach, to be used for estimating a system of equations made up of a translog (normalised) total cost relationship, plus two share equations relating to capital and labour, with materials being viewed as a residual input. Output definition issues will also be discussed, following Neuberg's (1977) seminal paper. The data set is made up of 147 cross-sectional observations for ENEL's local distributing zones in 1996. Standard statistics for the cost function will be computed, with special reference to scale and density economies, MES, input elasticities of substitution, own-price elasticities, optimal cost shares and factor demands, and (tentatively) input and output slacks[47]. Both natural monopoly (cost sub-additivity) and scope economies checks will be performed by re-running simulation regressions on particular output subsets. The drawbacks

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[45] Following Berrie (1983), Armstrong et al. (1994), and Burns and Weyman-Jones (1994a).
[46] Following Scarsi (1993), and IEA/OECD (1993, 1994).
[47] For a definition of 'slacks' and 'excesses' in the DEA/OR sense, see Seiford and Thrall (1990), as well as Chapter 5.

of deterministic frontier estimation (as compared to stochastic approaches) will be highlighted.

Chapter 3 will move to more advanced and up-to-date economic measurement topics by estimating a stochastic frontier (translog) model on the same data set. Significantly different outcomes for the stochastic analysis will be displayed, and reasons will be given for such differences. Again, standard statistics of interest will be computed, with special attention being paid to optimal scale estimates for both physical output (i.e., the total amount of final GWh delivered) and the number of customers served. A theoretical digression will also be made, in order to familiarise the reader with the 'Technical Efficiency Effects' (TEE) model by Battese and Coelli (1993, 1995)[48]. Apart from standard estimates, the TEE model will display efficiency scores[49] being utilised to build up a ranking of ENEL's zones according to their estimated efficiency levels. The role of environmental variables and/or 'fixed inputs' will be carefully assessed. A discussion of which relevant exogenous variables should be considered by the electricity regulator when comparing different local distributors throughout the country will be put forward.

Chapter 4 will make a tentative comparison of ENEL's local zones with Italy's municipal distributors or *Aziende Municipalizzate*. To this purpose, a small sample of 37 municipal utilities will be pooled with (parts of) the main sample of 147 ENEL's zones. Stochastic frontier techniques will be used again and - thanks to the FRONTIER programme[50] - 'pooled' efficiency scores will be constructed. Some dummies and other control variables will be introduced so as to smooth out possible differences between the two sub-samples to be mixed. A number of remarkable data caveats will be pointed out in this respect. Comments on the 184-observation pooled sample will explain why a more sensible analysis would include a

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[48] For a classical reading on stochastic production/cost frontiers, see also Aigner, Lovell, and Schmidt (1977).
[49] See also Chapter 5.

sub-sample of ENEL 'peers' only together with local units, instead of the whole national (147) sample. Furthermore, data constraints will force us to switch to (translog) production function estimation - rather than cost function estimation - and a more reasonable pooled sample of 76 utilities (made up of 37 municipalities plus 39 'peers' from ENEL's local distribution zones) will be built up. Final mixed rankings will then be computed for the selective (76) sub-sample. Extensive comments on relative performances and on the proposed merger of some municipalities into ENEL will be made. We shall draw some interesting conclusions about relative efficiency of local concerns in a number of Northern and Central medium-sized towns. Special comments will also be made on distribution efficiency within both metropolitan and rural/mountain contexts. The comparison proposed in Chapter 4 will provide a natural and useful link to the non-parametric (OR/DEA) analysis of Chapter 5.

Chapter 5 introduces a comparative approach between ENEL and local utilities, to be based on the ever increasingly used DEA (Data Envelopment Analysis) method. DEA is a linear programming approach which makes use of classical Farrell (1957), Debreu (1951), and Koopmans (1951) technical efficiency measures, by minimising hyperspatial distance functions within a multiple input-multiple output context. It does so by not imposing any functional structure upon production relationships, at the expense of sacrificing the distinction between inefficiency and purely random noise and/or measurement error, or imperfect information on the beholding econometrician's side[51]. Data Envelopment Analysis is sufficiently flexible to cater for price-dependent measurement (input-allocative efficiency), scale efficiency (returns to scale), congestion efficiency (presence of backward-bending isoquants), and 'purely' technical efficiency[52]. Finally, 'environmental' variables may also be inserted in the efficiency calculations, by introducing exogenous elements as additional

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[50] See Coelli (1996a) for further details.

constraints in the input-minimisation linear program. We shall not necessarily use input-oriented DEA, even though this is the standard method to be applied to public utilities, which are generally supposed to provide externally regulated amounts of output - while being left free to minimise input usage for a given level of output[53]. As a final step, Chapter 5 will compare different relative efficiency rankings for both ENEL's zones alone (initial sample) and ENEL plus municipalities (pooled sample of 76 observations), and put them in relation to those previously obtained in Chapter 4 by means of modern stochastic frontier (Technical Efficiency Effects) analysis. Several rank-order tests will be performed on different efficiency series, in order to investigate 'statistical agreement' among them[54]. The distribution-free tests which will be used include Wilcoxon, Kolmogorov-Smirnov, and Sign tests, whose options are available in the PCSAS/STAT and SPSS computer packages. With reference to the underlying idea of 'methodological cross-checking' between parametric (stochastic frontier) and non-parametric (DEA) approaches, the reader is referred to the clear and useful discussions provided by Pollitt (1995), and Kittelsen (1993, 1996).

Finally, Chapter 6 is a conclusion. It specially focuses upon the policy-making implications brought forward by the present analysis. Particularly, we shall try to highlight why electricity distribution restructuring in Italy should not be left with ENEL itself. According to our results, municipal authorities are often as efficient as ENEL's local zones, and might even be more efficient in some specific contexts. Therefore, automatic mergers among ENEL and local authorities should be ruled out. On the contrary, some territorial expansion ought to be granted to local utilities in several cases. Above all, the general conclusion is that

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[51] See also Hebden (1983).

[52] See Fare, Grosskopf, and Lovell (1985, 1994).

[53] However, ordinal efficiency is not affected by different orientation choices. Even though numerical efficiency scores do differ, the difference will generally be small (see Pollitt, 1993, 1995), and will shrink to zero each time constant returns to scale (CRS) DEA is used. However, Chapter 5 will explain why we decided to use variable

restructuring possibilities will differ according to peculiar local scenarios, so that - similarly to Burns and Weyman-Jones's (1994b) opinion - both restructuring and efficiency considerations about local utilities should be carried out on a rigorous case-by-case basis, since generalisation is by no means feasible in such a complex and techno-economically differentiated context as Italy's regional and provincial electricity distribution.

Post Scriptum

During March 1998, Italy's municipal distributors (MUNIs) applied for the status of 'exclusive dealers' of electricity (distribution, supply, and sometimes generation) within those urban contexts which currently feature a mixed distribution structure (MUNIs plus ENEL). Such a move on the municipal side was obviously aimed at gaining complete dominance over those urban and metropolitan areas which are today shared with ENEL's local branches[55], so as to increase the MUNIs' distribution fraction - on a national basis - from around 7% to 15% of total GWh being dispatched all around Italy every year. ENEL rejected municipal claims by counter-proposing a different scenario in which urban and metropolitan areas would be served by an exclusive franchisee (a sort of 'metropolitan REC', as London Electricity is in the United Kingdom) stemming from a consortium between ENEL itself and the local MUNI. Alternatively, ENEL is willing to take over municipal assets and serve urban areas as an exclusive dealer. As of end-March 1998, the compromise solution seems to be the most likely option: MUNIs will not be sold to ENEL, neither will they be allowed to act as exclusive electric utilities for their own towns and outskirts. Feasible consortia between ENEL,

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returns to scale (VRS) DEA instead. On CRS/VRS DEA, the usual reference papers are those by Charnes, Cooper, and Rhodes (1978), and by Banker, Charnes, and Cooper (1984).

[54] See Lehmann (1975) on non-parametric testing.

municipalities, and private investors (industrial groups) are being sought with respect to distribution and supply of electricity to the main metropolitan centres of the Peninsula (Rome, Milan, Turin).

Finally, the most recent news on MUNIs also point in the direction of integrated water and sewage management at regional levels, covering (minimum) efficient scales in the neighbourhood of 500,000 customers at least[56]. Expansion of municipal services might then be implemented for water - let alone gas - management, too[57].

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[55] Such places are Milan, Turin, Rome, Trieste, Verona, Brescia, plus a number of medium-sized Northern towns.

[56] Rationalisation and restructuring of integrated water purification, distribution, sewage, and sewerage for Italy's regions were outlined by Law no. 36/1994.

[57] Recall that the Italian electricity regulator based in Milan is responsible for gas regulation, too. Therefore, municipal authorities must turn to the same Authority when asking for licence modifications with respect to both their electricity and gas services at local/regional levels. However, both electricity and gas deregulation in Italy are only at an early stage and - apart from some metropolitan and urban municipalities which are already operating several utility services at the same time - no short-term prospects exist in Italy for the creation of such multi-utilities as Scottish Power, Hyder, and United Utilities (UK) being recently developed in Britain.

CHAPTER 2

EFFICIENCY ANALYSIS OF LOCAL ELECTRICITY DISTRIBUTION IN ITALY (ENEL): A DETERMINISTIC APPROACH

1. Introduction

This Chapter is aimed at analysing the global performance of 147 local distributors within ENEL, the Italian integrated electricity monopolist. A cross-sectional analysis for the year 1996 will be carried out by estimating a deterministic total cost function, together with two cost-share equations. The theoretical framework within which the main total cost analysis will be performed is a traditional, duality-based one. Such framework was developed so as to generalise more particular cost functions (Cobb-Douglas, CES) to a second-order (logarithmic) Taylor's series approximation to an arbitrary cost function, with the expansion point being set at the sample's arithmetic mean. In other words, the main econometric tool to be utilised is the now classic 'translog' cost function, which was first introduced by Christensen, Jorgenson, and Lau (1971, 1973)[1]. More advanced analytical tools will be introduced in the following Chapters, when we shall switch to both stochastic frontier estimation and non-parametric/DEA analysis (a linear programming approach).

The structure of Chapter 2 is as follows: Section 2 outlines some basic aspects of (deterministic) translog functions, which do not take any stochastic elements into consideration. In fact, deterministic frontiers ignore any distinction between 'pure' inefficiency - leading the firm to erroneously shift either within its production possibilities set,

or (equivalently) above its total cost contour - and random noise/measurement error. With special reference to cross-sectional analysis, random noise might be of paramount importance - e.g., due to exogenous events resulting in efficiency changes which cannot be controlled by the decision-making unit (DMU). Measurement error could occur, too, as a consequence of imperfect information affecting the beholding statistician or econometrician[2].

Section 3 provides a brief survey of the extant empirical literature regarding deterministic frontier estimation of total cost in electricity distribution and/or supply.

An explanation of the basic pros and cons of deterministic frontier estimation will be followed by some data issues. Section 4 deals with the examination of practical quantitative problems being encountered during data collection. Calculation of input prices will be disclosed, and some relevant caveats relating to the elaboration of raw data will be clarified. Some information will also be provided with special regard to the way local distributors are actually run within ENEL[3]. Again on data problems, Subsection 4.1 faces sample selection issues.

Section 5 is entirely concerned with estimation issues. Econometric results will be reported in standard format, and some basic statistics will be computed from the estimated translog system. In particular, expansion point (i.e., sample-mean) values will be displayed for scale economies, input elasticities of substitution, own-price elasticities, scope economies, cost sub-additivity, optimal factor shares, optimal input demands, and input 'slacks' (or 'excesses'). Estimation outcomes will be carefully analysed, and some plausible policy-making conclusions will also be outlined. Some of the outcomes will be labelled as 'tentative', as a

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[1] See also Christensen and Greene (1976) for a classic translog analysis of electricity generation in the US, extending Nerlove's work (1963) on a 1955 cross-section for 145 utilities to a 1970 cross-section for 99 generators.

[2] See Hebden (1983).

[3] This will add on the standard overview supplied in Chapter 1.

result of the deterministic nature of our approach, which turns to a (more realistic) stochastic dimension in Chapter 3.

Finally, Section 6 is a conclusion. It will comment on some relevant aspects of the Chapter, and introduce the more complex stochastic frontier analysis to be performed in Chapter 3 on the same cross-sectional data set (business year ending 31 December 1996).

2. Deterministic Translog Cost Functions: a Theoretical Summary

Following Christensen et al. (1973), and Berndt (1991, 1996), we now describe the basic theoretical foundations of translog cost relationships and associated cost-share equations. Some links to duality theory[4] will also be discussed.

The non-homothetic translog cost function can be envisaged as a second-order Taylor's series approximation in logarithms to an arbitrary cost function. Non-homothetic functions are very general, since their ratios of cost-minimising input demands are allowed to depend on the level of output. That is, both input demands and input elasticities of substitution, as well as returns to scale, will vary with the level of output Y, being either increasing or decreasing in it. On the contrary, with homothetic functions, relative input demands will be independent of output levels. The most general, non-homothetic translog total cost function is written - in logarithms - as follows:

[4] See Shephard (1970), and Diewert (1974).

$$\ln TC = \ln\alpha_0 + \sum_{i=1}^{n}\alpha_i \ln p_i + 0.5\sum_{i=1}^{n}\sum_{j=1}^{n}\beta_{ij} \ln p_i \ln p_j + \alpha_Y \ln Y + 0.5\beta_{YY}(\ln Y)^2 +$$

$$+ \sum_{i=1}^{n}\beta_{iY} \ln p_i \ln Y + u_i,$$

where:

TC = Total Cost;

p_i, p_j = input prices;

Y = output;

u_i = a stochastic disturbance term with (two - sided) normal distribution $N(0,\sigma^2)$. (1)

It should be noticed that, in the presence of three inputs only (the standard case being capital, labour, and materials), and with symmetry restrictions imposed upon input-price interactions[5], the translog specification reduces to

$$\ln TC = \beta_0 + \beta_1 \ln p_1 + 0.5\beta_2(\ln p_1)^2 + \beta_3 \ln p_2 + 0.5\beta_4(\ln p_2)^2 +$$

$$+ \beta_5 \ln p_3 + 0.5\beta_6(\ln p_3)^2 + \beta_7 \ln p_1 \ln p_2 + \beta_8 \ln p_1 \ln p_3 + \beta_9 \ln p_2 \ln p_3 +$$

$$+ \beta_{10} \ln Y + 0.5\beta_{11}(\ln Y)^2 + \beta_{12} \ln p_1 \ln Y + \beta_{13} \ln p_2 \ln Y + \beta_{14} \ln p_3 \ln Y + v_i,$$

where:

$\beta_0 = \ln\alpha_0$,

all other α parameters have been relabelled β,

$v_i \sim N(0,\sigma^2)$,

and the remaining notation is unchanged. (2)

According to the lemmas of duality theory[6], for a cost function to be well behaved the following requirements must be satisfied:

(*a*) degree-one homogeneity in input prices;

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[5] That is, $\beta_{ij} = \beta_{ji}$, $i \neq j$.

[6] See Gravelle and Rees (1992).

(*b*) non-decreasing monotonicity in both input prices and output(s)[7];

(*c*) concavity in input prices - as a result of Shephard's Lemma, Roy's Identity, and standard microeconomic demand theory.

With special reference to degree-one homogeneity in input prices (given output *Y*), the following restrictions on the most general translog equation will be imposed as a result:

$$\sum_{i=1}^{n}\alpha_i = 1;\ \sum_{i=1}^{n}\beta_{ij} = \sum_{j=1}^{n}\beta_{ji} = \sum_{i=1}^{n}\beta_{iY} = 0. \tag{3}$$

A number of additional parameter restrictions might be imposed on the translog cost function, corresponding with further restrictions on the underlying technology. For the translog cost function to be homothetic, it is necessary and sufficient that

$$\beta_{iY} = 0 \quad \forall i = 1,\ldots,n. \tag{4}$$

Homogeneity of a constant degree in output occurs if, in addition to these homotheticity restrictions, it also happens that

$$\beta_{YY} = 0. \tag{5}$$

[7] A famous study by Evans and Heckman (1984) on cost superadditivity in US telephony at the time when the Modification of Final Judgement (MFJ) deliberated on AT&T's break-up (see also Baumol and Sidak, 1994) was subsequently criticised because their translog cost function failed to satisfy non-decreasing monotonicity in output.

In this case, the degree of homogeneity equals $1/\alpha_Y$. Constant returns to scale of the dual production function (i.e., the translog production relationship associated to the translog total cost equation according to duality theory) occur when, in addition to the above homotheticity and homogeneity restrictions, it is also

$$\alpha_Y = 1. \tag{6}$$

Finally, the translog function reduces to the constant-returns-to-scale Cobb-Douglas relationship (which also enjoys constant input substitution elasticity, being constrained to equal one for all inputs) when, in addition to all the above restrictions, it is also true that

$$\beta_{ij} = 0 \quad \forall i, j = 1, \ldots, n. \tag{7}$$

One might of course estimate the general translog cost function directly, but gains in efficiency can be realised by estimating the optimal, cost-minimising input demand equations, transformed here into cost-share equations. If one logarithmically differentiates the total cost function with respect to each of the input prices and then employs Shephard's Lemma, cost-share equations of the following form will be obtained:

$$\frac{\partial \ln TC}{\partial \ln p_i} = \varepsilon_{TC,p_i} = \frac{\partial TC}{\partial p_i}\frac{p_i}{TC} = X_i \frac{p_i}{TC} = S_i\big|_{i=1,\ldots,n} = \alpha_i + \sum_{j=1}^{n} \beta_{ij} \ln p_j + \beta_{iY} \ln Y,$$

where: (8)

$$\sum_{i=1}^{n} p_i X_i = TC \text{ and } \sum_{i=1}^{n} S_i = 1.$$

The latest condition, also known as the 'adding-up' constraint of the share equation set (of course, each input will have its own share equation) has important implications for econometric estimation. First, one notices that the standard cost-share equation system for the symmetric three-input case will be written as follows:

$$\begin{cases} S_1 = \beta_1 + \beta_2 \ln p_1 + \beta_7 \ln p_2 + \beta_8 \ln p_3 + \beta_{12} \ln Y \\ S_2 = \beta_3 + \beta_7 \ln p_1 + \beta_4 \ln p_2 + \beta_9 \ln p_3 + \beta_{13} \ln Y \\ S_3 = \beta_5 + \beta_8 \ln p_1 + \beta_9 \ln p_2 + \beta_6 \ln p_3 + \beta_{14} \ln Y \end{cases} . \qquad (9)$$

To implement this share equation system empirically, it is necessary to specify a stochastic framework. Empirical researchers have typically added a random disturbance term (v,w,φ) to each share equation, and have then assumed that the resulting disturbance vector V=[v,w,φ] is multivariate normally distributed with mean vector zero and a constant covariance matrix (say, Ω^*). The rationale for the stochastic specification can simply consist of the argument that firms make random errors in choosing their cost-minimising input bundles. Moreover, errors should be one-sided, thus implying that firms are erroneously shifting inside their production possibilities sets. This paves the way to different specification of random errors, whose statistical distribution function should actually be one-sided. For example, one-sided or 'efficiency' errors might have half-normal, truncated normal, gamma, or exponential distribution functions[8]. Following McElroy (1987), one might even argue that errors are in the eyes of the beholding econometrician and are not due to firms. McElroy specifically suggests embedding the entire optimisation problem within a stochastic framework, and assumes that firms differ from one another according to parameters that are known by the firms' managers,

[8] See Aigner, Lovell, and Schmidt (1977), McElroy (1987), Burns and Weyman-Jones (1994a), Greene (1990), Battese and Coelli (1993, 1995), Coelli (1996a).

but are not observed by the econometrician. However, stochastic elements in total cost estimation will be examined at length in Chapter 3.

Now, let us concentrate upon the so-called 'adding-up condition' which was previously mentioned. All share equation systems (e.g., S_i, i=1,2,3) possess the intuitive property that, for each observation in the sample, the sum of the dependent variables - i.e., the cost shares S_i - over all equations equals one. Hence, if there are n factor share equations, only n-1 of them will be linearly independent. In terms of practical estimation work, this adding-up feature of the share equation system has two important econometric implications:

(*a*) since the shares always sum to unity and only n-1 of the equations will then be linearly independent, for each observation the sum of disturbances across equations must always equal zero. This implies that the disturbance covariance matrix Ω^* is singular and non-diagonal. Therefore, $det(\Omega^*) = 0$ at all observations, with Ω^* failing to invert;

(*b*) since the disturbance covariance and residual cross-products matrices will both be singular, Maximum Likelihood Estimation (MLE) - which minimises the residual matrix's ($\boldsymbol{e'e}$) determinant - will not be feasible, due to this determinant being zero for any feasible set of estimable parameters. Now, the most common procedure for handling this singularity problem is to drop an arbitrary equation, and then estimate the remaining n-1 share equations by either MLE or numerically equivalent methods to MLE, such as Zellner's (1962, 1963) Iterated Seemingly Unrelated Regression Estimation (ISURE)[9].

For example, in our simple three-input translog context, one could impose degree-one homogeneity in input prices, and then normalise the translog total cost relationship by

[9] As regards SURE, see also Harvey (1990), and Greene (1993a) for a standard textbook treatment.

dividing both total cost and input prices by an arbitrary scalar. Since Nerlove's (1963) pioneering work on returns to scale in US electricity generation, researchers have generally used one of the input prices as the total cost normaliser. This offered them the possibility of indirectly recovering parameter estimates for the input price being dropped from the main equation (as a result of it being chosen as the normaliser). Furthermore, it seems plausible to drop the cost-share equation relating to the same input which was chosen as a 'numeraire', thus coping with Ω^*'s singularity resulting from the adding-up condition. To sum up:

(*a*) the total cost function has been normalised in terms of one of the input prices (say, input three's), following degree-one homogeneity restrictions;

(*b*) input three's cost share has been dropped from the cost-share system because of the above-mentioned 'adding-up' singularity problem.

Hence, the final system to be estimated by either MLE or its numerically equivalent counterpart ISURE will be made up of three equations (the main post-normalisation translog relationship, plus two cost-share equations for inputs 1 and 2) as follows:

(i) degree-one homogeneous normalised translog cost function:

$$\ln(\frac{TC}{p_3}) = \gamma_0 + \gamma_1 \ln(\frac{p_1}{p_3}) + 0.5\gamma_2[\ln(\frac{p_1}{p_3})]^2 + \gamma_3 \ln(\frac{p_2}{p_3}) + 0.5\gamma_4[\ln(\frac{p_2}{p_3})]^2 + \gamma_5 \ln(\frac{p_1}{p_3})\ln(\frac{p_2}{p_3}) +$$
$$+\gamma_6 \ln Y + 0.5\gamma_7[\ln Y]^2 + \gamma_8 \ln Y \ln(\frac{p_1}{p_3}) + \gamma_9 \ln Y \ln(\frac{p_2}{p_3}) + w; \qquad (10)$$
$$w \sim N(0,\sigma^2).$$

(ii) normalised cost-share equations (S_i*) for inputs 1 and 2:

$$\begin{cases} \dfrac{\partial(TC/p_3)}{\partial(p_1/p_3)} = S_1^* = \gamma_1 + \gamma_2 \ln(\dfrac{p_1}{p_3}) + \gamma_5 \ln(\dfrac{p_2}{p_3}) + \gamma_8 \ln Y \\ \dfrac{\partial(TC/p_3)}{\partial(p_2/p_3)} = S_2^* = \gamma_3 + \gamma_5 \ln(\dfrac{p_1}{p_3}) + \gamma_4 \ln(\dfrac{p_2}{p_3}) + \gamma_9 \ln Y \end{cases} . \qquad (11)$$

One might then regard equations sub (i) and (ii) as a system, to be jointly estimated by appropriate iterated non-linear least squares techniques (Zellner's method in particular) which are valid alternatives to MLE. Unfortunately, although arbitrarily dropping one share equation (for example, input three's share in total cost) from the direct estimation of parameters appears to be a reasonable procedure, it does raise the issue of whether parameter estimates will be invariant to the choice of which equation is deleted. If such invariance is lacking, it would be a troubling feature of the estimation process, since it would permit users to report only those estimation results that are most agreeable with prior beliefs or judgements. However, as long as MLE procedures are employed on the *n-1* cost-share equations in the linearly independent system, all parameter estimates, log-likelihood values, and estimated standard errors will be invariant to the choice of which *n-1* equations are directly estimated. The linearly independent system's invariance also holds for the Zellner or SURE estimator, provided that the first-round estimate of Ω^*_{n-1} - that is, the disturbance covariance matrix Ω^* with the *n*-th row and column deleted in order to cope with the singularity issue resulting from adding-up - is based on equation-by-equation OLS estimation *without* the symmetry restrictions imposed[10]. All major statistical/econometric packages are able to perform SURE in such a way that it is numerically equivalent to MLE, thus ruling out the 'choice' problem. With MLE-equivalent SURE, system estimation will deliver such outcomes that are invariant

to the choice of which equation is deleted from the original complete set of n cost-share (input) relationships.

Another problem with translog estimation, which is however common to every other total cost estimation technique, is that using highly aggregated data might lead the econometrician to suppose that input prices are endogenous. Therefore, to avoid simultaneous equations problems, one could employ an instrumental variable estimator, provided that appropriate instruments were available. As for the estimation technique to be utilised, the three-stage least squares estimator (3SLS) would do the job, provided that the estimation sequence satisfies those requirements which were mentioned before in relation to SURE. Iterated 3SLS - or I3SLS - is also good in eliminating the 'lack of invariance' problem for estimated parameters in the *n-1* (linearly independent) cost-share system, provided that the procedure is iterated until changes from one iteration to the next in the directly estimated parameters and Ω^*_{n-1} become arbitrarily small. With reference to the data aggregation issue, we shall rule this problem out by examining fairly disaggregated figures, summing up to either a 147- or a 76-observation sample, depending on which econometric analysis is carried out[11].

We now move on to a discussion of estimation of substitution elasticities based on the translog functional form. Recalling the classic article by Uzawa (1964) on duality principles in the theory of cost and production, the Hicks-Allen-Uzawa (HAU) partial elasticities of substitution between generical inputs i and j for a general dual cost function TC having n inputs are computed as

$$\sigma_{ij} = \frac{TC \cdot TC_{ij}}{TC_i \cdot TC_j}, \tag{12}$$

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[10] See Section 5 on this issue.
[11] See Chapters 3 and 4.

where the *i,j* subscripts refer to first and second partial derivatives of the cost function *TC* with respect to input (*i,j*) prices. These HAU elasticities can be computed, once estimates of the translog function's parameters are available. Using the above-mentioned formula, the HAU partial elasticities of substitution for the translog case turn out to be equal to

$$\begin{aligned} \sigma_{ij} &= (\beta_{ij} + S_i S_j) / S_i S_j, \qquad i,j = 1,...,n; \;\; i \neq j; \\ \sigma_{ii} &= (\beta_{ii} + S_i^2 - S_i) / S_i^2, \qquad i = 1,...,n. \end{aligned} \tag{13}$$

Further, since from theory one knows that $\varepsilon_{ij} = S_j \sigma_{ij}$, it follows that, for the translog cost function, price elasticities might be computed as

$$\begin{aligned} \varepsilon_{ij} &= (\beta_{ij} + S_i S_j) / S_i, \qquad i,j = 1,...,n; \;\; i \neq j; \\ \varepsilon_{ii} &= (\beta_{ii} + S_i^2 - S_i) / S_i, \qquad i = 1,...,n. \end{aligned} \tag{14}$$

Of course, parameter estimates and fitted shares should replace the above symbols when computing translog estimates for both substitution and own-price elasticities. This implies that, in general, estimated elasticities will vary across observations. Second, since both parameter estimates and fitted cost shares have variances and covariances, estimated elasticities will also have stochastic distributions[12]. In the present study, we shall compute all relevant statistics at the translog equation's 'expansion point', that is, the sample's mean. Finally, regarding input substitution elasticities, the encompassing nature of translog models must be once more stressed: particular cases of the translog equation include both the CES

[12] See Kulatilaka (1985), and Anderson and Thursby (1986).

(where σ is always invariant throughout the sample) and Cobb-Douglas (where σ is constant and equal to one) models.

Finally, the estimated translog cost function should be checked to ensure that it is monotonically increasing and strictly (quasi) concave in input prices, as required by theory. Of course, fitted shares should be positive and add up to one. Returns to scale in the translog model are not constrained *a priori*: on the contrary, given the total cost equation's generality, they will be allowed to freely depend on the level of both input prices and - above all - output[13]. The non-homothetic translog implies that (variable) returns to scale may be calculated, according to Hanoch's (1975) suggestion, as the inverse of the elasticity of total cost (TC) with respect to output (Y). More specifically,

$$\text{Returns to Scale (RTS): } \mu = 1/\varepsilon_{TC,Y}, \text{ where } \varepsilon_{TC,Y} = \frac{\partial \ln TC}{\partial \ln Y} . \tag{15}$$

Therefore, in our normalised three-input translog relationship, returns to scale will be computed as follows:

$$\mu = \left[\frac{\partial \ln TC}{\partial \ln Y}\right]^{-1} = \left[\gamma_6 + \gamma_7 \ln Y + \gamma_8 \ln(\frac{p_1}{p_3}) + \gamma_9 \ln(\frac{p_2}{p_3})\right]^{-1} . \tag{16}$$

Even though some researchers usually estimate cost-share equation systems only, it should be noticed that the first two parameters in the returns-to-scale formula cannot be recovered by using the share equation system only. To estimate returns to scale, it is usually necessary to add the translog cost function to the share equation system. Of course, in our deterministic

frontier estimation work, a full system of both the translog relationship and the cost-share equations will be estimated by ISURE, in order to compute the most complete possible range of useful statistics from estimated parameters.

We now turn to discuss three more topics of interest, which might be related to our translog estimation work. They are Overall Scale Economies (OSE), Scope Economies (SE), and Cost Sub-Additivity (CS).

OSE were introduced by Panzar and Willig (1977). They are a simple generalisation of the concept of 'returns to scale' as defined by Hanoch (1975). When the cost function includes more than one output, returns to scale might be globally measured as the sum of partial returns to scale, each one relating to a single output. When one computes partial RTS for output *j* within multiple-output contexts, the calculation is such that all the remaining *m-1* outputs are kept fixed (in other words, partial RTS are calculated as a partial log derivative). Therefore, in order to recover the concept of 'returns to scale' when multiple outputs are present, one would rather consider the partial RTS effects together, by summing up each partial effect. Therefore, we define Global Returns to Scale (GRTS) for *m* outputs as

$$GRTS = \sum_{j=1}^{m} \left[\left(\frac{\partial \ln TC}{\partial \ln Y_j} \right)^{-1} \right], \quad j = 1,\ldots,m. \tag{17}$$

Then, OSE will be given by the standard expression *OSE = GRTS–1*. We shall compute GRTS (and OSE) in Chapter 3, where a multiple-output translog cost function will be used within a stochastic frontier estimation framework[14].

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[13] See Christensen and Greene (1976), following problems encountered by Nerlove (1963) with a Cobb-Douglas dual cost relationship.

[14] See Neuberg (1977), for the presence of multiple outputs, or output proxies, in electricity distribution and supply.

Scope Economies (SE) refer to the possibility of producing two or more different outputs at a lower cost than the one which would be implied by separate (i.e., stand-alone) production. SE will be found if and only if

$$TC(\sum_{k=1}^{K} Y_k) < \sum_{k=1}^{K} TC(Y_k). \tag{18}$$

With special reference to our analysis, SE are relevant in that electricity distribution is directed towards different customers consuming different 'versions' of the basic product. Typically, industrial customers will use high and medium-voltage electricity, whereas domestic users will generally consume low-voltage output.

Finally, Cost Sub-Additivity (CS) - first introduced by Baumol, Panzar, and Willig (1982) as part of their famous 'Contestable Markets' proposal[15] - relates to the fact that a single firm might produce output Y at a lower cost than any combination of two or more firms could do (ceteris paribus). Formally, sub-additivity of cost is present whenever

$$TC(Q) < TC(q_1) + TC(q_2) + TC(q_3)+...+TC(q_n), \quad q_1+...+q_n \equiv Q, \text{ homogeneous product.} \tag{19}$$

Cost sub-additivity should be carefully distinguished from scope economies. The former (CS) relates to homogeneous products, and may exist in the absence of any scope (i.e., cross-product) economies. On the contrary, scope economies may be encountered in the absence of sub-additivity. In general, neither sub-additivity nor scope economies imply each other, since they are conceptually linked to different output dimensions (homogeneous vs. heterogeneous products, respectively). Practically, CS is relevant when assessing natural monopoly issues

within highly concentrated, capital-intensive industries (where investment is often lumpy, and most costs are sunk). A famous application of CS analysis within a natural monopoly debate is provided by Evans and Heckman (1984), who evaluated break-up prospects for AT&T and the Baby Bells. This article is briefly reviewed in de Mendonça e Silva (1997). We shall use CS analysis to assess natural monopoly questions at local levels (ENEL's zones) by running 'auxiliary' regressions, and splitting up output artificially in order to put the above-mentioned CS formula into practice. This will be quite a tentative analysis.

The next Section is aimed at examining the basic empirical literature regarding deterministic frontier analysis of electricity distribution. An overview of the stochastic frontier literature will be provided in Chapter 3. Finally, a survey of some electricity-related non-parametric (DEA) studies will be proposed in Chapter 5.

3. Electricity Distribution: A Literature Survey of Deterministic Frontier Studies

The economic aspects of electricity distribution have been analysed much less deeply than those of generation. Applied econometric studies of both transmission and distribution have been generally limited as a result of either data collection problems or naturally monopolistic conditions being assumed as an *a priori* fact.

A first set of studies on electricity (and, more generally, public utilities) concentrates upon the ownership issue. In particular, Boardman and Vining (1989, 1992) criticise previous studies of the effects of ownership for failing to allow for the degree of competition as a determinant of observed differences. Their 1989 study of the largest 500 non-US manufacturing firms in the year 1983 jumps to the conclusion that private firms are more

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[15] See also Tirole (1988) for an Industrial Organisation textbook treatment.

efficient than public concerns when they operate in competitive markets. A following study by the same authors (1992) uses a Canadian data set for 1985 and comes to the same conclusion using a similar methodology. Public utilities, however, were excluded from the data set. In addition, ownership structure studies are not particularly instructive to our analysis, since both ENEL's local zones and municipal distributors were in public ownership at the time of the available cross-sections (1996 and 1994, respectively). Planned privatisation of both ENEL and some municipalities should not affect our analysis, which - in any case - cannot capture any 'privatisation threat' effects due to its cross-sectional nature.

A more interesting literature development in the light of the present study is the one concerning economies of scale and vertical structure. It has been said that ENEL should be split up prior to privatisation. Moreover, optimal scale considerations would suggest to break up ENEL's distributing departments - which are currently in the number of eight throughout the whole Italian territory - in order to create slimmer distributing units, to be structured on a regional (or even provincial in some instances) basis.

The empirical evidence on the existence of scale economies suggests that the electricity generating industry exhibits a classic U-shaped AC curve with falling average cost up to the 1,500-4,000 MW range. As noted by Green and Newbery (1991) among others, this is rather interesting if one considers that, at privatisation, the two main UK generating companies (National Power and PowerGen) enjoyed 30,000 MW and 18,000 MW generating power, respectively. The seminal paper on returns to scale in electricity generation (it does not say anything on distribution) is Nerlove's (1963) article dealing with a 1955 cross-sectional data set for 145 US electric utilities. Nerlove used a dual Cobb-Douglas cost function in input prices and output, which was normalised in terms of one of the input prices (fuel), so as to impose degree-one homogeneity. By examining regression residuals, Nerlove discovered

heteroscedasticity which, coupled with a U-shaped residuals pattern and a strangely low Durbin-Watson statistic within a cross-sectional analysis, suggested model re-specification. By fitting a corrected Cobb-Douglas cost function to include a quadratic element in output to the same data set, the author was able to detect that returns to scale were non-constant in output. As a result, he concluded that the AC curve resulting from his data set was not monotonically increasing/decreasing: it rather was a U-shaped curve, with Minimum Efficient Scale (MES) occurring at a high output level.

The fact that returns to scale do generally vary with output size - so as to give rise to either U-shaped or L-shaped average cost relationships - stimulated the search for more general total cost functions which do not impose any *a priori* restrictions on both scale economies and input substitution elasticities. Therefore, after the translog cost function was first put forward by Christensen, Jorgenson, and Lau (1973), an extension of Nerlove's work to a 1970 cross-section was proposed by Christensen and Greene (1976), who used a restricted sample - ranging from 114 to 99 utilities - in order to examine economies of scale in US electricity generation within a deterministic translog framework. They concluded that the use of the more general translog functional form resulted in a flattening of the U-shaped AC curve identified by Nerlove for the 1955 data. Their study pointed in the direction that scale economies had been almost fully exploited in US generation since at least 1970, with almost all generating firms working within the flat region of the AC curve by that date. Since Nerlove's study, then, a rationalisation process had occurred, with both mergers and break-ups, whose main outcome was to create a generation structure being acceptably compatible with average cost minimisation.

Other studies on returns to scale in electricity generation include those by Huettner and Landon (1977), Stewart (1979), and Roberts (1986). The New Zealand Ministry of Energy

(1989) investigated economies of scale in the New Zealand electricity distribution industry. This study uses data on 60 distribution companies operating in 1987, and specifies four translog functional forms with associated cost-share equations for the firms in the industry. The study's outcomes in terms of MES imply only 8-11 firms in a restructured industry, even though cost savings become not particularly significant beyond 500 GWh. Economies were found to exist in sales per customer, but not in the number of customers (which is often viewed as a proxy for output). This NZ study also notes the difficulty of using a single year's data to reach conclusions, as shocks may affect cross-sectional figures and no effective tools are available in order to improve on this within a deterministic context. As we shall see in Chapter 3, even cross-sectional analysis might be capable of separating random shocks from inefficiency, provided that a stochastic frontier approach is adopted.

Even though regulation is not the main topic of the current work, it is however interesting to recall the study by Primeaux and Nelson (1980), who used a sample of 80 publicly-owned electricity firms and found support for non-marginal cost pricing in electricity, in spite of public ownership[16]. Within a public ownership framework, non-marginal cost pricing may be politically motivated in the sense that the biggest users of peak-load electricity are being subsidised by off-peak customers. If peak-load users are residential customers using electricity at certain hours (early morning, evening) - e.g., for domestic heating - then non-marginal cost pricing will imply a subsidy to peak-load residential users. As regards ownership and efficiency, several US studies aiming at discussing the effects of ownership on productive efficiency are reviewed in De Alessi (1974), Yarrow (1986), Vickers and Yarrow (1988), and Boardman and Vining (1989, 1992).

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[16] As Pollitt (1995) points out, it is worth noticing that the pioneers of marginal cost pricing - at least in theory - as regards electricity have been two publicly-owned European companies (EdF and the CEGB). On this issue, the reader is referred to the famous EdF study by Boiteux (1956).

Turning to electricity distribution in particular, the most traditional explanatory variables being used in total cost regression analysis are physical electricity delivered and the number of customers as outputs, and prices of labour, capital, materials, and purchased electricity as input price variables. Nonetheless, it must be noticed that simultaneously inserting both customers and electricity deliveries as outputs might give rise to possible co-linearity problems.

The first modern approach to cost function analysis in distribution is provided by Neuberg (1977), who specifies a cost function which accommodates differences in factor prices. The author looks at two large samples of distribution companies in 1972 - consisting of both publicly-owned and privately-owned utilities - and runs separate regressions on both samples. The dependent variable is total distribution costs, and the regressors are number of customers (a new definition of output which has been almost universally accepted by researchers in electricity distribution), number of MWh delivered to final customers, number of miles of distribution line, square miles of service territory, price of labour, and a dummy variable for ownership type. Although Neuberg's one is the first 'almost complete' cost function for electricity distribution, it still lacks some basic input components such as capital and materials. Moreover, it does not take different customers and voltage types into proper account.

Lucas (1985) examines the electricity supply industry in Germany, France, Italy, Sweden, and Denmark using an institutional approach. His findings show that, in general, Denmark and Germany perform well while Italy does badly. It is useful to recall that in Denmark and Germany either privately-owned or mixed enterprises produce most of the power, whereas in both Italy and France production is dominated by one large publicly-owned monopolist (ENEL, EdF). However, publicly-owned local distributors are present in Denmark and

Germany, too, so that the above results are not clear-cut - even though they suggest that competition (rather than ownership) is, whenever possible, the real efficiency driver. It should also be noticed that, among the publicly-owned firms, EdF has been traditionally run according to political pressures regarding nuclear power (irrespective of cost-efficiency considerations), whereas ENEL has been subject to delays in power station construction as a result of political interference (corruption) and environmental concern in rural districts.

Helm and McGowan (1988) analyse the European ESI, and spot three working models: France/UK (EdF, former CEGB) (integrated public system), Sweden (mixed ownership with a dominant publicly-owned incumbent), and Germany/Holland (decentralised mixed ownership). Of course, their study could not examine the post-restructuring UK scenario. They concluded that none of the above-named systems was obviously superior, and that the major sources of inefficiency were due to the nature of government regulation relating to the industry.

Filippini (1994) fits a translog cost function to a cross-sectional data set of Swiss local electricity distributors for the time interval 1988-1991. He calculates some basic statistics and finds that scale economies are not exhausted at the sample mean. There is a suggestion for merging the smallest units, and perhaps encouraging off-peak usage by reshaping time-of-day tariffs. Filippini's findings can be easily applied to Italy's municipalities, but are hardly applicable to Nordic countries - where electricity distribution is not exclusively locally-based. Italy itself has local distributors (not ENEL-owned) in the North and Centre only, whereas the South is completely dominated by the national monopolist, except for the tiny centre of Trani in the Apulia region on the Adriatic coast.

It should be noticed that all major studies on electricity distribution do not fall into the classical category of deterministic frontier estimation. On the contrary, they have been

developed within either a stochastic frontier context[17] or following a non-parametric, linear-programming 'DEA' approach[18]. Therefore, a quick overview of both stochastic frontier and DEA studies will be provided in those Chapters which relate to more modern techniques than traditional deterministic translog cost analysis[19].

Section 4 introduces the deterministic analysis of 147 ENEL distributing units for 1996 by specifying data collection issues which might be of some interest when looking at estimation results.

4. Deterministic Frontier Analysis: Data Issues

This Section discusses data issues which apply to this Chapter, as well as to following ones. Therefore, it is not replicated in Chapters 3 to 5.

We managed to get confidential figures from ENEL's distribution arm because the national monopolist is now compelled to provide the energy regulator with both cost and input-output data. Thanks to the regulator itself and Carlo Scarpa at Bologna University, internal accounting figures for 1996 were extracted from ENEL. As an integrated company, ENEL runs distribution activities together with generation, transmission, and final supply to customers. However, the actual organisational structure of ENEL is such that internal vertical separation occurs to a considerable extent. Moreover, electricity distribution in particular is also horizontally separated within ENEL's internal accounts. ENEL's distribution division consists of eight territorial departments, each one covering either a regional or inter-regional area, with headquarters in Turin, Milan, Venice, Florence, Rome, Naples, Palermo, and

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[17] Aigner, Lovell, and Schmidt (1977), Price and Weyman-Jones (1993), Battese and Coelli (1993, 1995), Burns and Weyman-Jones (1994a), Pollitt (1995).

[18] Hjalmarsson and Veiderpass (1992a, 1992b), Pollitt (1993, 1995), Forsund and Kittelsen (1997), Kittelsen (1993, 1996), Burns and Weyman-Jones (1994b).

Cagliari. Apart from Sicily and Sardinia, continental Italy has just six main ENEL electricity distributors, with the Roman and Neapolitan 'departments' together covering about 108,000 square kilometres throughout the Centre and South of Italy. Therefore, ENEL's departments are much bigger than the Regional Electricity Companies (RECs) of England and Wales. However, as ENEL's internal data clearly show, substantial disaggregation is present within each of the eight distribution departments. First, each department is subdivided into 'districts', which generally embrace smaller regional or provincial areas[20]. Secondly, each district is made up of several 'zones', which relate to single towns and rural areas. Given that Italy also runs a parallel system of local, municipally-owned electricity distributors (especially in the North), it then comes natural to envisage a comparison between ENEL's 147 zones and the 37 municipalities which regularly release disaggregated data on their electricity distribution businesses.

The analysis which follows considers a total cost function whose arguments are - according to duality theory - outputs and input prices. Chapter 2 takes a traditional approach by considering only one output (electricity) in its cost specification. However, Chapter 3 will extend the analysis to a multi-output specification featuring the number of customers as well, so as to capture a more 'exogenous' variable for output. As regards input prices, the standard factors which should be taken into account are capital, labour, materials, and purchased power. We computed proxies for the first three input prices, but were not able to gather any information relating to purchased electricity, as ENEL does not publish its internal transfer prices for electricity being shifted from its transmission grid to local distributing units. The dataset we were provided with is highly disaggregated but does not provide any hint on how to evaluate electricity shifts, neither does it account for common cost allocation, which is not

[19] Chapter 3 is on stochastic frontiers, whereas Chapter 5 is on DEA and linear programming topics.

explicitly performed by ENEL - even though the underlying suggestion is to simply divide common costs and overheads by the number of local distributing units.

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 models (both stochastic and deterministic):

(*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;

(*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,

$$p_l = LC / N; \tag{20}$$

(*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

[20] There are 24 ENEL distribution districts throughout the country.

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. (21)

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

$$(r + \delta) = 7\% = 0.07. \tag{22}$$

Of course, within a cross-sectional analysis such a correction factor for the user cost of capital would simply rescale 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 rescaling 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

$$p_k =_{def} c_K = (0.07)\frac{COSTMTBT}{LINES}, \tag{23}$$

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[21];

(*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.

[21] As for 'fully meshed' distribution systems with overlapping peripheral high-voltage lines, see Berrie (1983), Burns and Weyman-Jones (1994a), and Chapter 1.

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,

$$p_m = THIRDPT / TRANS. \tag{24}$$

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 - will be usefully carried out by using materials as the 'numeraire' input;

(*e*) traditional output (*Y*), being viewed as total GWh[22] 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

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

the statutory right to buy electricity from the national operator[23], the 'total customers' variable has been successfully used in the recent literature[24] as a really exogenous proxy for output. We shall introduce total customers as a second definition of output in a multiple input-multiple output translog total cost function to be outlined in Chapter 3. However, Chapter 2 will use electricity delivered only, as it is the most traditional output measure.

Apart from the standard input-price and output measures to be inserted in the translog cost function[25], a number of 'environmental' variables were also specified, in order to capture 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;

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[23] Total customers are exogenously given by Nature at a certain moment in time.
[24] E.g., see Pollitt (1995).
[25] This provides for it to be a valid dual representation of a traditional production relationship.

(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[26], 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).

Following the alternative models to be proposed in the following Chapters, the above variables will be discussed until a final model - including a strict subset of them - is accepted as the closest approximation to the 'true' model.

Before concluding this Section, 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,

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[26] See Chapter 1, Section 5.

municipally-owned distributors are not compelled to deliver their 'regulatory accounts' to the electricity regulator (AEG, or *Autorità per l'Energia Elettrica ed il Gas*). Therefore, we only obtained production figures on municipalities[27]. The input-output data which were collected are to be used within a dual production function approach in Chapter 4, dealing with stochastic frontier analysis of both ENEL and local utilities. Moreover, input-output figures may be successfully applied to DEA calculations (Chapter 5).

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[28]. 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 in Chapter 4 - 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*);

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[27] Again, I am indebted to Carlo Scarpa at Bologna University with regard to data collection.

[28] 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.

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

(*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 disaggregation (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 developed in Chapter 5. Section 5 below finally discusses estimation work on ENEL's local zones.

4.1 Sample-Selection Problems

The main limitation of the analysis carried out in this thesis concerns the availability and reliability of data on ENEL's local distributing zones. As elsewhere emphasised, the Italian national electricity monopolist only started to internally separate its different production subsets (generation, transmission, distribution, and final supply) in 1994, following restructuring plans implemented during the same year[29]. Even though ENEL is still a monolith and retains monopolistic powers which are similar to EdF's ones in France, its distributing arm has traditionally been viewed by internal managers as a relatively independent department within the main organisational structure. Therefore, ENEL's eight

[29] Recall that the regulatory agency for electricity and gas was only established at the end of 1996.

distributing 'compartments' - or, better, its 24 provincial distributing 'districts' - may be regarded as similar units to the former British ESI's 'Area Boards' (now, Regional Electricity Companies). Furthermore, each ENEL 'district' is subdivided into intercommunal - or just urban - 'zones', which again show a degree of decision-making power[30].

ENEL's 147 distributing zones provided the newly-born regulatory agency with both input-output and cost figures, so as to build up a cross-sectional data set relating to the business year ending 31 December 1996. Figures up to 1994 were useless, as a result of different internal accounting criteria being introduced by ENEL at that time. Two-year analysis for 1995-96 was not a really valuable choice either, because of (*a*) the limited explanatory power of a two-year panel, and (*b*) the dubious reliability of 1995 ENEL figures, i.e. those from the first year after modification of internal accounting guidelines. Finally, 1997 data will not be made available until mid-summer 1998. Since no serious panel data analysis would have been feasible, we preferred to restrict our investigation to a 1996 cross-section. A similar reasoning pushed us to limit municipal utility analysis (Chapter 4) to a cross-section covering internal accounting figures (physical data) for the business year ending 31 December 1994.

The main sample-selection problem being encountered in regulatory studies about the Italian ESI lies in the heterogeneity of ENEL's distributing zones. By assuming total customers as the main output indicator[31], concentration of customers within metropolitan areas turns out to be a relevant feature of our sample, in that it gives rise to a number of 'statistical outliers' which might be excluded from the cross-section altogether. Even though Italy does not have a dominant metropolitan area similar to the Greater London and Paris/Île-de-France districts in the UK and France (respectively), its electricity customers show a

[30] Local zones have full control over medium and low-voltage distribution to private customers, thus excluding

significant degree of concentration, as the following Table attempts to clarify.

Zones	% of Customers
1. Rome* (Latium)	2.4
2. Turin* (Piedmont)	1.83
3. Bologna (Emilia-Romagna)	1.79
4. Milan* (Lombardy)	1.77
5. Florence (Tuscany)	1.72
6. Genoa (Liguria)	1.66
7. Naples (Campania)	1.61
8. Bari (Apulia)	1.31
9. Padua (Veneto)	1.11
10. Palermo/Centre (Sicily)	1.1
11. Cagliari (Sardinia)	1.08
12. Taranto (Apulia)	1.06
Total	**18.44%**
Total ENEL Customers (1996)	**28,660,811**
These Zones/Total Zones (12/147)	**8.16%**
* Also served by a municipal electric utility (MUNI).	

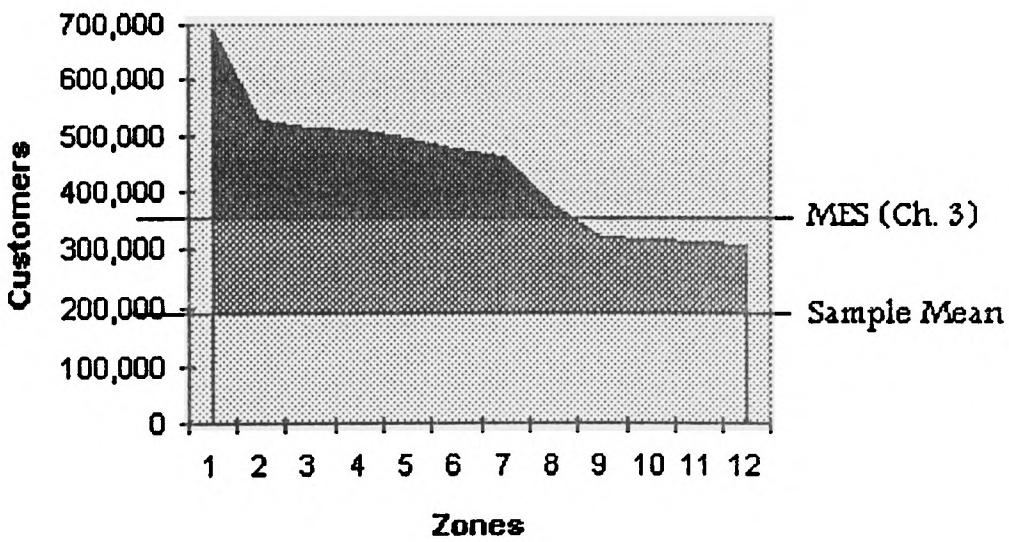


Table 2.1: The Largest ENEL Distribution Zones in Terms of Customers.

national railways and big publicly-owned industrial concerns.

[31] Neuberg (1977), Pollitt (1995).

As a result of the extent of concentration being found for the largest 10-12 ENEL units, a sample-selection problem arose. For the sake of sample homogeneity, the outliers corresponding to metropolitan ENEL zones should have been dropped from the analysis altogether, thus giving rise to a 138-140 units' cross-section (out of 147 data points making up the 'uncensored' sample). Such a sub-sample, however, would have made efficiency analysis seriously incomplete, because we could not assume with certainty that metropolitan zones would have necessarily been *ex ante* 'efficient by default'. In fact, as Chapters 3 and 5 will show, some metropolitan units were not automatically placed at the top of efficiency rankings. On the other hand, in the DEA Chapter they sometimes turned out to be moderately useful as 'peers' to inefficient units. Therefore, even though we were aware of the 'outlier' problem[32], a full sample analysis was preferred in the end, thus including even the largest ENEL zones in our (sometimes crude) efficiency comparisons.

5. Deterministic Frontier Analysis: Estimation and Results (ENEL, 1996)

We instrumented a symmetric translog cost function where both total cost and input prices were normalised by the price of materials (p_m), to yield the following, degree-one homogeneous form:

$$\ln(\frac{TDC}{p_m}) = \beta_0 + \beta_1 \ln(\frac{p_l}{p_m}) + 0.5\beta_2[\ln(\frac{p_l}{p_m})]^2 + \beta_3 \ln(\frac{p_k}{p_m}) + 0.5\beta_4[\ln(\frac{p_k}{p_m})]^2 +$$
$$+ \beta_5[\ln(\frac{p_l}{p_m})\ln(\frac{p_k}{p_m})] + \beta_6 \ln Y + 0.5\beta_7(\ln Y)^2 + \beta_8 \ln Y \ln(\frac{p_l}{p_m}) + \beta_9 \ln Y \ln(\frac{p_k}{p_m}) + \quad (25)$$
$$+ \sum_{i=10}^{28} \beta_i INTEV_i + \beta_{29} BORD + \beta_{30} INDUSD + \beta_{31} GEND + u,$$

[32] Linear programming techniques are particularly sensitive to the presence of 'weird' data points in the sample.

where all variables are as defined before, u is a two-sided error such that $u \sim N(0,\sigma^2)$, and no efficiency errors are explicitly considered. Finally, *INTEV* is the lengthy series of environmental variables and their full interactions[33] - as well as quadratic terms. The list of environmental variables being considered in the final run (i.e., after dropping insignificant cost drivers) is reported below:

$$INTEV = \{AIRMT, AIRBT, DENS\}. \tag{26}$$

In order to improve on estimation efficiency, we viewed the above translog model in conjunction with two share equations. Since including all cost-share equations would have resulted in singularity problems stemming from the fact that only two out of three equations in the system would have been linearly independent[34], we dropped the materials equation and estimated the first two cost-share relationships (capital and labour). Since we also used materials as the 'numeraire' input when normalising the main translog cost function, dropping the materials share from the cost-share system appeared to be the most natural choice. The two surviving share equations are written as follows:

[33] All interactions are accounted for in this translog cost function, except for the three dummies, which enter as one-off non-logarithmic variables. This meets the homotheticity requirement which was discussed - together with other generality features of translog models - in Section 2 above.
[34] This is due to the 'adding-up' condition previously outlined in this Chapter.

$$
\begin{cases}
S_k = \dfrac{\partial \ln(TDC / p_m)}{\partial \ln(p_k / p_m)} = \beta_3 + \beta_4 \ln(\dfrac{p_k}{p_m}) + \beta_5 \ln(\dfrac{p_l}{p_m}) + \beta_9 \ln Y + \\
+ \sum_{j=1}^{3} \gamma_j ENV_j + \text{interactions} + v; \\
S_l = \dfrac{\partial \ln(TDC / p_m)}{\partial \ln(p_l / p_m)} = \beta_1 + \beta_5 \ln(\dfrac{p_k}{p_m}) + \beta_2 \ln(\dfrac{p_l}{p_m}) + \beta_8 \ln Y + \\
+ \sum_{i=1}^{3} \delta_i ENV_i + \text{interactions} + w;
\end{cases}
\tag{27}
$$

The equations above include three environmental effects under the *ENV* heading. We used different letters for their coefficients in order to stress the point that they are not the same throughout the two equations. However, it must be said that these coefficients are absolutely the same βs being derived from the main translog cost relationship by means of first-order differentiation of normalised total distribution cost with respect to capital and labour prices.

Moreover, we used Iterated SURE[35] to estimate the cost system. As SURE is numerically equivalent to Maximum Likelihood Estimation (MLE), the choice of which equation is deleted from the cost-share system will be absolutely neutral on the final estimates to be obtained, provided that symmetry is not imposed on the cross-product coefficients in the translog cost relationship. Unfortunately, if no symmetry restrictions had been imposed on interaction coefficients, the system would have been so bulky as to drastically reduce degrees of freedom even in the presence of 147 observations. Therefore, with symmetry restrictions imposed, SURE will no more be numerically equivalent to MLE[36] and, as a consequence, estimation outcomes will depend on which cost-share equation has been deleted. However, we preferred to give up the 'invariant results' condition in favour of a slimmer, more

[35] Among several textbooks, cf. Greene (1993a), Johnston (1984), and Harvey (1990).
[36] See Berndt (1991, 1996).

parsimonious model with fewer parameters to be estimated and much more statistical degrees of freedom being left as a result.

It is interesting to notice that the above model was recovered, within a deterministic frontier approach, according to the 'general-to-simple' econometric methodology[37]. We started from the most general model - which implied more than 80 parameters - and tested that 'fat' specification against the data available. Surprisingly, the vast majority of environmental effects (cost drivers) were statistically insignificant. Moreover, we preferred to keep the model within a traditional one-output context, and dropped the total number of customers from the translog specification accordingly. We then defined Y as total energy delivered to final customers. Among the above-mentioned environmental variables, the only three ones which survived our general-to-specific testing methodology were customer density - which, as expected, showed statistical significance - and two 'engineering' variables, i.e. the percentage of overhead lines on total medium and low-voltage lines. All other variables were progressively dropped[38].

Nonetheless, it must be noted that a stochastic specification with explicit 'Technical Efficiency Effects' (TEE)[39] would be able to separate environmental variables (or '*Z*s') from the translog regressors (or '*X*s'), in order to increase estimation efficiency. By doing so, we might discover that some other environmental variables are significant. Moreover, total customers would be a better output specification than energy delivered, because of the 'suspect endogeneity' problems outlined above. However, such improvements will only be possible within a multiple input-multiple output stochastic frontier methodology which, following the seminal paper by Aigner et al. (1977), is proposed in Chapter 3.

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[37] See Gilbert (1986).
[38] A total of five alternative deterministic models were instrumented before refining the analysis to the above, more parsimonious specification.
[39] Battese and Coelli (1995).

Going back to our deterministic frontier estimation, regression results are reported below for the most parsimonious model discussed in the previous paragraphs. Then, some basic statistics of interest (returns to scale, etc.) will be computed at the Taylor series approximation's expansion point (sample mean). Finally, issues of both scope economies (SE) and cost sub-additivity (CS) will be tackled. The outcomes below were computed by means of the Iterated SURE estimator being applied to a three-equation symmetric system (translog relationship plus two cost-share equations). Finally, in order to cope with non-sphericality problems, the TSP program computed all standard errors from White's (1980) robust or 'heteroscedastic-consistent' matrix (Ω_W)[40].

Table 2.2: Deterministic Translog Model (ENEL, 1996): Regression Outcomes (Note: Variables - instead of parameters - are indicated. Dependent Variable: $\ln(TDC / p_m)$. All variables in natural logs)

Coefficient Relating to Variable...	Parameter Estimat	Standard Erro	*t*-statistic
(Constant)	7.32247	2.65987	2.75294
p_l	0.30854	0.06632	4.65258
$0.5p_l^2$	-0.07231	0.01509	-4.79119
p_k	0.87258	0.06962	12.53350
$0.5p_k^2$	-0.08627	0.01403	-6.14909
$p_l p_k$	0.07859	0.01374	5.71969
AIRMT	1.03066	0.66705	1.54509
$0.5(AIRMT)^2$	-0.00236	0.00786	-0.30073
AIRBT	0.80264	0.31232	2.56998
$0.5(AIRBT)^2$	0.02163	0.01965	1.10093
(AIRMT)(AIRBT)	-0.02665	0.04794	-0.55588
$(AIRMT)p_l$	-0.00060	0.00116	-0.51427
$(AIRMT)p_k$	0.00174	0.00134	1.29771
$(AIRBT)p_l$	-0.00767	0.00328	-2.33928
$(AIRBT)p_k$	0.00301	0.00382	0.78666
BORD	-0.17817	0.07785	-2.28848
INDUSD	-0.10589	0.05155	-2.05423
GEND	0.02739	0.04154	0.65939
Y	0.32206	0.16857	1.91059
$0.5Y^2$	0.14709	0.08320	1.76796
DENS	-0.56554	0.30434	-1.85824
$0.5(DENS)^2$	-0.07046	0.07335	-0.96053
Y(DENS)	-0.06592	0.09669	-0.68175

[40] See Maddala (1992).

$(DENS)p_l$	0.03484	0.00538	6.47302
$(DENS)p_k$	-0.05050	0.00623	-8.10827
(DENS)(AIRMT)	-0.02598	0.04850	-0.53561
(DENS)(AIRBT)	0.01653	0.03873	0.42670
Yp_l	-0.02662	0.00859	-3.09722
Yp_k	0.00995	0.00990	1.00446
Y(AIRMT)	-0.16523	0.11097	-1.48898
Y(AIRBT)	-0.10048	0.05641	-1.78113

MAIN TRANSLOG EQUATION
Mean of dependent variable = 12.2365
Std. error of regression = .238581
Std. dev. of dependent var. = .724377
Adjusted R-squared = .891158
Sum of squared residuals = 8.36736
Variance of residuals = .056921

CAPITAL SHARE EQUATION
Mean of dependent variable = .4812
Std. error of regression = .044696
Std. dev. of dependent var. = .068101
Adjusted R-squared = .569339
Sum of squared residuals = .293661
Variance of residuals = .199769E-02

LABOUR SHARE EQUATION
Mean of dependent variable = .4637
Std. error of regression = .032223
Std. dev. of dependent var. = .044696
Adjusted R-squared = .479266
Sum of squared residuals = .152636
Variance of residuals = .103834E-02

We now comment upon the above outcomes. First, one must check for the main translog cost function to be well-behaved. After imposing degree-one homogeneity in input prices by means of normalisation, we must also ensure that the total cost function is non-decreasing in both input prices and output. By looking at first-order coefficients, this seems to be the case. Moreover, by calculating first-order derivatives with respect to factor prices and output, we found out that the standard monotonicity conditions are satisfied. Quasi-concavity in input prices is also verified (look at second-order price effects). Incidentally, the above derivatives are used to compute fitted cost shares and returns to scale, respectively, which we shall

discuss later. Second-order output effects would also be interesting to compute, as they would give us an idea of the 'extent' of scale economies with respect to changes in output.

Looking at first-order coefficients, capital seems to have stronger effects on total cost than labour does (0.87 against 0.31). However, as we shall see later, fitted cost shares will be much more similar in value. Output is only slightly significant[41], which pushed us to adopt 'Total Customers' as the really exogenous output proxy in our subsequent, stochastic frontier analysis. Consumer density is slightly significant to a first order, and its coefficient has the 'right' (negative) sign. Overhead medium-voltage cables show the wrong sign, but their coefficient is statistically insignificant at a 95% confidence level. On the contrary, overhead low-voltage lines show the right sign with more than 95% statistical significance, thus supporting the view according to which overhead lines are not always cheaper than underground cables, especially when low-voltage electricity has to be delivered. This mainly happens within urban contexts and affects residential customers. In fact, urban areas are served by underground cables, which reach residential buildings and houses via roughly the same (street) channels as those used by telephone lines and gas/heat pipelines.

The generation dummy's coefficient does not contradict the view according to which location of generators may perhaps affect transmission and vice versa (note the simultaneity problem)[42], but it has no effects on electricity distribution. Nonetheless, the *BORD* and *INDUSD* dummies are statistically significant and both show negative coefficients, thus meaning that borderline distributors and distributors working within industrial districts are more efficient on average. Whereas the latter result is almost self-explanatory - since industrial districts are less dispersed and much easier to serve via medium-voltage lines connecting industrial access points - the former outcome is less intuitive. Borderline

distributors might be more efficient simply because they all belong to Northern regions for obvious geographical reasons. Furthermore, they could also benefit from a positive 'spill-over' effect originating from bordering districts in France, Switzerland, and Austria which discipline public utility management at Italy's borders. Such an explanation turns out to be much less bizarre by examining overall efficiency levels for public services in some borderline towns belonging to Piedmont, Valle d'Aosta, Lombardy, and Alto Adige (South Tyrol)[43].

Finally, interaction (cross-product) terms are reported for the sake of completeness. Some of them are statistically significant, especially those involving interaction of environmental variables with input prices. Such interaction terms are relevant in calculating first-order derivatives of normalised total distribution cost with respect to variables of interest (input prices, output, consumer density). After the above general overview of results, we now turn (Subsection 5.1) to comment upon specific issues which are commonly treated by production/cost analysis[44]. We shall examine expansion point values for scale economies, economies of customer density, input elasticities of substitution, own-price elasticities, optimal cost shares, optimal factor demands, scope economies, and cost sub-additivity.

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[41] Output significance is weak at 5%, and fails the 1% significance test. The second-order effect is particularly dubious, thus jeopardising the reliability of scale efficiency (MES) outcomes.

[42] On locational issues for generators, see Vickers and Yarrow (1991), and Armstrong et al. (1994).

[43] See Il Sole-24 Ore (1997). Pollard (1981, 1991) explains the concept of 'economic regions' spreading across several European national borders. Some prominent examples are: South of Belgium/North of France (*Nord*), South-East of France/Piedmont (Italy), Bavaria (Southern Germany)/Tyrol (Austria)/North-East of Italy (Eastern Lombardy, Triveneto, German-speaking South Tyrol).

[44] See Hanoch (1975).

5.1 Deterministic Frontier Analysis: Statistics of Interest

We start with returns to scale (RTS). RTS are defined as the variation in output following equiproportional changes in all inputs. They may be increasing, constant, or decreasing. As shown by Hanoch (1975), RTS can also be calculated within a cost function analysis, by viewing them as the inverse of total cost elasticity with respect to output. By calculating such a value for our translog equation at its expansion point[45] (that is, taking sample-mean values), we found that

$$RTS = \mu = \left(\frac{\partial \ln(TDC / p_m)}{\partial \ln Y} \right)^{-1} = 2.19562 > 1. \qquad (28)$$

Such a high value implies that strongly increasing returns to scale were found at the sample mean. This is not a surprise, given that our data were highly disaggregated, with the average local unit operating at a city level only. The second-order log derivative of normalised total distribution cost with respect to output is constant and equal to

$$\frac{\partial^2 \ln(TDC / p_m)}{\partial \ln Y^2} = 0.147085 > 0, \qquad (29)$$

meaning that returns to scale decrease as output rises. This is consistent with the idea of a U-shaped AC curve. However, if the Minimum Efficient Scale (MES) is very large, the relevant region of the average cost relationship will much more resemble a L-shaped curve. In order to clarify this, we took sample-mean values for all variables excluding ln$Y$, and imposed average cost minimisation by solving the following equation:

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[45] However, scale economies might also have been evaluated at other points, e.g. at real units instead of sample mean values. Also notice that unit-specific measures are more easily obtained via DEA - which is not a central-tendency method - as is clarified in Chapter 5.

$$\left.\frac{\partial \ln(TDC / p_m)}{\partial \ln Y}\right|_{smpl.mean} = 1, \tag{30}$$

which has a solution for Y(MES) = 45,320 GWh, comparable to the total amount of electricity delivered in the whole Lombardy region in 1996 (around 42,000 GWh[46]). This is clearly a very large value, thus suggesting that the AC curve is basically L-shaped at local levels. Any decreasing returns would then occur at much higher output values than those observed in our sample. In fact, consider that the largest output value in the 1996 cross-section was Rome's, standing at 3,770 GWh. Therefore, even though economies of scale decrease as output rises, they tend to be substantial for every local zone in the sample. A RTS value exceeding 2 means that scale economies were severely non-exhausted at local levels for ENEL's distributing zones in 1996.

However, some important caveats should be mentioned before subscribing to the above conclusions:

(*a*) the second-order coefficient for Y was weakly significant at 5%, and insignificant at 1%. Therefore, the curvature of AC(Y) is not 'robust' when checked against the data, thus making the whole MES issue an ambiguous one;

(*b*) concerning the real organisational structure at ENEL, it must be noticed that the national monopolist is not really organised as a series of tiny local zones. On the contrary, its distributing departments are subdivided into districts, which again are made up of local zones.

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[46] Lombardy is a regional distributing department for ENEL. Together with Sicily and Sardinia, it is the only department which has no supra-regional dimension (the only one in continental Italy). To give a rough idea of the size of individual ENEL 'zones', we notice that Milan's zone distributed less than 3,000 GWh in 1996 - also because of the presence of a municipal distributor for Milan's city centre - with the whole region (ca. 23,000

The total amount of inter-regional departments (Italy's 'Area Boards') is just eight. Therefore, ENEL's distributing arm exploits economies of scale and scope by running zones jointly, even though internal accounting separation is indeed thorough. The real problem is perhaps to investigate the possibility that ENEL's departments and districts are not optimally sized. However, this would imply a detailed analysis of departments which would be seriously constrained by obvious small sample problems;

(*c*) stochastic frontier analysis will deal with the RTS issue more carefully by examining two outputs: energy delivered and the number of customers. While increasing RTS are still found at sample-mean values, they will revert to decreasing returns much faster, thus being compatible with a more realistic (i.e., sample-consistent) value for MES. Such a difference is mainly due to the fact that two outputs instead of one generally 'break up' the potential for scale economies, thus exhausting it more quickly[47]. Even though total customers are not a 'real' output, they - however - can be separately 'priced' as a result of different tariff schemes being applied to different consuming units. In other words, within a multiple output context, MES will - ceteris paribus - occur at lower levels for each output, since the optimal scale is 'split up' into two different quantities (*Y*, *CUST*). This has a significant effect on the electricity MES (expressed in GWh), which will be reduced to sample-consistent values. The MES outcomes resulting from a stochastic frontier methodology will, however, be carefully discussed in Chapter 3.

A further topic of analysis is the one relating to customer density effects. It is generally believed that more densely populated areas are, ceteris paribus, a better deal for electricity

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square km) being subdivided into twenty-one separated distributing zones, each one delivering - on average - 2,000 GWh a year, against 1,107 GWh national average.

[47] However, in the presence of multiple outputs, economies of scale and scope tend to be intertwined (Panzar and Willig, 1977).

distributors, since networks will be less dispersed, and electricity delivery to the average customer will turn out to be less costly because economies in exploiting the same lines arise. On the other hand, scarcely populated areas, generally coinciding with rural and/or mountain districts, will force the distributor to build up additional lines - which will be underexploited - in order to meet universal service obligations. Nonetheless, excessively populated areas may lead the distributor to face congestion effects, especially in crowded towns where electricity delivery might involve the purchase of additional land rights and the connection of multiple (i.e., duplicated) lines to the same sites. The expansion-point total cost elasticity with respect to density in our deterministic translog function was found to equal

$$\varepsilon_{TDC,DENS} = \frac{\partial \ln(TDC / p_m)}{\partial \ln DENS} = -0.2468, \tag{31}$$

implying that total distribution cost falls as population density rises. This is not particularly surprising. Since our production possibilities were not bounded *a priori*, increasing density would not create any congestion problems to the average local zone, so that consumer density is expected to be beneficial in terms of total cost reduction even to a second order. By examining the second-order log derivative of normalised total cost with respect to density, one finds that

$$\frac{\partial^2 \ln(TDC / p_m)}{\partial \ln DENS^2} = -0.07046 < 0. \tag{32}$$

This confirms that costs are slightly decreasing in density to a second order. However, since the second-order effect of density on cost is not statistically significant at a 5% level, we

conclude that the model is not able to spot any consistent second-order effects of consumer density, thus leaving the possibility of congestion as a concrete option to be tested within a different setting[48].

Since our equation system was made up of two cost-share equations in addition to the main translog function, it seems plausible to compute the fitted share expressions as elasticities of total cost with respect to input prices, following Shephard's Lemma. As materials were initially dropped from the system, their share equation will be recovered 'residually'. The figures being used considered materials as a 'residual' input, so that the materials share in total cost is expected to be low. However, those variables which were excluded from the deterministic equations might considerably alter the picture with respect to input cost shares, too, as Chapter 3 will clarify. Fitted cost shares for the present analysis turned out to be the following:

$$\begin{aligned}
\hat{S}_k &= \frac{\partial \ln(TDC / p_m)}{\partial \ln(p_k / p_m)} = \frac{p_k K}{TDC} = 0.47805_{smpl.mean}; \\
\hat{S}_l &= \frac{\partial \ln(TDC / p_m)}{\partial \ln(p_l / p_m)} = \frac{p_l N}{TDC} = 0.46944_{smpl.mean}; \\
\hat{S}_m &= 1 - (\hat{S}_k + \hat{S}_l) = 0.05251_{smpl.mean}.
\end{aligned} \tag{33}$$

Therefore, capital and labour were the main internal cost drivers at ENEL's local distributing zones for 1996. Electricity distribution is traditionally regarded as a capital-intensive sector, even though it probably employs much more labour than generation and transmission, and considerably less labour than final supply[49]. Nonetheless, we are not

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[48] For instance, consider a production relationship featuring input-output congestion within a non-parametric approach: see Koopmans (1951), Farrell (1957), and Fare et al. (1985, 1994).

[49] The above results point in the direction of substantial overmanning at ENEL's distribution arm. Alternatively, the high labour share in total cost might be due to labour being overpaid, which is a traditional ENEL characteristic. Excessive usage of labour at unfavourable relative prices leads to input-allocative inefficiency in

completely convinced by the limited share of materials in total cost (just slightly above 5%). Such a result might be due to the fact that measurement error 'jammed' the materials figure, thus leading to the materials cost share being grossly understated - in favour of capital and labour - by the deterministic cost analysis. It should also be said that we approximated materials expenses by the costs incurred by ENEL as a result of goods and services being supplied by external contractors. This clearly underestimates materials cost, and - consequently - understates their fitted share in total distribution cost. Furthermore, efficiency errors in input management are not correctly captured by non-stochastic analyses. Once again, Chapter 3 will report more realistic outcomes for factor shares in cost, too, thanks to the stochastic nature of the TEE model.

Following the theoretical introduction to the present analysis (Section 2), we recall that Hicks-Allen-Uzawa input substitution elasticities for our translog equation are written and computed as

$$\begin{aligned} \sigma_{ij} &= (\beta_{ij} + S_i S_j)/S_i S_j, \qquad i,j = K,L; \quad i \neq j; \\ \sigma_{ii} &= (\beta_{ii} + S_i^2 - S_i)/S_i^2, \qquad i = K,L. \\ \beta_{ij} &= \beta_{KL} = \beta_5; \;\; \beta_{KK} = \beta_4; \;\; \beta_{LL} = \beta_2. \end{aligned} \tag{34}$$

According to the above expressions, the estimated expansion-point values for input substitution elasticities at ENEL are

$$\begin{aligned} \sigma_{KL} &= 0.6516; \\ \sigma_{KK} &= -0.70877; \\ \sigma_{LL} &= -0.8004. \end{aligned} \tag{35}$$

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the sense of Fare et al. (1985). However, see how the above results are altered by virtue of a stochastic frontier approach (Chapter 3).

With these translog estimates of σ, capital and labour are substitutes. Moreover, own-price elasticities can also be computed according to the following relationships:

$$\begin{aligned}
&\varepsilon_{ij} = (\beta_{ij} + S_i S_j)/S_i, \qquad i,j = K,L; \quad i \neq j; \\
&\varepsilon_{ii} = (\beta_{ii} + S_i^{\,2} - S_i)/S_i, \qquad i = K,L. \\
&\beta_{ij} = \beta_{KL} = \beta_5; \;\; \beta_{KK} = \beta_4; \;\; \beta_{LL} = \beta_2.
\end{aligned} \tag{36}$$

This leads to the following sample-mean values for estimated own-price and cross-price elasticities (1996)[50]:

$$\begin{aligned}
&\varepsilon_{KL} = 0.30625; \\
&\varepsilon_{KK} = -0.34021; \\
&\varepsilon_{LL} = -0.3762.
\end{aligned} \tag{37}$$

Of course, by construction the above values are in agreement with those for σ, thus confirming that capital and labour are substitutable inputs for ENEL's electricity distribution zones. First, demand for capital shows moderate rigidity. Secondly, labour demand is more price-elastic than demand for capital: this is also a standard result for a capital-intensive industry whose basic need is capital input. However, there is no big difference between the two own-price elasticity values, thus confirming that ENEL has also a fairly inelastic demand for labour. Once again, this might result from an exaggeration of the role of both capital and labour in our estimates, following the fact that materials were simply regarded as a 'residual' production factor. Chapter 3 will shed some light upon this important issue.

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[50] By running a rough OLS regression of log-quantity on log-price (using revenue figures from ENEL, 1996), we found that the elasticity of quantity with respect to price was in the neighbourhood of –0.5, thus showing moderate rigidity.

Following the fact that, thanks to Shephard's Lemma, cost-share equations may be calculated by logarithmically differentiating normalised total cost with respect to input prices, we were also able to compute 'optimal' factor demands at sample-mean input prices, by solving the following equation in which fitted values for both total cost and factor shares were plugged[51]:

$$\frac{\bar{p}_i X^*}{T\hat{D}C} = \hat{S}_i, \qquad i = k,l; \quad X = \{K, L\}. \tag{38}$$

The optimal factor demands which solve the above equation are K^* = 4,517.45km (against sample-mean value: 5,008.68km), and N^* = 278.131 (against s.m. value: 306.878).

The final part of this Section is aimed at examining Scope Economies (SE) and Cost Sub-Additivity (CS) issues. First, we ran two simulation regressions looking for the existence of SE with respect to two separate electricity outputs. In particular, the basic assumptions being made were the following:

(*a*) output was subdivided into medium-voltage and low-voltage electricity, thus trying to capture both industrial and residential/domestic output;

(*b*) disaggregated data about costs and lines enabled us to consider a 'new' unit cost of capital, being obtained as the ratio between medium(low)-voltage capital costs and medium(low)-voltage lines;

(*c*) subsequently, we managed to get disaggregated data for labour costs as well. We then built up a new value for the price of labour, too, which was obtained as the ratio between

[51] Notice that the p_m normaliser gets cancelled from the cost-share expression.

med./low-voltage labour costs and med./low-voltage full-time equivalent employees (31.12.1996);

(*d*) finally, materials costs were already disaggregated in our original data set (similarly to capital and labour expenses). We divided medium-voltage external expenses by the number of primary (*PTP*) substations, and low-voltage external expenses by the number of secondary (non-*PTP*) transformers;

(*e*) total distribution cost for both medium and low-voltage activities was obtained by summing up disaggregated costs, as they were supplied by our original ENEL data set.

After defining new values for both output and input prices, we re-ran two translog system regressions, which were estimated by iterated SURE to get the following sample-mean results[52]:

$$\begin{aligned} &\hat{TDC}(Y_{TOT}) = 12.238; \\ &\hat{TDC}(Y_{MV}) = 6.21; \\ &\hat{TDC}(Y_{LV}) = 6.05; \\ &\hat{TDC}(Y_{MV}) + \hat{TDC}(Y_{LV}) = 12.26 > 12.238 = \hat{TDC}(Y_{TOT}). \end{aligned} \tag{39}$$

The above partial outcomes (6.21, 6.05, 12.26) depend on the fact that common capital costs (especially those relating to transforming substations and capacitors) are generally charged to medium-voltage distribution. Moreover, some double-counting is also encountered: in general, ENEL uses to duplicate some costs relating to different voltages. However, the global inequality says that joint distribution of both medium-voltage and low-voltage electricity is still cheaper than separate operation of medium-voltage and low-voltage networks. Therefore, slight scope economies are found, meaning that the technical structure of

[52] All figures are expressed in natural logarithms. Total distribution cost is normalised by the price of materials.

electricity distribution at ENEL should be kept as it is today. Nonetheless, competition for industrial deliveries (e.g., coming from independent generators) should not be prohibited, as it would probably rely on alternative technologies to which the above SE result might not apply. Whereas competition in residential distribution does not seem to be a feasible option for the foreseeable future, a series of contracts for industrial distribution may well be envisaged between industrial customers and independent generators. More precisely, although distribution networks should not be duplicated, industrial *supply* on ENEL's distribution lines might be liberalised, whereas domestic supply liberalisation[53] is definitely a remote prospect for Italian electricity customers.

Sub-additivity of cost (CS) was also analysed, albeit at a more tentative level. In fact, simulating a fifty-fifty pair of firms would also imply allocating a fixed amount of quantity-independent costs which would be clearly duplicated. Therefore, by re-running a regression on pairs of 'virtual' local firms producing half output each, with some 'stand-by' fixed costs being assigned to both of them, we obviously obtained the sub-additivity result according to which (sample-mean values in natural logs)

$$\hat{TDC}(Y_{TOT}) = 12.238 < 12.282 = 2\hat{TDC}(0.5Y_{TOT}). \tag{40}$$

This actually sounds as a self-verifying prophecy, since we intentionally duplicated fixed costs to a moderate extent, by ex-ante assigning +10% of total capital costs to each of the two 'fifty-fifty' hypothetical local units, in addition to 50% of all (variable plus fixed) costs. This obviously forced the results to show '*a priori*' cost sub-additivity at sample-mean values. Therefore, this outcome only amounts to an econometric exercise. It should then be seen

[53] Due to start in England and Wales (1998), and California (2003).

which the *real* duplicate assets are in reality, before focusing on cost sub-additivity and natural monopoly. Indeed, there are some stand-by costs which must be duplicated, irrespective of whatever amount of electricity is delivered (think, for instance, of costs relating to administration, basic fund-raising, security requirements, etc.), so that the +10% 'rule of thumb' applied above might not be that far from reality. The general impression is that cost sub-additivity should be found in electricity distribution with respect to local zones at least, due to the presence of fixed - and sunk - costs which result in uneconomic asset duplication. However, things could be different provided that much bigger areas and higher demand levels are accounted for. To conclude: as regards ENEL's local distribution zones, cost sub-additivity seems to apply almost certainly, even though an empirical proof for such a statement is not easy.

6. Conclusions

Chapter 2 was concerned with deterministic frontier estimation of a translog cost system relating to 147 ENEL local electricity distribution zones for the business year 1996. A three-equation system, made up of a translog total cost function and two cost-share equations, was estimated by Seemingly Unrelated Regression Estimation (SURE). Input prices (capital, labour, and materials) - as well as output - were inserted in the cost function. Some external variables were also taken into account. Estimation of the three-equation system led to parameter values which were used in order to compute some relevant statistics. The main outcomes of the above analysis are outlined below:

(*a*) scale economies were found at sample-mean values. The numerical value for returns to scale turned out to be very high (above 2), thus suggesting that economies of scale were severely non-exhausted. However, second-order effects guaranteed that the AC curve had a minimum, thus pointing towards a L-shaped (relevant) pattern for average cost. As previously noticed, our one-output equation probably over-estimated the extent of returns to scale[54] by failing to include a second, really exogenous output in the calculations. By following the most recent literature on electricity distribution, we then decided to include the number of customers as a second output within a more advanced stochastic frontier estimation to be carried out in Chapter 3. Estimates for returns to scale actually became more realistic and sensible as a result (see next Chapter);

(*b*) density of customers was found to be beneficial in terms of total distribution cost. Moreover, the second-order effect was not significantly different from zero, thus failing to show that there was congestion in production following increased density. However, our model would have never been able to spot any congestion effects resulting from saturating variables. This might be made possible by means of different techniques to be discussed in Chapter 5;

(*c*) scope economies were found by subdividing total input-output (and cost) according to different electricity voltages. This does not mean that competition in electricity supply should not be introduced, at least with reference to industrial customers. At the distribution level, however, our analysis discovered that it is still best to keep electricity distributors as integrated units, operating both medium-voltage and low-voltage electricity. Scope economies obviously result from common plants being used (lines, substations) in order to handle electricity at different voltages: any duplication of such plants would be uneconomic;

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[54] Recall that statistical significance for the second-order effect of *Y*(GWh) was weak, thus leading to limited

(*d*) the cost sub-additivity issue remains an open one. We tried to split up production and cost according to a rough 'fifty-fifty' rule, and assigned some duplicated fixed costs to pairs of hypothetical local firms. This obviously forced our results to show cost-efficient production for a single firm *vis-à-vis* a combination of two (or more) firms. However, with duplication of fixed assets being imposed *ex ante*, this was just a self-verifying prophecy. The real issue should then be: is uneconomic asset duplication still so important as to imply natural monopoly at the distribution level? Even though this should be empirically proved, there are strong reasons to believe that, at least for local (urban/rural) zones, cost sub-additivity is still a dominant factor which excludes the possibility of splitting up distribution activities in order to increase productive efficiency;

(*e*) fitted cost shares showed that capital is (slightly) more used than labour in electricity distribution at ENEL (in cost terms), with materials acting as a 'residual' input. However, deterministic analysis is not able to 'extract' inefficiency from cost-share figures. By examining the allocation of cost among inputs within a stochastic frontier approach, fitted cost shares will broaden the spread between capital and labour, with materials playing a more relevant role, too, in total cost. Whereas input cost shares roughly amounted to 0.48, 0.47, and 0.05 for capital, labour, and materials (respectively) in the present analysis, they will assume more balanced values when viewed within such a different approach as the one displayed in Chapter 3;

(*f*) by constructing Hicks-Allen-Uzawa input substitution elasticities, we were able to spot that capital and labour were substitutable inputs in electricity distribution (even though the elasticity of substitution was worth no more than 0.65). Moreover, from own-price elasticities we also found that demand for both labour and capital was inelastic, with demand for capital

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reliability of MES outcomes.

being more inelastic than labour demand. Differences in demand elasticities, however, were slight - as a consequence of the strong weight placed by our data on both capital and labour as key inputs, with materials being viewed again as a 'residual' production factor;

(*g*) we did not use total customers as an output in this Chapter because of the likely co-linearity between the former variable and *DENS* (consumer density), which would have biased estimation outcomes for the whole model. However, after observing the significance outcomes with regard to delivered energy (GWh), we moved to a two-output specification within a stochastic frontier analysis which separated input-output variables from exogenous cost drivers, thus overcoming the co-linearity problem between *CUST* and *DENS* (Ch. 3);

(*h*) this Chapter was only concerned with econometric estimation within a deterministic frontier setting. No efficiency study was put forward here because of the characteristics of the above analysis. Efficiency will be examined in the following Chapters thanks to more up-to-date methodologies.

Chapter 3 will extend the above total cost analysis by using a stochastic frontier methodology being implemented thanks to the dedicated program FRONTIER[55], whereas Chapter 4 will use stochastic frontier techniques in order to compare efficiency levels at ENEL's zones with those computed for 37 municipally-owned utilities. Chapter 5 will basically face the same efficiency issues within a non-parametric context (DEA), with batteries of rank-order tests (Wilcoxon, et al.) being also performed to 'cross-check' parametric (stochastic frontier) techniques against non-parametric (linear programming/DEA) methodologies.

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[55] See Coelli (1996a).

CHAPTER 3

A STOCHASTIC FRONTIER ANALYSIS OF EFFICIENCY IN LOCAL ELECTRICITY DISTRIBUTION (ENEL)

1. Introduction

This Chapter is concerned with the efficiency analysis of Italy's local distributors (ENEL) in 1996, using the same data set which was introduced in Chapter 2. As clarified in Section 2, 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 Chapter 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. The efficiency ranking approach being devised in this Chapter will also be useful to introduce the

subsequent, comparative efficiency analysis of ENEL's local branches *vis-à-vis* 37 municipally-owned electricity distributors (cross-sectional pooled sample)[1].

Chapter 3 is organised as follows. Section 2 is a theoretical introduction to stochastic frontier analysis (production, cost). Section 3 presents a quick literature review of stochastic-frontier empirical work, with special reference to public utilities and electricity. Section 4 contains the main empirical analysis of efficiency for ENEL's local distributors (1996). Three alternative models will be proposed, and a final efficiency ranking of the 147 local units will be reported from the 'final' model. Some policy-making comments (especially on the North-South issue) will also be made. Section 5 is an *ex post* Tobit analysis of efficiency scores on external variables. We shall explain why second-stage Tobit regressions of scores are less effective than single-stage analyses based on the most recent stochastic frontier models. Estimation efficiency considerations generally lead the investigator to incorporate second-stage regressions into the main model, by separating standard cost determinants (input prices, output) from environmental effects (landscape, etc.). Such a separation has been effectively proposed by Battese and Coelli (1993, 1995). Finally, Section 6 is a conclusion which also discusses the links between the stochastic frontier analyses being carried out in Chapters 3 and 4. In view of the econometric outcomes resulting from Chapters 2 and 3, the Appendix to this Chapter addresses the issue of feasibility for ENEL's territorial restructuring with special respect to the electricity distribution business.

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[1] See Chapter 4.

2. Stochastic Frontier Estimation: a Theoretical Summary

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:

$$Y_i = X_i\beta + (v_i + u_i), \qquad i = 1,\ldots,N, \tag{1}$$

where:

Y_i = production (possibly logged) of the i - th firm;

X_i = a $k \times 1$ vector of (transformations of the) input quantities of the i - th firm;

β = a vector of unknown parameters;

v, u = two separate random variables.

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 error' u is often

[2] Nerlove (1963), in Zellner (1968); Christensen and Greene (1976).

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

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 (1993b).

Going back to the one-sided or 'efficiency' error, it must be emphasised that the (in)efficiency component cannot be observed directly. In fact, it must be inferred from the composite error

$$\varepsilon_i = v_i + u_i . \qquad (2)$$

Jondrow, Lovell, Materov, and Schmidt (1982) derived an explicit form that decomposes the total error term. For the most used distributional assumption on u, that is the half-normal model, the expected value of u - conditional upon ε - is given by

[4] See also Greene (1990).

$$E[u_i|\varepsilon_i] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi(\frac{\varepsilon_i\lambda}{\sigma})}{\Phi(-\frac{\varepsilon_i\lambda}{\sigma})} - \frac{\varepsilon_i\lambda}{\sigma}\right], \tag{3}$$

where:

$\sigma = \sqrt{(\sigma_v^2 + \sigma_u^2)}$; $\lambda = \sigma_u / \sigma_v$; $\phi, \Phi =$ probability / cumulative density function of the standard normal distribution (pdf, cdf).

The particular Jondrow *et al.* expected value of u which Battese and Coelli use in their TEE model with efficiency effects and allowance for panel data is set out in Battese and Coelli (1988, pg. 388-393). Given the specification of the frontier production function [equations (1) and (2)] and the time-after-time ($t=1,2,3,...,T$) sample values for the random vector

$$\varepsilon_i = (\varepsilon_{i1}, \varepsilon_{i2}, ..., \varepsilon_{iT})', \text{ denoted by } e_i = (e_{i1}, e_{i2}, ..., e_{iT})', \tag{3a}$$

then the conditional distribution of u_i, given $\varepsilon_i = e_i$, is defined by the truncation (at zero) of the normal distribution with mean

$$\mu_i = (-\sigma^2 \bar{e}_i + T^{-1}\mu\sigma^2_v)(\sigma^2 + T^{-1}\sigma^2_v)^{-1}, \text{ and variance}$$
$$\sigma^2_* = \sigma^2\sigma^2_v(\sigma^2_v + T\sigma^2)^{-1}, \text{ where } \bar{e}_i = T^{-1}\sum_{t=1}^{T} e_{it}. \tag{3b}$$

Furthermore, the conditional expectations of u_i and $\exp(u_i)$, given $\varepsilon_i = e_i$, are

$$E(u_i|\varepsilon_i = e_i) = \mu_i{}^* + \sigma_*\left\{\phi(-\mu^*_i/\sigma_*)\left[1 - \Phi(-\mu^*_i/\sigma_*)\right]^{-1}\right\}, \text{ and} \tag{3c}$$

$$E[\exp(u_i)\Big|\varepsilon_i = e_i] = \left\{\frac{1-\Phi[\sigma_* - (\mu_i^*/\sigma_*)]}{1-\Phi(-\mu_i^*/\sigma_*)}\right\}\exp(-\mu_i^* + \frac{1}{2}\sigma_*^2), \tag{3d}$$

where [ϕ, Φ] are again the probability and cumulative density functions (respectively) of the standard normal distribution, as previously defined. The proof of the above expressions involves straightforward - but tedious - algebra. The interested reader is referred to Battese and Coelli (1988, pg. 392-393).

Cost efficiency will then be simply given by[5]

$$EFF_i = \exp(u_i) \gtreqless 1, \tag{4}$$

depending on the main relationship being either a production or a cost function, respectively. Notice that, if the dependent variable is not expressed in natural logs, the above expression will not be valid. The following one should be used instead:

$$EFF_i(linear) = \frac{X_i\beta + u_i}{X_i\beta} \begin{cases} \in (0,1] \text{ for a stochastic production frontier;} \\ \in [1,+\infty) \text{ for a stochastic total cost frontier.} \end{cases} \tag{5}$$

Jondrow *et al.* (1982) also derived similar expressions for exponentially-distributed efficiency errors, whereas Stevenson (1980) did the same for the truncated model. Moreover, Schmidt and Sickles (1984) identified three shortcomings of the cross-sectional estimation of stochastic frontiers: first, the assumption that firm-specific inefficiency is uncorrelated with the explanatory variables can be violated; secondly, the error term may not always be

[5] This is computed by software packages in order to construct efficiency scores for every firm in the sample, being used to build up a final 'efficiency ranking' of all observed units.

normally distributed; finally, the estimate of u, the efficiency error, may not be consistent. Panel data estimation of stochastic frontier models, which is able to overcome the above limitations, is reviewed and implemented by Burns and Weyman-Jones (1994a). Battese and Coelli (1988) provided a panel data counterpart to the above reported cross-sectional decomposition of the error term. As it will be clarified later, estimation of both cross-sectional and panel data stochastic frontier models is carried out by Maximum Likelihood Estimation (MLE) techniques.

Battese and Coelli (1992) propose a stochastic frontier production function for (unbalanced) panel data which has firm-specific efficiency effects being distributed as truncated normal random variables. Such firm-specific efficiency errors are also permitted to vary systematically with time. A cost-function alternative to more traditional production functions is also provided by the authors. There are obviously a large number of model choices that could be considered for any particular application. For example, a half-normal distribution for the (in)efficiency effects might be assumed, instead of the more general truncated normal distribution. Furthermore, provided that panel data is available, one could assume either time-invariant or time-varying inefficiencies. One could even revert to deterministic OLS estimation if she believes that the u term is not significant, and should then be removed from the model altogether. However, we believe that substantial inefficiency is present among ENEL's local distributing zones, so that a stochastic frontier approach seems to be the most suitable option to our purposes.

Similarly to other public utility services, electricity distribution is influenced by 'external' factors which are not under the decision-making unit's (DMU) direct control. Therefore, we

needed a model such that environmental factors[6] are correctly accounted for, while still being separated from standard regressors of either production or cost relationships.

Traditionally, a number of empirical studies[7] have estimated stochastic frontiers and predicted firm-level efficiencies by using these estimated functions. Then, they regressed predicted efficiency scores on environmental variables (including ownership types) in an attempt to identify some of the reasons for differences in predicted efficiency scores among firms in a given industry. This has long been recognised as a useful exercise. Lovell (1993, pg. 53), with reference to both stochastic frontier and DEA[8] analyses, points out that "[...] It is worth thinking hard about what variables are inputs and outputs that belong in the first stage [i.e., either production/cost estimation or first-stage DEA], and what variables are explanatory variables that belong in the second stage. This must be done on a case-by-case basis, of course. The only general guideline I have to offer is that variables under the control of the decision-maker during the time period under consideration belong in the first stage. Variables over which the decision-maker has no control during the time period under consideration belong in the second stage. Candidates for second-stage variables include quasi-fixed variables, site-specific characteristics, socio-economic and demographic characteristics, the weather, and so on". The author also discusses the possibility of estimating efficiency scores by limited-dependent variables techniques (e.g., Tobit) because of the censoring problem resulting from the 0/1 scale.

However, as Coelli (1996a) observes, the two-stage estimation procedure has also been long recognised as one which is inconsistent in its implicit assumption regarding the independence of the inefficiency effects (the *u*s) in the two estimation stages. The two-stage estimation procedure is unlikely to provide estimates which are as efficient as those that could

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[6] For a description of external cost drivers, see Chapter 2.
[7] E.g., see Pitt and Lee (1981).

be obtained by using a single-stage estimation procedure. This issue was addressed by Kumbhakar, Ghosh, and McGuckin (1991), and Reifschneider and Stevenson (1991), who proposed stochastic frontier models in which the inefficiency effects (u) are expressed as an explicit function of a vector of firm-specific variables plus a random error.

Battese and Coelli (1995) propose the 'Technical Efficiency Effects' (TEE) model, which will be used in both this Chapter and Chapter 4. Their stochastic frontier specification is equivalent to the Kumbhakar, Ghosh, and McGukin (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:

$$Y_{it} = X_{it}\beta + (v_{it} + u_{it}), \qquad i = 1,...,N; \quad t = 1,...,T, \tag{6}$$

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 previously 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

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[8] See Chapter 5.

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:

$$u_{it} \sim N(m_{it}, \sigma_u^2), \text{ where } m_{it} = Z_{it}\delta \text{ is a contemporaneous auxiliary regression such that}$$
$$Z_{it} = \text{a } p \times 1 \text{ vector of variables which may externally influence the efficiency of a firm;}$$
$$\delta = \text{a } p \times 1 \text{ vector of unknown parameters to be estimated simultaneously with (albeit separately from) } \beta. \qquad (7)$$

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. However, cross-checking of the two methodologies will be provided by Section 5, which regresses efficiency scores on environmental variables thanks to a Tobit approach[9]. In the end, Battese and Coelli's Technical Efficiency Effects (TEE) stochastic frontier specification will be taken as a first-best option for estimation (Section 4), whereas a second-stage Tobit regression of efficiency scores will be subsequently proposed for the sake of completeness (Section 5).

The model to be used in Section 4 also encompasses a number of other model specifications as special cases. If we set $T = 1$ and the Z vector of environmental variables

contains the value one and no other elements (i.e., only a constant term), then the model reduces to the original, truncated normal specification in Stevenson (1980).

All 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[10]:

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

where:

TC_{it} = Total Cost;
P_{it} = a vector of input prices;
Y_{it} = a vector of outputs;
β,γ = vectors of unknown parameters to be estimated;
v,u = the two components of ε, with $v \sim N(0,\sigma_v^2)$ and $u \geq 0$, $u \sim N(m_{it},\sigma_u^2)$. (8)

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

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[9] See also Pollitt (1995).
[10] Recall Uzawa (1964), and Shephard (1970) on duality theory.

function will be less clear, with both technical and input-allocative[11] 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[12]. 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[13].

The FRONTIER 4.1 computer program which was used in our calculations is capable of reporting predictions of firm-specific technical efficiencies from estimated stochastic production/cost frontiers. The *EFF* scores for both the log-linear and linear specifications have already been discussed in this Section (see above). For production functions, *EFF* scores will take a value between zero and one, whereas they will take a value between one and plus infinity in the cost function case (which may be easily rescaled to zero-plus infinity in order to perform a Tobit regression with left censoring). As outlined above, the *EFF* expressions all rely upon the value of the unobservable u being predicted. This is achieved by deriving expressions for the conditional expectation of u - conditional, of course, upon the observed value of $\varepsilon = v+u$. The resulting expressions are generalisations of the formulas provided by Jondrow *et al.* (1982), plus the panel data version computed by Battese and Coelli (1988). Cost-function expressions for *EFFs* are simply obtained by inverting u's sign in the *EFF*

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[11] Unless differently stated, throughout this thesis 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 approach to be discussed in Chapter 5.

[12] See Section 4.

[13] See Coelli (1996a).

scores being calculated for stochastic frontier production functions (ceteris paribus). We shall be using a stochastic cost function approach in this Chapter, so that, for a logged dependent variable,

$$EFF_i = \exp(u_i) \in [1,+\infty). \tag{9}$$

We shall switch to a stochastic production function analysis in Chapter 4, as a result of binding data constraints on the 1994 sample of Italy's 37 municipally-owned electric utilities. Therefore, for a stochastic production function - e.g., a translog - the FRONTIER 4.1 program will compute (with the dependent variable being logged as usual)

$$EFF_i = \exp(u_i) \in (0,1]. \tag{10}$$

The TEE model being estimated in Section 4 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;

(*c*) the values selected in the grid search sub (*b*) are used as starting values[14] in an iterative procedure (which makes use of the Davidson-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[15] 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 (Section 4) will be made up of standard ML parameter estimates - resulting from the three-step procedure outlined above - plus the usual statistics which have already been described in Chapter 2. In addition, we shall report a complete ranking of the 147 units in our 1996 cross-section, according to their efficiency scores. Alternative models will be proposed in order to deal with 'environmental' cost drivers. After reporting efficiency rankings, Section 5 will provide a Tobit supplementary regression of efficiency scores on external variables[16].

The next Section is concerned with a quick overview of the stochastic frontier literature.

3. Stochastic Frontier Analysis: A Brief Literature Survey

The main practical problem encountered by empirical researchers with stochastic frontier analysis is given by the fact that computed efficiency scores - resulting from the

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[14] 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.
[15] Cf. Törnqvist (1936), and Malmquist (1953).
[16] Second-stage Tobit analysis of *EFF* scores will be helpful within the DEA study developed in Chapter 5.

decomposition of ε into *v* and *u* - are not capable of separating input-allocative efficiency from technical efficiency. This is especially true when total cost functions are analysed. More recent models have assumed that allocative efficiency is present *ex ante*, thus implying that computed efficiency scores reflect technical (in)efficiency only. The TEE model to be used in the present work will simply assume that efficiency scores reflect technical inefficiency.

The literature on stochastic frontier (SF) methods has mainly developed over the last twenty years. Early studies could not produce unit-specific efficiency measures without panel data. In particular, Meeusen and van den Broeck (1977) compared the efficiency of a sample of French manufacturing companies. They assumed a Cobb-Douglas production function and imposed an exponential distribution on the *u* term. Pitt and Lee (1981) estimated a production function with truncated-normal efficiency errors in relation to a sample of Indonesian weaving firms: they still needed panel data in order to calculate firm-specific efficiency scores. Following Jondrow *et al.* (1982), subsequent studies were able to calculate firm-specific effects even in the absence of panel data, thanks to the statistical formula for the expected value of *u* (conditional upon the observed ε) which was reported in the previous Section[17]. Danilin *et al.* (1985) examined technical efficiency for a sample of cotton refining enterprises in the former Soviet Union, by using a traditional production function taken from Aigner, Lovell, and Schmidt (1977), with half-normal distributed efficiency errors.

Green, Harris, and Mayes (1991) also estimated an Aigner-Lovell-Schmidt production function assuming both half-normal and truncated normal distributions for the efficiency errors in relation to a sample of Australian and British manufacturing firms. As regards total cost studies in either single or multi-output environments, Hammond (1992) examines the (cost) efficiency of pre-war electric power plants in the UK by using a multi-output total cost

[17] Again, recall that the Jondrow *et al.* formula may also be adapted to panel data, as shown by Battese and Coelli (1988).

function with both gamma and truncated-normal efficiency errors. Similarly, we shall instrument a translog two-output total cost function with truncated-normal technical efficiency errors, whose arithmetic distribution mean will be centred upon environmental effects.

Given the serious difficulties encountered in separating technical and allocative efficiency effects within the *EFF* formula, relatively few papers have attempted a decomposition of cost efficiency into technical and allocative elements. Kumbhakar (1988) examines technical efficiency for a sample of US railroads by using an analytically derived cost frontier. Ferrier and Lovell (1990) use a multiple-output translog cost function[18] in order to decompose inefficiency in a sample of US banks. Similarly, Kumbhakar follows the same decomposition approach to get inefficiency estimates for panel data on US airlines. Kalirajan and Yong (1993) employ a Cobb-Douglas relationship by fitting it to a sample of Chinese iron and steel enterprises.

Turning to electricity distribution, two main studies are worth recalling. Burns and Weyman-Jones (1994a) fit both translog and Cobb-Douglas stochastic cost functions to a panel of the 12 Regional Electricity Companies of England and Wales (RECs) over the pre-privatisation period (1980-1990). They compute efficiency scores via Jondrow *et al.*'s (1982) formula. They also extend their panel to 1993, in order to analyse privatisation effects. Following Neuberg's (1977) paper, they assume that the total number of customers (*CUST*) is a valid proxy for (exogenous) output in the total cost relationship. After working out efficiency scores within a stochastic frontier approach, the authors discover that the main cost drivers in electricity distribution are total customers in each area and simultaneous maximum demand. They also try with different distributional assumptions for the u term. Economies of scale are found at sample-mean values. Finally, they find a small but significant variation in

[18] See also Schmidt (1984).

cost efficiency as a result of privatisation in 1990, but this is probably a one-off effect reflecting the persistence of a long-lasting time trend. It might have been partially determined either by

(*a*) different accounting policies for pre-privatisation Area Boards and post-divestiture RECs, or by

(*b*) initially generous regulation which did not force the RECs to improve on their previous efficiency levels over the first regulatory period (1990-1994).

Similar results on privatisation effects, with special reference to low efficiency enhancement owing to loose regulatory constraints during the early Nineties, are shown for electricity distribution in England and Wales by the same authors[19] within a non-parametric (DEA/Malmquist) context. This will be reviewed in Chapter 5. Finally, a look at Price and Weyman-Jones's (1993) results on gas in England and Wales would also be useful in order to compare different outcomes, with special reference to post-privatisation regulatory effects. Environmental/economic aspects, such as trends in regional GDPs and economic cycles, are also taken into account by the authors.

Pollitt (1995) follows Huettner and Landon (1977) in specifying a total cost model for electricity distribution within a private/public ownership context. The number of customers is again assumed as a proxy for output. The author basically develops a DEA specification for distribution, even though he refers to both econometric and linear programming articles in order to construct the model (choice of inputs and outputs). A 1990 cross-sectional sample of both US and UK public/private-sector electricity distribution companies is analysed. By also

[19] Burns and Weyman-Jones (1994b).

looking at electricity transmission, the author concludes that it is not possible to reject the null hypothesis according to which publicly-owned and privately-owned electricity transmission/distribution companies exhibit no significant difference in technical efficiency. DEA results are cross-checked against econometric ones. By failing to reject the no-difference hypothesis between publicly and privately-owned firms, the author finds a consistent outcome with that obtained, within a panel data context, by Burns and Weyman-Jones (1994a, 1994b) on the British RECs. Dubious efficiency effects as a result of privatisation (probably due to regulatory slackness) are confirmed by both econometric and DEA/Malmquist techniques. Finally, Pollitt outlines that, together, both the econometric and DEA results suggest no evidence for the belief that the British RECs were performing poorly - relatively to US distribution utilities - prior to privatisation (1990).

Data issues on our analysis have been previously discussed in Chapter 2. Since the data set we are going to use is exactly the same as that utilised in the deterministic translog analysis, we directly move to our stochastic-frontier estimation results being obtained by fitting the Technical Efficiency Effects model to ENEL's 1996 cross-section.

4. Stochastic Frontier Analysis (TEE model, ENEL, 1996): Estimation and Outcomes

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:

(Equation 11 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;

$u \geq 0$, $u \sim N(m_i,\sigma_u^2)$, where $m_i = Z_i\delta$ is a contemporaneous auxiliary regression such that

$Z_i =$ 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;

$$m_i = \delta_1 \ln DENS + \delta_2 \ln INDCUS + \delta_3 \ln INDLIN + \delta_4 \ln INDY + \delta_5 \ln THIRD + \delta_6 \ln AIRMT +$$

$$+ \delta_7 \ln AIRBT + \delta_8 \ln PTP + \delta_9 SOUD + \delta_{10} MOUNTD + \delta_{11} METRD + \delta_{12} MUNID + \delta_{13} SEAD +$$

$$+ \delta_{14} BORD + \delta_{15} INDUSD + \delta_{16} GEND.$$

It should be noticed that the computer program which we used did not allow the analysis to include equation systems. Therefore, we basically utilised the same translog specification as before, but excluded the two cost-share equations for capital and labour. Moreover, a second output was introduced. Apart from energy delivered (Y), we now 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. Apart from the $CUST$ output variable, no major changes were made to our translog total cost function, which was again normalised in terms of the materials price p_m (degree-one homogeneity in input prices). Non-homotheticity was also guaranteed by full interaction terms.

Nonetheless, 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[20] 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 $N(m, \sigma^2)$ 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*, so that the efficiency scores being computed will be interpreted as technical inefficiency indicators.

By instructing the computer to estimate the above translog-cum-environmental effects model, we *de facto* imposed the three-stage estimation procedure previously described in Section 2. The final ML estimation procedure also provides estimates for the 'delta' (i.e., environmental) effects on a separate basis. The computer program then delivers final (iterated) ML estimates for both the 'betas' (translog cost function) and 'deltas', plus log-likelihood functions and Likelihood Ratio (LR) tests for the main estimated equation.

We did not impose any parameter starting values upon the Technical Efficiency Effects model to be analysed. Of course, if starting values are specified *ex ante* by the investigator, the computer program will automatically perform final ML estimation[21]. 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

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[20] Environmental effects are discussed in Chapter 2. The reader is referred to that Chapter (Section 4) for an explanation of abbreviations, too.

[21] For further details on how to compute ML estimates and stochastic efficiency scores for TEE on a IBM/PC, see Coelli (1996a).

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

Coefficient Relating to Variable...	**Parameter Estimate**	**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 Variable... [Dependent Variable: m_u]	**Parameter Estimate**	**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[22]	17.659		
No. of Iterations	55/100		
Sample Size	147		
Time Periods	1		

With respect to the above results, notice that all quadratic elements in the translog entered directly, i.e. with no 0.5 rescaling (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, following the theoretical concepts already outlined in Chapter 2.

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

4.1 Stochastic Frontier Translog Estimation (ENEL, 1996): 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

$$GRTS = \left[\frac{\partial \ln(TDC / p_m)}{\partial \ln Y} + \frac{\partial \ln(TDC / p_m)}{\partial \ln CUST} \right]^{-1} = 1.50987 > 1 \text{ (sample - mean value), so that} \quad (12)$$

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

Therefore, increasing returns to scale are detected at sample-mean values (the Taylor's series expansion points). However, their amount is not as large as that found in the previous deterministic analysis. It also seems to be a more plausible value, which should be compatible with a U-shaped AC curve - instead of a L-shaped one. The second-order effect of output on total cost was computed as

$$SOE = \frac{\partial^2 \ln(TDC / p_m)}{\partial \ln Y^2} + \frac{\partial^2 \ln(TDC / p_m)}{\partial \ln CUST^2} = 2(0.10035 + 0.336612) = 0.873924 > 0. \quad (13)$$

The above (constant) value implies that global returns to scale are definitely decreasing as both outputs rise. Therefore, one could 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

$$\left[\frac{\partial \ln(TDC / p_m)}{\partial \ln Y} + \frac{\partial \ln(TDC / p_m)}{\partial \ln CUST}\right]^{-1}\Bigg|_{sample\ mean} = 1 \qquad (14)$$

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

$$Y_{MES}\big|_{\overline{CUST}} = 403 \text{ GWh}; \quad CUST_{MES}\big|_{\overline{Y}} = 364{,}687.9; \quad Y_{mean} = 1{,}107 \text{ GWh}; \quad CUST_{mean} = 195{,}417. \quad (15)$$

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. If one considers overall scale economies, it is obvious that the multi-output stochastic translog function will deliver similar outcomes to those reported by the previous, single-output deterministic model. However, if one investigates scale economies more thoroughly - by splitting them up among different outputs - it will be clear that stronger returns to scale exist in the number of customers rather than in physical output. However, the three-dimensional average cost curve will much more resemble a U-

shaped contour, rather than a L-shaped one (as it happened in Chapter 2). 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. We do think that a U-shaped contour for average cost - albeit unbalanced in favour of smaller-than-MES units - is by far more plausible than the L-shaped relationship in output - featuring a very high *Y*-MES - which resulted from the single-output deterministic analysis of Chapter 2.

Overall scale economies were then present at sample-mean values, even though MES occurred at much more realistic levels than those found in the previous Chapter. Moreover, global returns to scale were found to be driven much more by customers than by energy delivered. This might lead the investigator to believe that consumer density matters 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, and also confirms the density-economies outcomes displayed in Chapter 2, where density had been inserted as a direct translog regressor, with its first-order effect amounting to around –0.24. Once again, 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. The

deterministic model's second-order effect suggested no congestion, but it was statistically insignificant at 5%. Then, the congestion issue still remains an open one.

Looking at optimal factor demands, we are now able to make new calculations for cost-share equations. We recall from Chapter 2 that fitted cost shares were probably biased in favour of labour and capital, with no input inefficiency being taken into account. The new stochastic specification may help shed some light on the cost-share issue, by 'extracting' technical inefficiency, so as to display cost shares more correctly. From duality theory, cost-share equations are obtained as the elasticity of total cost with respect to input prices[23]. By log-differentiating normalised total cost with respect to capital and labour prices - and taking sample-mean values - we found that

$$\hat{S}_k = \varepsilon_{TDC,p_k} = 0.6306;\ \hat{S}_l = \varepsilon_{TDC,p_l} = 0.2495;\ \hat{S}_m = 1 - (\hat{S}_k + \hat{S}_l) = 0.1199. \quad (16)$$

The above values are much more balanced and plausible than those obtained, at sample-mean values, by the previous deterministic analysis. Inefficiency in labour usage has probably been captured by the efficiency errors, so that the fitted labour share in total cost, according to a multi-output stochastic specification, is definitely lower than the deterministic-based one. As a result, capital usage (in terms of cost) increases (63%), and materials, too - as a residual input - enjoy a larger share in total cost (12%), with labour's share standing at 25%. Such values are consistent with capital intensity of electricity distribution. They were probably influenced by both statistical assumptions about the error term - and, consequently, by external effects - and by the fact that the translog cost function was estimated by MLE on a two-output basis. The two outputs chosen (*Y*, *CUST*) probably drove up capital intensity, so as

[23] See Chapter 2.

to rise the capital cost share at the expense of labour's one. By the same token, materials also rose, in cost terms, to reach a respectable 12% cost share.

By computing optimal (fitted) input demands thanks to Shephard's Lemma being applied to the cost-share log derivative, one also discovers that

$$S_i = \frac{\partial \ln(TDC / p_m)}{\partial \ln(p_i / p_m)} = \frac{p_i X_i^*}{TDC}, \quad i = k,l \Rightarrow X_k^* = 5{,}929 \; km; \; X_l^* = 148 \; units. \tag{17}$$

Therefore, the stochastic frontier outcomes for fitted input demands are not in agreement with those stemming from the deterministic analysis. In particular, the average zone now appears to be under-capitalised in terms of kilometres of distribution line, whereas overmanning persists. However, recall that a stochastic approach may extract measurement error or noise (especially within cross-sectional contexts) - together with inefficiency - to an excessive extent, thus influencing factor demand estimates considerably. Therefore, the present analysis might be excessively punitive towards labour efficiency. Anyhow, even though estimated sample-mean labour inefficiency seems to be frankly excessive, it is consistent with the stylised fact according to which ENEL is employing too much labour because of extra-economic pressures[24]. Overmanning at ENEL has been traditionally caused by the political process, which determined 'electoral swaps' between jobs and votes (especially in the South), so as to inflate the firm's labour force well beyond any economically acceptable limit. Informal comments on ENEL have traditionally pointed out huge overmanning at the Southern/Naples ENEL branch in particular. However, input 'slacks' will be calculated for every (real) unit in the sample - and not only for the purely virtual 'sample-mean' electricity distributor - thanks to the DEA methodology (see Chapter 5).

Both Hicks-Allen-Uzawa input elasticities of substitution, and standard own and cross-price elasticities confirmed that capital and labour were substitutes. In particular,

$$\sigma_{KN} = 1.13 > 1 \text{ (from fitted input cost shares)}, \tag{18}$$

which is a sufficiently large value, even though not much larger than unity[25]. Given current input relative prices (p_K/p_l), this should encourage labour-saving technical progress at ENEL, with capital gradually replacing labour. This has happened to both the National Grid Company and the RECs in England and Wales over the last 6-7 years, following privatisation and regulation[26]. It is expected that effective regulation of ENEL would stimulate a great deal of labour shedding in the years to come. This is obviously opposed by trade unions, and political reasons will certainly hinder such a process. However, gradual reduction in ENEL's labour force is actually needed on purely input-allocative efficiency grounds.

As regards scope economies (SE) and cost sub-additivity (CS) checks, we refrained from running experimental regressions since the complexity of three-stage estimation in the TEE model did not allow us to rapidly check for SE/CS. Moreover, we believe that the deterministic results would have been confirmed within a stochastic setting, too. Therefore, we stick to the two facts that, from Chapter 2, slight scope economies were found between

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[24] Compare the above input slacks with those obtained via DEA in Chapter 6.

[25] It is worth noticing that 1.13 is not far from the unit value which would be compatible with a Cobb-Douglas total cost specification. Translog equations are easily restricted to Cobb-Douglas, by imposing that all parameters for both second-order and interaction terms equal zero. $\sigma = 1$ would imply that our original model might be viewed as a Cobb-Douglas expansion. However, statistical significance of second-order terms guarantees that the translog envelops the data more tightly than the C-D does. Therefore, the 1.13 value should be regarded as being *significantly* different from 1.

[26] Haskel and Szymanski (1992) investigate the labour shedding issue within a labour productivity growth (not TFP) analysis. As regards the British experience with electricity distribution after divestiture and regulation, some Regional Electricity Companies (RECs) nearly halved their labour force as a result of both privatisation and eventual mergers/take-overs. For instance, MANWEB of Merseyside and North Wales cut labour force from 5,551 in 1989/90 to 2,975 in 1996/97, after being taken over by Scottish Power. SWEB of South Wales reduced its personnel from 5,641 units in 1989/90 to 2,821 units in 1996/97, after being transferred to an American utility company during 1995.

medium-voltage and low-voltage electricity, and that cost sub-additivity should be assumed as a default condition for the tiny local distribution zones (147 units, each one distributing 1.1 TWh = 1,100 GWh on average) which make up our cross-section. Proofs of cost super-additivity at local (urban/rural) levels are very hard, and hardly credible: one would rather assume cost sub-additivity throughout the vast majority of local distribution zones[27].

We conclude this Subsection 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;

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[27] Recall that 'metropolitan areas' in Italy - according to Law no. 142/1990 - are only nine, against 147 local ENEL zones and 37 municipally-owned electric utilities in 1996. More generally, Italy's demographic structure is - for historical reasons - such that population is uniformly distributed across the country, with a large number of medium-sized towns (resulting from ancient communal units) and a few big conurbations.

(*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[28];

(*d*) once again, overhead cables in low-voltage distribution are more expensive than standard underground connections (this was also spotted by the deterministic analysis);

(*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[29];

(*g*) both landscape effects (*MOUNTD*) and metropolitan areas (*METRD*) were found to be statistically insignificant with respect to total cost minimisation[30];

(*h*) the presence of municipal distributors at zonal borders was again discovered to rise distribution cost. This is probably due to urban 'cream-skimming'[31] 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

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

[29] It is worth noticing that the 'Southern' dummy turned out to be irrelevant in the deterministic analysis, too.

[30] This is a 'weird' result, which will be discussed in detail in Section 5.

[31] 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

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 deterministic analysis's findings, according to which location of generating units may perhaps influence transmission and vice versa - with distribution being left unaffected, though.

The next Subsection reports efficiency scores for all units in the sample. Excessive 'forgiveness' of stochastic frontier measures will be clarified, with special reference to technical inefficiency effects. The presence of some Southern units among the top performers will also be discussed. Section 5 cross-checks the findings stemming from TEE (environmental effects) by performing a second-stage Tobit regression of estimated efficiency scores on a significant selection of environmental variables. Finally, Section 6 concludes the Chapter and introduces the main topics of Chapter 4, which are strictly linked to those analysed here.

4.2 Stochastic Frontier Analysis (ENEL, 1996): Estimated Efficiency Scores and Rankings

The stochastic cost frontier which was estimated by TEE/MLE resulted from a previous, unrestricted model with 16 environmental effects (*Zs*). Four external variables have been excluded at the outset because they were either insignificant, collinear with other ones, or carried the 'wrong' sign. Therefore, we estimated a 12-environmental effects model, previously labelled 'Model 12TE'. This is the result of a general-to-simple estimation

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allowed to compete on the same territories. Therefore, 'cream-skimming' is here meant in a non-traditional sense.

strategy. The efficiency scores which are reported later on were taken from Model 12TE. Efficiency scores, or *EFFs*, were computed by using the general expected-value formula first proposed by Jondrow *et al.* (1982), and subsequently generalised to panel data by Battese and Coelli (1988). The 'exponential' version of the efficiency formula was selected by the FRONTIER computer program, as a result of the dependent variable being expressed in natural logarithms. Efficiency scores being calculated within a stochastic frontier framework have a very nice format, in that they are normalised to well-defined intervals. This also allows the investigator to simply compare stochastic efficiency score series (estimated values) with *computed* efficiency scores stemming from such non-parametric methodologies as DEA. Comparisons among different efficiency score series are statistically implemented by using rank-order (non-parametric) testing methodologies (Wilcoxon, Kolmogorov-Smirnov, Sign)[32].

DEA users are aware of the high sensitivity of efficiency scores to changes in model 'specification'[33] (that is, the accurate choice of inputs and outputs). Rather than either input or output-oriented DEA (with variable returns to scale being assumed *ex ante*), input and output choices are the real determinants of efficiency rankings. Quite similarly, estimated efficiency scores (*EFFs*) from stochastic frontier techniques are strongly dependent on both the main production/cost specification and the choice of environmental effects. Given that we assumed a two-output translog total cost function as the 'best' model[34], changes in model specification were hypothesised with regard to environmental variables only. The latest specification which was accepted is the one named Model 12TE, featuring twelve environmental effects. However, in order to show to what extent sensitivity relating to the selection of environmental variables is able to affect final efficiency rankings, we decided to let the computer package

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[32] These are comprehensively outlined in Lehmann (1975). Rank-order efficiency score comparisons will be performed in Chapter 5.

[33] See Seiford and Thrall (1990), and the references therein, for a useful overview of DEA.

[34] Alternative regressions were performed on a single-output function, with bad results.

calculate efficiency scores for a 'default' translog model, featuring the main total cost function plus zero environmental effects. Such a model, labelled 'Model 0TE', will be used as a benchmark against which efficiency scores from Model 12TE can be set. The following analysis highlights the fact that Model 12TE is much more forgiving towards Southern zones, as a result of the efficiency error's distribution being influenced by some pro-Southern environmental variables (socio-economic effects, industrial customers, demographic/landscape characteristics, and the like). We also tried to build up efficiency scores for Model 16TE (the unrestricted specification), and found out that the majority of efficient zones were made up of Central and Southern units. Such a bizarre result was clearly driven by the fact that Model 16TE is over-specified, with some insignificant/distortionary environmental effects.

To sum up, the following efficiency rankings are those from Models 0TE (zero effects) and 12TE (twelve effects), whereas Model 16TE's rankings have been excluded from the comparison altogether because of their very low reliability. Of course, Model 12TE's ranking will be taken as the 'best' one for subsequent inference and (tentative) policy-making suggestions[35]. Finally, notice that efficiency scores resulting from production functions make use of non-positive efficiency errors, leading the firm to shift inside its production possibilities set. Therefore, inefficient firms will have smaller-than-one (normalised) efficiency scores. On the contrary, stochastic cost functions imply non-negative efficiency errors, corresponding to erroneous shifts above the total cost curve. Hence, inefficient DMUs will have larger-than-one reported efficiency scores. Of course, all scores may be easily converted to (0,1] values. Fully efficient firms will show efficiency scores equalling 1 in both

[35] As Pollitt (1995) recalls, in every quantitative analysis the results are just as good as the data are. ENEL's figures for 1996 were extremely disaggregated, but they still related to a totally integrated monopolist which is left free to allocate common costs and transfer prices among its internal branches. The Italian electricity

cases. Moreover, in order to perform censored regressions (e.g., Tobit) of scores, [0,+∞) re-scaling is necessary. This is also easily obtained, especially from [1,+∞) values. Generally, both (0,1] and [1,+∞) efficiency scores are very easy to re-scale in order to make Tobit estimation possible[36].

The following scores for 147 ENEL local distribution zones (1996) are reported in the [1,+∞) format, meaning that they result from stochastic translog total cost estimation. Table 1a reports Model 0TE's scores; Table 2 is for Model 12TE; finally, Table 3 reports 'group shifts' as a result of Model 12TE being considered. For the sake of reading ease, local zones are subdivided into 'groups', according to their position in the global ranking, and shifts from one group to another - reflecting the M0TE→M12TE change - are separately provided[37].

Tables 3.1a and 3.2: Efficiency Rankings

Table 1a				Table 2			
MODEL 0TE				MODEL 12TE			
Local Units	Efficiency Scores	[0/1]	Ranking	Local Units	Efficiency Scores	[0/1]	Ranking
TORINO	1.00E+00	1	1	VENEZIA	1.01E+00	0.99009901	1
MELZO	1.00E+00	1	1	VARESE	1.02E+00	0.98039216	2
BOVISIO	1.00E+00	1	1	TORINO	1.02E+00	0.98039216	2
CORSICO	1.00E+00	1	1	VESUVIANA	1.02E+00	0.98039216	2
MILANO EXT.	1.00E+00	1	1	NAPOLI	1.02E+00	0.98039216	2
MONZA	1.00E+00	1	1	BUSTO ARSIZIO	1.02E+00	0.98039216	2
MILANO	1.00E+00	1	1	LECCO	1.02E+00	0.98039216	2

regulator, being active since September 1996, has not been able to monitor ENEL's 1996 figures sufficiently. Better accounting separation will probably be obtained from ENEL for future years' accounting data.

[36] See also Section 5.

[37] In order to confirm that models M0TE and M12TE gave rise to statistically different efficiency score series, we tested for normality of the two series via Kolmogorov-Smirnov and, after normality failed to be rejected, proceeded with paired-samples *t*-tests (see also Chapter 5), which gave strong rejection (*t*-prob. = 0.000, with 146 degrees of freedom) of the null hypothesis according to which M0TE and M12TE agreed with respect to efficiency scores. Rejection of statistical concordance was confirmed by non-parametric tests as well (Wilcoxon's *Z*: 0.000; Sign Test's *Z*: 0.005, at 5% significance level). We then went on with model M12TE, as it seemed to be more sensible in that it incorporated significant external variables (thus dropping the insignificant ones which popped up in M16TE). This note further justifies the future utilisation of paired-samples statistical tests in the present thesis: see Chapter 5 for the main applications [on SFE vs. DEA methodological cross-checking, refer to Pollitt (1995)].

BUSTO ARSIZIO	1.00E+00	1	1	**CORSICO**	1.02E+00	0.98039216	2
COMO	1.00E+00	1	1	**MONZA**	1.03E+00	0.97087379	9
LECCO	1.00E+00	1	1	**MILANO**	1.03E+00	0.97087379	9
VARESE	1.00E+00	1	1	**PALERMO CTR.**	1.03E+00	0.97087379	9
VENEZIA	1.00E+00	1	1	**COMO**	1.03E+00	0.97087379	9
PRATO	1.00E+00	1	1	**BOVISIO**	1.03E+00	0.97087379	9
ROMA	1.00E+00	1	1	**MELZO**	1.03E+00	0.97087379	9
TORRE ANNUNZ.	1.00E+00	1	1	**MILANO EXT.**	1.04E+00	0.96153846	15
NAPOLI	1.00E+00	1	1	**LA SPEZIA**	1.04E+00	0.96153846	15
TRIESTE	1.01E+00	0.99009901	17	**LODI**	1.04E+00	0.96153846	15
BERGAMO EXT.	1.02E+00	0.98039216	18	**GENOVA**	1.05E+00	0.95238095	18
VESUVIANA	1.02E+00	0.98039216	18	**NOCERA**	1.05E+00	0.95238095	18
PALERMO CTR.	1.04E+00	0.96153846	20	**AOSTA**	1.05E+00	0.95238095	18
BIELLA	1.06E+00	0.94339623	21	**CATANIA**	1.05E+00	0.95238095	18
BERGAMO	1.07E+00	0.93457944	22	**SONDRIO**	1.05E+00	0.95238095	18
NOVARA	1.07E+00	0.93457944	22	**NOLA**	1.06E+00	0.94339623	23
NOCERA	1.09E+00	0.91743119	24	**POZZUOLI**	1.06E+00	0.94339623	23
RIVOLI	1.09E+00	0.91743119	24	**BERGAMO EXT.**	1.06E+00	0.94339623	23
MESTRE	1.10E+00	0.90909091	26	**PRATO**	1.07E+00	0.93457944	26
MASSA	1.11E+00	0.9009009	27	**TRIESTE**	1.07E+00	0.93457944	27
BRENO	1.12E+00	0.89285714	28	**MASSA**	1.07E+00	0.93457944	27
UDINE	1.12E+00	0.89285714	28	**MESTRE**	1.07E+00	0.93457944	27
POZZUOLI	1.13E+00	0.88495575	30	**ALBENGA**	1.08E+00	0.92592593	30
CASERTA	1.13E+00	0.88495575	30	**SAVONA**	1.08E+00	0.92592593	30
NOLA	1.13E+00	0.88495575	30	**TORRE ANNUNZ.**	1.08E+00	0.92592593	30
PINEROLO	1.15E+00	0.86956522	33	**LIVORNO**	1.08E+00	0.92592593	30
VERCELLI	1.15E+00	0.86956522	33	**FIRENZE**	1.10E+00	0.90909091	34
LUCCA	1.15E+00	0.86956522	33	**PISTOIA**	1.10E+00	0.90909091	34
SONDRIO	1.16E+00	0.86206897	36	**BIELLA**	1.10E+00	0.90909091	34
BRESCIA	1.17E+00	0.85470085	37	**BERGAMO**	1.10E+00	0.90909091	34
ANCONA	1.18E+00	0.84745763	38	**ACIREALE**	1.10E+00	0.90909091	34
LATINA	1.19E+00	0.84033613	39	**VIGEVANO**	1.11E+00	0.9009009	39
SAVONA	1.19E+00	0.84033613	39	**CHIAVARI**	1.11E+00	0.9009009	39
PADOVA	1.20E+00	0.83333333	41	**NOVARA**	1.11E+00	0.9009009	39
GENOVA	1.20E+00	0.83333333	41	**PINEROLO**	1.12E+00	0.89285714	42
IVREA	1.21E+00	0.82644628	43	**RIMINI**	1.12E+00	0.89285714	42
TERAMO	1.21E+00	0.82644628	43	**VERBANIA**	1.12E+00	0.89285714	42
ALBANO	1.22E+00	0.81967213	45	**VERONA NORD**	1.13E+00	0.88495575	45
TREVISO	1.22E+00	0.81967213	45	**ALBANO**	1.13E+00	0.88495575	45
REGGIO EMIL.	1.23E+00	0.81300813	47	**BARI**	1.14E+00	0.87719298	47
FROSINONE	1.24E+00	0.80645161	48	**CASERTA**	1.14E+00	0.87719298	47
BOLOGNA	1.24E+00	0.80645161	48	**FERRARA**	1.15E+00	0.86956522	49
CATANIA	1.24E+00	0.80645161	48	**CUNEO**	1.16E+00	0.86206897	50
MODENA	1.24E+00	0.80645161	48	**RIVOLI**	1.18E+00	0.84745763	51
VERBANIA	1.24E+00	0.80645161	48	**PAVIA**	1.18E+00	0.84745763	51
PESCARA	1.25E+00	0.8	53	**SALO'**	1.19E+00	0.84033613	53
ASTI	1.27E+00	0.78740157	54	**LATINA**	1.19E+00	0.84033613	53
LODI	1.27E+00	0.78740157	54	**BRENO**	1.19E+00	0.84033613	53
LA SPEZIA	1.28E+00	0.78125	56	**BARLETTA**	1.19E+00	0.84033613	53
ALBA	1.28E+00	0.78125	56	**UDINE**	1.19E+00	0.84033613	53
BARI	1.28E+00	0.78125	56	**LUCCA**	1.19E+00	0.84033613	
RAVENNA	1.29E+00	0.7751938	59	**PADOVA**	1.19E+00	0.84033613	

PISA	1.29E+00	0.7751938	59	**IMPERIA**	1.20E+00	0.83333333	60
SALERNO	1.29E+00	0.7751938	59	**SALERNO**	1.20E+00	0.83333333	60
VICENZA	1.30E+00	0.76923077	62	**FORMIA**	1.20E+00	0.83333333	60
CUNEO	1.30E+00	0.76923077	62	**RAVENNA**	1.20E+00	0.83333333	60
ALBENGA	1.30E+00	0.76923077	62	**BOLOGNA**	1.20E+00	0.83333333	60
MESSINA	1.31E+00	0.76335878	65	**FORLI'**	1.21E+00	0.82644628	65
RIMINI	1.31E+00	0.76335878	65	**LECCE**	1.21E+00	0.82644628	65
FORMIA	1.32E+00	0.75757576	67	**PISA**	1.21E+00	0.82644628	65
AOSTA	1.32E+00	0.75757576	67	**NOVI LIG.**	1.21E+00	0.82644628	65
CHIETI	1.32E+00	0.75757576	67	**ASTI**	1.23E+00	0.81300813	69
BASSANO	1.33E+00	0.7518797	70	**IVREA**	1.23E+00	0.81300813	69
IMPERIA	1.33E+00	0.7518797	70	**ANCONA**	1.23E+00	0.81300813	69
TRENTO	1.34E+00	0.74626866	72	**SAN DONA'**	1.24E+00	0.80645161	72
SALO'	1.34E+00	0.74626866	72	**TIVOLI**	1.24E+00	0.80645161	72
CHIAVARI	1.34E+00	0.74626866	72	**ALBA**	1.24E+00	0.80645161	72
FORLI'	1.34E+00	0.74626866	72	**PIACENZA**	1.24E+00	0.80645161	72
PORDENONE	1.35E+00	0.74074074	76	**REGGIO EMIL.**	1.25E+00	0.8	76
MANTOVA	1.35E+00	0.74074074	76	**AREZZO**	1.26E+00	0.79365079	77
BELLUNO	1.35E+00	0.74074074	76	**MESSINA**	1.26E+00	0.79365079	77
LIVORNO	1.36E+00	0.73529412	79	**ISERNIA**	1.26E+00	0.79365079	77
BOLZANO	1.36E+00	0.73529412	79	**TREVISO**	1.26E+00	0.79365079	77
VERONA NORD	1.36E+00	0.73529412	79	**MONOPOLI**	1.26E+00	0.79365079	77
FIRENZE	1.36E+00	0.73529412	79	**RAGUSA**	1.27E+00	0.78740157	82
PERUGIA	1.36E+00	0.73529412	79	**ROMA**	1.27E+00	0.78740157	82
ASCOLI PICENO	1.36E+00	0.73529412	79	**TRAPANI**	1.28E+00	0.78125	84
FERRARA	1.37E+00	0.72992701	85	**ASCOLI PICENO**	1.28E+00	0.78125	84
PISTOIA	1.37E+00	0.72992701	85	**PESCARA**	1.29E+00	0.7751938	86
CIVITAVECCHIA	1.37E+00	0.72992701	85	**CONEGLIANO**	1.29E+00	0.7751938	86
Average Score	1.38E+00	0.72463768	-	**Average Score**	1.30E+00	0.76923077	-
CONEGLIANO	1.38E+00	0.72463768	88	**BELLUNO**	1.30E+00	0.76923077	88
PESARO	1.38E+00	0.72463768	88	**CIVITAVECCHIA**	1.31E+00	0.76335878	**88**
CAGLIARI	1.40E+00	0.71428571	88	**BASSANO**	1.32E+00	0.75757576	**90**
VERONA SUD	1.41E+00	0.70921986	91	**BRINDISI**	1.33E+00	0.7518797	91
ROVIGO	1.41E+00	0.70921986	92	**ALESSANDRIA**	1.33E+00	0.7518797	92
VIGEVANO	1.44E+00	0.69444444	92	**MAGLIE**	1.33E+00	0.7518797	92
PIACENZA	1.44E+00	0.69444444	94	**PESARO**	1.34E+00	0.74626866	92
ALESSANDRIA	1.44E+00	0.69444444	94	**TARANTO**	1.34E+00	0.74626866	95
CREMONA	1.44E+00	0.69444444	94	**SIRACUSA**	1.34E+00	0.74626866	95
PAVIA	1.44E+00	0.69444444	94	**L' AQUILA**	1.35E+00	0.74074074	95
SAN DONA'	1.45E+00	0.68965517	94	**VERONA SUD**	1.38E+00	0.72463768	98
L' AQUILA	1.45E+00	0.68965517	99	**CHIETI**	1.38E+00	0.72463768	99
ACIREALE	1.46E+00	0.68493151	99	**MODENA**	1.38E+00	0.72463768	99
ISERNIA	1.46E+00	0.68493151	101	**AGRIGENTO**	1.39E+00	0.71942446	99
REGGIO CAL.	1.47E+00	0.68027211	101	**CREMONA**	1.39E+00	0.71942446	102
TIVOLI	1.47E+00	0.68027211	103	**PORDENONE**	1.40E+00	0.71428571	102
MACERATA	1.47E+00	0.68027211	103	**CAMPOBASSO**	1.41E+00	0.70921986	104
PARMA	1.49E+00	0.67114094	103	**PALERMO EXT.**	1.42E+00	0.70422535	105
NOVI LIG.	1.49E+00	0.67114094	106	**VERCELLI**	1.42E+00	0.70422535	106
LECCE	1.49E+00	0.67114094	106	**VICENZA**	1.43E+00	0.6993007	106
SESSA AURUNCA	1.54E+00	0.64935065	106	**TERAMO**	1.43E+00	0.6993007	108
CAMPOBASSO	1.54E+00	0.64935065	109	**SESSA AURUNCA**	1.43E+00	0.6993007	108
BARLETTA	1.57E+00	0.63694268	109	**AVELLINO**	1.44E+00	0.69444444	108

MAGLIE	1.57E+00	0.63694268	111	**ROVIGO**	1.45E+00	0.68965517	111
SASSARI	1.58E+00	0.63291139	111	**TRENTO**	1.45E+00	0.68965517	112
ORISTANO	1.60E+00	0.625	113	**MANTOVA**	1.45E+00	0.68965517	112
AVELLINO	1.60E+00	0.625	114	**FROSINONE**	1.46E+00	0.68493151	112
RAGUSA	1.61E+00	0.62111801	114	**REGGIO CAL.**	1.48E+00	0.67567568	115
MONOPOLI	1.65E+00	0.60606061	116	**BRESCIA**	1.48E+00	0.67567568	116
PALERMO EXT.	1.65E+00	0.60606061	117	**PARMA**	1.48E+00	0.67567568	116
TERNI	1.65E+00	0.60606061	117	**S. AGATA MIL.**	1.49E+00	0.67114094	116
PALMI	1.66E+00	0.60240964	117	**CAGLIARI**	1.50E+00	0.66666667	119
VITERBO	1.68E+00	0.5952381	120	**SIENA**	1.50E+00	0.66666667	120
NUORO	1.69E+00	0.59171598	121	**SAN SEVERO**	1.51E+00	0.66225166	120
TRAPANI	1.69E+00	0.59171598	122	**FOGGIA**	1.52E+00	0.65789474	122
VIBO VALENTIA	1.69E+00	0.59171598	122	**GROSSETO**	1.52E+00	0.65789474	123
RIETI	1.70E+00	0.58823529	122	**MACERATA**	1.53E+00	0.65359477	123
FOGGIA	1.70E+00	0.58823529	125	**OLBIA**	1.54E+00	0.64935065	125
TARANTO	1.72E+00	0.58139535	125	**CALTANISSETTA**	1.55E+00	0.64516129	126
OLBIA	1.73E+00	0.57803468	127	**CALTAGIRONE**	1.55E+00	0.64516129	127
CATANZARO	1.74E+00	0.57471264	128	**CATANZARO**	1.56E+00	0.64102564	127
POTENZA	1.77E+00	0.56497175	129	**PERUGIA**	1.58E+00	0.63291139	129
BRINDISI	1.78E+00	0.56179775	130	**COSENZA**	1.60E+00	0.625	130
AREZZO	1.78E+00	0.56179775	131	**SASSARI**	1.62E+00	0.61728395	131
SIENA	1.80E+00	0.55555556	131	**VITERBO**	1.63E+00	0.61349693	132
MATERA	1.81E+00	0.55248619	133	**VIBO VALENTIA**	1.65E+00	0.60606061	133
SIRACUSA	1.81E+00	0.55248619	134	**PALMI**	1.66E+00	0.60240964	134
SAN SEVERO	1.81E+00	0.55248619	134	**SALA CONSILINA**	1.68E+00	0.5952381	135
AGRIGENTO	1.82E+00	0.54945055	134	**RIETI**	1.68E+00	0.5952381	136
GROSSETO	1.84E+00	0.54347826	137	**BOLZANO**	1.69E+00	0.59171598	136
BENEVENTO	1.85E+00	0.54054054	138	**TERMINI IMER.**	1.70E+00	0.58823529	138
COSENZA	1.86E+00	0.53763441	139	**BENEVENTO**	1.70E+00	0.58823529	139
S. AGATA MIL.	1.86E+00	0.53763441	140	**CASTROVILLARI**	1.72E+00	0.58139535	139
CALTANISSETTA	1.87E+00	0.53475936	140	**NUORO**	1.74E+00	0.57471264	141
SALA CONSILINA	1.90E+00	0.52631579	142	**TERNI**	1.79E+00	0.55865922	142
TERMINI IMER.	1.91E+00	0.52356021	143	**POTENZA**	1.79E+00	0.55865922	143
CALTAGIRONE	1.93E+00	0.51813472	144	**ORISTANO**	1.79E+00	0.55865922	143
LAURIA	1.94E+00	0.51546392	145	**ENNA**	1.95E+00	0.51282051	143
CASTROVILLARI	1.98E+00	0.50505051	146	**MATERA**	1.96E+00	0.51020408	146
ENNA	1.99E+00	0.50251256	147	**LAURIA**	2.10E+00	0.47619048	147

Table 3.3: Merit Groups

MODEL	MODEL	GROUP SHIFTS	#
M0TE	**M12TE**	**(Model 0TE to ⇒ Model 12TE)**	
Group 1			
TORINO	VENEZIA	**ALBA**	**-1**
MELZO	VARESE	**IVREA**	**-1**
BOVISIO	TORINO	**PINEROLO**	**-1**
CORSICO	VESUVIANA	**RIVOLI**	**-1**
MILANO EXT.	NAPOLI	**ASTI**	**-1**
MONZA	BUSTO ARSIZIO	**CUNEO**	**1**
MILANO	LECCO	**TORINO**	**0**
BUSTO ARSIZIO	CORSICO	**BIELLA**	**0**

COMO	MONZA	**NOVI LIG.**	**2**
LECCO	MILANO	**VERBANIA**	**0**
VARESE	PALERMO CTR.	**VERCELLI**	**-4**
VENEZIA	COMO	**ALESSANDRIA**	**0**
PRATO	BOVISIO	**NOVARA**	**0**
ROMA	MELZO	**ALBENGA**	**2**
TORRE ANNUNZIATA	MILANO EXT.	**CHIAVARI**	**2**
NAPOLI	LA SPEZIA	**IMPERIA**	**1**
TRIESTE	LODI	**LA SPEZIA**	**2**
BERGAMO EXT.	GENOVA	**SAVONA**	**0**
VESUVIANA	NOCERA	**GENOVA**	**2**
PALERMO CTR.	AOSTA	**AOSTA**	**3**
	CATANIA	**MELZO**	**0**
	SONDRIO	**PAVIA**	**2**
Group 2		**BOVISIO**	**0**
BIELLA	NOLA	**CORSICO**	**0**
BERGAMO	POZZUOLI	**MILANO EXT.**	**0**
NOVARA	BERGAMO EXT.	**MONZA**	**0**
NOCERA	PRATO	**CREMONA**	**-1**
RIVOLI	TRIESTE	**LODI**	**2**
MESTRE	MASSA	**VIGEVANO**	**3**
MASSA	MESTRE	**MILANO**	**0**
BRENO	ALBENGA	**BUSTO ARSIZIO**	**0**
UDINE	SAVONA	**COMO**	**0**
POZZUOLI	TORRE ANNUNZIATA	**LECCO**	**0**
CASERTA	LIVORNO	**SONDRIO**	**1**
NOLA	FIRENZE	**VARESE**	**0**
PINEROLO	PISTOIA	**BERGAMO EXT.**	**-1**
VERCELLI	BIELLA	**BRENO**	**-1**
LUCCA	BERGAMO	**MANTOVA**	**-2**
SONDRIO	ACIREALE	**SALO'**	**1**
BRESCIA	VIGEVANO	**BERGAMO**	**0**
ANCONA	CHIAVARI	**BRESCIA**	**-4**
LATINA	NOVARA	**MESTRE**	**0**
SAVONA		**PADOVA**	**0**
Group 3		**BASSANO**	**-1**
PADOVA	PINEROLO	**VICENZA**	**-2**
GENOVA	RIMINI	**VERONA NORD**	**1**
IVREA	VERBANIA	**VERONA SUD**	**0**
TERAMO	VERONA NORD	**ROVIGO**	**-1**
ALBANO	ALBANO	**VENEZIA**	**0**
TREVISO	BARI	**SAN DONA'**	**1**
REGGIO EMILIA	CASERTA	**TREVISO**	**-1**
FROSINONE	FERRARA	**CONEGLIANO**	**0**
BOLOGNA	CUNEO	**BELLUNO**	**-1**
CATANIA	RIVOLI	**UDINE**	**-1**
MODENA	PAVIA	**PORDENONE**	**-2**
VERBANIA	SALO'	**TRIESTE**	**-1**
PESCARA	LATINA	**BOLZANO**	**-3**
ASTI	BRENO	**TRENTO**	**-2**
LODI	BARLETTA	**LIVORNO**	**2**
LA SPEZIA	UDINE	**PISA**	**-1**

ALBA	LUCCA	**LUCCA**	**-1**
BARI	PADOVA	**AREZZO**	**3**
RAVENNA	IMPERIA	**GROSSETO**	**0**
PISA	SALERNO	**MASSA**	**0**
SALERNO	FORMIA	**PISTOIA**	**3**
	RAVENNA	**PRATO**	**-1**
	BOLOGNA	**SIENA**	**1**
Group 4		**FIRENZE**	**2**
VICENZA	FORLI'	**FERRARA**	**2**
CUNEO	LECCE	**MODENA**	**-2**
ALBENGA	PISA	**REGGIO EMILIA**	**-1**
MESSINA	NOVI LIG.	**FORLI'**	**0**
RIMINI	ASTI	**PARMA**	**0**
FORMIA	IVREA	**PIACENZA**	**1**
AOSTA	ANCONA	**RAVENNA**	**0**
CHIETI	SAN DONA'	**RIMINI**	**1**
BASSANO	TIVOLI	**BOLOGNA**	**0**
IMPERIA	ALBA	**CAMPOBASSO**	**0**
TRENTO	PIACENZA	**ISERNIA**	**2**
SALO'	REGGIO EMILIA	**FROSINONE**	**-3**
CHIAVARI	AREZZO	**LATINA**	**-1**
FORLI'	MESSINA	**ALBANO**	**0**
PORDENONE	ISERNIA	**RIETI**	**0**
MANTOVA	TREVISO	**VITERBO**	**-1**
BELLUNO	MONOPOLI	**CIVITAVECCHIA**	**0**
LIVORNO		**TIVOLI**	**2**
BOLZANO		**FORMIA**	**1**
VERONA NORD		**ROMA**	**-4**
FIRENZE		**PERUGIA**	**-3**
PERUGIA		**TERNI**	**-1**
ASCOLI PICENO		**ASCOLI PICENO**	**-1**
Group 5		**MACERATA**	**-1**
FERRARA	RAGUSA	**PESARO**	**0**
PISTOIA	ROMA	**ANCONA**	**-2**
CIVITAVECCHIA	TRAPANI	**L' AQUILA**	**0**
Average Unit	ASCOLI PICENO	**CHIETI**	**-1**
CONEGLIANO	PESCARA	**PESCARA**	**-2**
PESARO	CONEGLIANO	**TERAMO**	**-3**
CAGLIARI	Average Unit	**AVELLINO**	**0**
VERONA SUD	BELLUNO	**BENEVENTO**	**0**
ROVIGO	CIVITAVECCHIA	**SESSA AURUNCA**	**0**
VIGEVANO	BASSANO	**NOLA**	**0**
PIACENZA	BRINDISI	**SALERNO**	**0**
ALESSANDRIA	ALESSANDRIA	**NOCERA**	**1**
CREMONA	MAGLIE	**TORRE ANNUNZIATA**	**-1**
PAVIA	PESARO	**SALA CONSILINA**	**0**
SAN DONA'	TARANTO	**POZZUOLI**	**0**
L' AQUILA	SIRACUSA	**CASERTA**	**-1**
ACIREALE	L' AQUILA	**VESUVIANA**	**0**
	VERONA SUD	**NAPOLI**	**0**
	CHIETI	**BRINDISI**	**2**
	MODENA	**LECCE**	**2**

	AGRIGENTO	**BARI**	**0**
Group 6		**SAN SEVERO**	**1**
ISERNIA	CREMONA	**FOGGIA**	**0**
REGGIO CALABRIA	PORDENONE	**MAGLIE**	**1**
TIVOLI	CAMPOBASSO	**TARANTO**	**2**
MACERATA	PALERMO EXT.	**BARLETTA**	**3**
PARMA	VERCELLI	**MONOPOLI**	**2**
NOVI LIG.	VICENZA	**CATANZARO**	**0**
LECCE	TERAMO	**VIBO VALENTIA**	**0**
SESSA AURUNCA	SESSA AURUNCA	**COSENZA**	**0**
CAMPOBASSO	AVELLINO	**CASTROVILLARI**	**0**
BARLETTA	ROVIGO	**REGGIO CALABRIA**	**0**
MAGLIE	TRENTO	**PALMI**	**-1**
SASSARI	MANTOVA	**POTENZA**	**0**
ORISTANO	FROSINONE	**LAURIA**	**0**
AVELLINO	REGGIO CALABRIA	**MATERA**	**0**
RAGUSA	BRESCIA	**TRAPANI**	**2**
MONOPOLI	PARMA	**CALTANISSETTA**	**0**
PALERMO EXT.	S. AGATA MIL.	**TERMINI IMER.**	**0**
TERNI	CAGLIARI	**PALERMO EXT.**	**0**
PALMI	SIENA	**AGRIGENTO**	**2**
VITERBO	SAN SEVERO	**PALERMO CENTRE**	**0**
Group 7		**CATANIA**	**2**
NUORO	FOGGIA	**ACIREALE**	**3**
TRAPANI	GROSSETO	**CALTAGIRONE**	**0**
VIBO VALENTIA	MACERATA	**ENNA**	**0**
RIETI	OLBIA	**S. AGATA MIL.**	**1**
FOGGIA	CALTANISSETTA	**RAGUSA**	**1**
TARANTO	CALTAGIRONE	**SIRACUSA**	**2**
OLBIA	CATANZARO	**MESSINA**	**0**
CATANZARO	PERUGIA	**CAGLIARI**	**-1**
POTENZA	COSENZA	**ORISTANO**	**-1**
BRINDISI	SASSARI	**NUORO**	**0**
AREZZO	VITERBO	**SASSARI**	**-1**
SIENA	VIBO VALENTIA	**OLBIA**	**0**
MATERA	PALMI		
SIRACUSA	SALA CONSILINA		
SAN SEVERO	RIETI		
AGRIGENTO	BOLZANO		
GROSSETO	TERMINI IMER.		
BENEVENTO	BENEVENTO		
COSENZA	CASTROVILLARI		
S. AGATA MIL.	NUORO		
CALTANISSETTA	TERNI		
SALA CONSILINA	POTENZA		
TERMINI IMER.	ORISTANO		
CALTAGIRONE	ENNA		
LAURIA	MATERA		
CASTROVILLARI	LAURIA		
ENNA			

The above results are accompanied by a map which attempts to clarify different locations of efficient firms on the Italian territory[38].

The first two Tables highlight technical efficiency scores for Models 0TE (no environmental effects) and 12TE (twelve effects). First, one notices that inserting no environmental effects in the model resulted in severe punishment for less favoured units. Moreover, a 'smooth' model with no external variables exposes one of the main drawbacks of stochastic frontier estimation, that is its incapability of strongly differentiating efficiency scores between decision-making units in the sample. By failing to spot inefficiency, stochastic frontier estimation may confine efficiency differences to the random noise term (especially within cross-sectional samples), thus 'smoothing out' the ranking of firms. We observed that, for Model 0TE, sixteen zones were found to be 100% efficient on technical grounds[39], and that the whole ranking was generally 'flat', thus failing to acceptably differentiate between firm-specific inefficiencies. Furthermore, Southern firms were heavily punished by Model 0TE, due to the absence of any corrective environmental variables relating to non-controllable effects. Among the best sixteen units, we found 13 Northern zones, one Central zone, and only two zones from the South. In addition, 10 units out of 16 were from Lombardy (the Milanese regional district).

It is then apparent that Model 0TE was not able to capture the difference between internal inefficiency and externally-led inefficiency. By doing so, such a model over-rewarded the most favoured zones (North, Lombardy), and under-rewarded less favoured ones. It is however interesting to notice that the two Neapolitan zones of Naples and Torre Annunziata were found among the sixteen 100% efficient units. While the Naples result has to be taken

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[38] A detailed map of Italy is provided at the end of this thesis.

[39] Recall that input-allocative efficiency has been imposed *ex ante*.

with caution because of the lack of comparability between metropolitan areas and rural ones (leading to the biggest 8-9 towns being efficient 'by default'), Torre Annunziata's outcome is a surprising one. If one looks at Model 0TE's efficiency ranking, it is easy to discover that the vast majority of Southern units are found at the league's bottom (with a few exceptions).

By examining Model 12TE's efficiency ranking, it appears that the insertion of environmental effects penalised the 'luckiest' units and rewarded the least favoured ones. Moreover, environmental variables were useful in separating inefficiency from random noise more effectively, so as to limit the 'over-rewarding' drawback of stochastic-frontier cross-sectional estimation[40]. This made the general ranking less flat, with fewer *ex-aequo* ranks[41]. Higher differentiation also leads to clearer policy-making conclusions. First, after allowing for environmental effects, the stochastic frontier approach became less 'forgiving' towards Northern zones and more friendly to Southern ones. Secondly, *ex-aequo* top firms disappeared, and none of them managed to get 100% efficiency. We now have one top-class zone only (Venice), featuring 1.01 inefficiency (or, in 0-1 terms, more than 99% efficiency), and seven runner-ups. Southern zones climbed the ranking, even though the majority of efficient units still come from the North and Centre of Italy. However, we also observe some Northern units which performed rather badly (Vicenza, Trento, Brescia, Mantova, Parma, Bolzano[42]).

Among the runner-ups, five were Northern zones, and two were form the South. Among the Northern ones, four zones were from the Milanese outer province, and the remaining one was Turin's. Naples was still among the best ones, together with its immediate outskirts

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[40] It is worth noticing that DEA, by failing to recognise random noise, treats any disturbance as inefficiency, thus being more 'penalising' (on average) rather than 'rewarding'. This is a further reason for methodological cross-checking (see Chapter 5).

[41] '*Ex-aequo*' ranks stands for 'tied' ranks (or values).

[42] Bad performances for some Northern zones might also be due to the contemporaneous presence of municipal utilities serving profitable city centres (e.g., Brescia, Parma, Bolzano/Bozen).

(Vesuviana). It is interesting to note that Rome, one of the best units in Model 0TE, plummeted to no. 82 after allowing for external cost drivers. On the contrary, Milan was still found in the first group. Among the best Southern zones in Model 12TE, some 'default efficient' metropolitan units (Naples, Vesuviana, Pozzuoli, Palermo, Catania) were found, together with smaller, suburban zones (Nocera, Nola, Torre Annunziata, Acireale). However, most Southern zones were still left at the ranking's bottom, thus showing that ENEL's Northern distributing units were - on average - more efficient than their Southern counterparts even after allowing for twelve external effects. The majority of such effects were intended to free Southern units from non-controllable inefficiency[43].

Table 3 is intended to subdivide the 147 DMUs into seven groups, each one consisting of 21 units on average, according to their efficiency scores for both models (M0TE, M12TE). Then, a 'group shifts' column is added in order to show the rank changes brought about by the insertion of twelve external efficiency effects into the model. Generally, Northern and Central units were penalised by environmental effects, whereas Southern zones gained, even though this is by no means a fixed rule. On the contrary, outcomes are much more mixed, showing some Southern zones which were not rewarded as a result of environmental effects being allowed for (Caserta, Palmi, Cagliari, Oristano, Sassari). Furthermore, some less-favoured Northern zones climbed the league thanks to Model 12TE's cost drivers (Albenga, Chiavari, Genoa in Liguria, Aosta in the Alps, and - more surprisingly - Vigevano and Lodi in Southern Lombardy).

However, Northern zones lost and Southern units won, as a result of Model 12TE being considered instead of Model 0TE. Nonetheless, this did not jeopardise the Northern dominance - indeed, it refined the analysis by spotting a limited number of 'bugs' within

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[43] To get a rough idea of environmental/economic differences, consider that industrial output accounts for just 50% of total energy delivered in Sicily, against Lombardy's 81% *INDY* share.

Northern units, plus some 'surprises' among their Southern counterparts. Nevertheless, this was by no means sufficient to turn Model 0TE's ranking upside down. Our stochastic frontier analysis showed overall robustness, by leaving the North-South efficiency dichotomy unchanged even after allowing for a substantial number of environmental cost drivers. The biggest changes from M0TE to M12TE were for Vercelli (Central Piedmont, North, which stepped down by 4 levels), Aosta (Valle d'Aosta, North, +3 levels), Vigevano (Southern Lombardy, North, +3), Brescia (Eastern Lombardy, North, -4), Bolzano (South Tyrol, North, -3), Arezzo (Eastern Tuscany, Centre, +3), Pistoia (Northern Tuscany, Centre, +3), Frosinone (Southern Latium, Centre, -3), Rome (Latium, Centre, -4), Perugia (Umbria, Centre, -3), Teramo (Northern Abruzzi, Centre, -3), Barletta (Apulia, South, +3), and Acireale (Sicily, South, +3). Therefore, even though no Southern unit was penalised by Model 12TE, it is also true that, apart from a couple of exceptions, those Southern zones which were among the best ones in Model 0TE kept their status, whereas the vast majority of zones from the South only gained marginally (+1, +2 levels) in M12TE, which was not enough to take them away from the sample's bottom. In fact, Model 12TE's ranking still features 19 Southern units in the sample's last group (Group 7), against one Northern zone and six Central ones.

Metropolitan zones did well in Model 12TE, with six large towns being found in Group 1 and one in Group 2. The worst performance was shown by Rome, which M12TE penalised heavily. However, recall that metropolitan areas enjoy peculiar demand conditions, so that they are not easily comparable to remaining units in the sample. As outliers, they are generally deemed 'efficient by default', due to the lack of comparable 'peers'. This problem is also encountered in DEA[44]. Therefore, metropolitan units should not be used in comparing

[44] See Lovell (1993).

Northern zones with Southern ones. In fact, it is much more useful to refer to similar, medium-sized zones when outlining North vs. South comparisons.

To conclude, it is worth spending a final word on Bolzano/Bozen, the only Northern unit which was found in Model 12TE's last group (Group 7). Bolzano is a peculiar zone, as it embraces the bilingual mountain province of South Tyrol (Südtirol). Moreover, it is connected to a high number of small municipally-owned distributors, as well as to Bolzano's own electric municipality. Therefore, costly mountain distribution is (in addition) penalised by the simultaneous presence of active municipal concerns. In particular, Bolzano's municipal electric utility covers the only profitable district in the province, thus jeopardising efficiency prospects for the South Tyrolian ENEL zone. Municipal utilities, which are more common in Trentino/South Tyrol than in any other Italian region, are going to be analysed in Chapter 4, whose comparative outcomes will show 'joint' inefficiency of both ENEL/Bolzano's zone and the town's municipal utility (AEC Bozen).

Section 5 is concerned with providing a cross-check for Model 12TE/1996, by running a second-stage, Tobit regression of efficiency scores on environmental variables. As Coelli (1996a) points out, this is a second-best option, which - however - may still be chosen in order to cross-check single-stage results stemming from the TEE model.

5. A Second-Stage, Tobit Regression of Efficiency Scores on Environmental Variables

Tobit (Tobin's Probit analysis) originated from Tobin's (1958) paper on a censored regression of automobile expenditures for a sample of US households. In the classical logit

and probit models[45], a latent variable (say, y^*) is not observed. Such a variable is explained according to the following model:

$$y_i^* = \beta x_i + u_i. \tag{19}$$

For simplicity of exposition, let us just assume that there is only one explanatory variable (or, alternatively, a vector of explanatory variables), which causes no loss of generality. In the logit and probit models, what we observe is a dummy dependent variable such that

$$y_i = \begin{cases} 1 & \text{if} \quad y_i^* > 0; \\ 0 & \text{if} \quad y_i^* \leq 0. \end{cases} \tag{20}$$

Suppose now that y^* is only observed if $y^* > 0$, whereas it is not observed if y^* is non-positive. Then, the actually observed y_i will be defined as

$$y_i = \begin{cases} y_i^* = \beta x_i + u_i & \text{if} \quad y_i^* > 0; \\ 0 & \text{if} \quad y_i^* \leq 0, \qquad \text{with} \quad u_i \sim N(0,\sigma^2). \end{cases} \tag{21}$$

This is known as the 'Tobit' model, and was first analysed in the econometrics literature by James Tobin. It is also known as a 'censored normal' regression model, because some observations on y^* (specifically, those for which y^* is either zero or negative) are 'censored', in the sense that we are not allowed to see them. The example that Tobin considered was that of automobile expenditures. For example, if the income elasticity of demand for automobiles has to be estimated on a sample of households, we shall have a large number of observations

[45] See Greene (1991).

in the sample for which the expenditures on automobiles equal zero. That is, the dependent variable will be 'censored' at zero, since the econometrician will only be able to observe strictly positive expenditures. Nothing can be said of those households whose behaviour is not to spend anything on automobiles because, by showing no expenditures, they will not completely 'reveal' their preferences on automobiles. In other words, the dependent variable will be restricted to positive values. Then, Tobin argued that one should use a 'censored' regression model in such cases.

There have been a large number of applications of the Tobit model, with special reference to the labour branch of microeconometrics[46]. It should be noticed that y^* (the latent variable) could, in principle, assume negative values (e.g., 'negative' efficiency levels). However, negative values are not observed because some economic measures, such as *relative* efficiency and productivity, are generally censored at zero. A common problem of all efficiency measures is that they are relative. That is, even though the sample is comprehensive, it will generally fail to include all the relevant information. For example, our 147 sample of ENEL's local zones did not consider municipal electricity distributors. Moreover, it was not capable of incorporating any 'as if' efficiency information such as that resulting - for instance - from local zones being transferred to private investors. This is why both stochastic frontier and non-parametric/DEA measures are only able to compute 'relative' efficiency scores, i.e. such scores which result from all units being compared to other firms *within* the sample. In this sense, one could in principle expect to get greater-than-one efficiency scores within production/DEA analyses, or smaller-than-one scores from stochastic cost estimation. Alternatively, one might say that even the 'best' units are 100% efficient just because they are subject to comparison with the remaining DMUs in the sample. However,

[46] See Amemiya (1984) for a comprehensive survey of models of labour participation decisions, gender discrimination, and the like.

they could be discovered to be inefficient *vis-à-vis* other firms which were *not* included in the sample. Indeed, they might even be deemed inefficient *vis-à-vis* themselves acting within different, 'counterfactual' contexts[47], e.g. under private vs. public ownership.

In the end, cost-based efficiency scores are 'censored' at either zero or one (depending on rescaling) because the econometrician is not able to 'look' beyond those values. This is, basically, the difference between 'relative' and 'absolute' efficiency[48]. Lack of observability, given informational constraints, results in the dependent variable (y^*) being censored (left censoring), thus justifying the need for Tobit estimation. Tobit models are estimated by the major statistical packages[49].

Efficiency scores may then be estimated by means of a Tobit censored regression. Left censoring problems are easily overcome for $[1,+\infty)$ efficiency scores. Moreover, OLS might be used instead of Tobit when there is no real 'censoring' pressure, as a result of efficiency scores being significantly far from 100% efficiency. If one rescales stochastic cost-derived efficiency scores by subtracting unity, they will be ready for $[0,+\infty)$ Tobit estimation. In general, models with either upper or lower truncation at any constant point can be estimated by transforming the dependent variable to the standard case. Tobit uses analytic first and second-order derivatives to obtain Maximum Likelihood estimates via the Newton-Raphson algorithm[50]. This algorithm usually converges fairly quickly. Starting values for the parameters are obtained from a regression on the observations with positive y values. A globally concave parameterisation of the likelihood function is used for the iterative procedure.

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[47] See Galal *et al.* (1994).

[48] As it was previously noticed, some firms within the sample generally have no 'peers' to be compared to, e.g. because their scale is too big. Such outliers - to which DEA is particularly sensitive: see Chapter 5 for details - are generally deemed 'efficient by default' simply because nothing else can be said about them, given the sample's available information. This reinforces the conceptual difference between 'relative' and 'absolute' efficiency, as outlined in the text.

Technically, computer packages halt the estimation whenever they find more independent variables than the number of observations with positive y values. Multicollinearity of the independent variables is handled with generalised inverse matrices[51]. The numerical implementation involves evaluating the normal density and cumulative normal distribution functions. The cumulative normal distribution function is computed from an asymptotic expansion, since it has no closed form. The ratio of the density to the distribution function is also known as the 'Inverse Mills Ratio', or IMR[52].

As it is easily noticed from the previous tables, Model 0TE's efficiency scores suffer from lack of differentiation between different DMUs. Their trend is basically 'flat' because no differentiating environmental features were taken into account. In other words, for M0TE's treatment, the TEE model was constrained to be a standard stochastic cost estimation, with the efficiency error being truncated-normally distributed with zero (instead of $m \geq 0$) mean. As a result, Model 0TE was not able to acceptably differentiate between efficiency levels, and it unduly penalised Southern units. For example, sixteen zones were found to be 100% efficient in M0TE, with $EFF = 1.0$. As 16/147 almost equals 11%, this means that the data will 'feel' left censoring, and OLS estimates will automatically become inappropriate because the assumption of constant variance for disturbances is invalid. Tobit analysis will then be used, thus estimating a Maximum Likelihood function censored at 1.0 (or, alternatively, at zero, if rescaling of *EFF* scores takes place). We also tried to regress scores from models 16TE (unrestricted) and 12TE (final, restricted) by OLS[53], but this just amounted to a self-verifying exercise, since environmental effects were already 'built-in' for those models. More correctly,

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[49] Some examples: LIMDEP (microeconometrics), RATS, and TSP/TLG.
[50] See Greene (1981), and Maddala (1983).
[51] See Johnston (1984), and Kmenta (1986).
[52] See the above-mentioned econometric textbook references for further details on Tobit, IMR, and some famous microeconometric applications.
[53] Tobit was not needed in those cases, because no 100% efficient firms were found.

Tobit analysis was applied to Model 0TE's *EFFs*, so as to cross-check M12TE's quality via a second-stage regression of M0TE's scores on the same twelve environmental effects as those reported by M12TE.

Therefore, we took efficiency scores from M0TE, rescaled them so as to be shifted to the $[0,+\infty)$ interval, and regressed them by Tobit/censored MLE, with left censoring imposed at zero. We took as regressors the same twelve environmental variables which were also inserted in Model 12TE as *Z* effects. Second-stage regression of Model 0TE's scores on M12TE's external effects, then, amounts to a valid robustness proof of Model 12TE itself[54]. Hence, the Tobit regression was instrumented as follows:

$$\begin{aligned} &EFF_{i,rescaled} = \gamma_0 + \gamma_1 \ln DENS + \gamma_2 \ln INDY + \gamma_3 \ln THIRD + \gamma_4 \ln AIRBT + \gamma_5 \ln PTP + \\ &+ \gamma_6 SOUD + \gamma_7 MOUNTD + \gamma_8 METRD + \gamma_9 MUNID + \gamma_{10} SEAD + \gamma_{11} BORD + \\ &+ \gamma_{12} INDUSD + v > 0 \ \text{ for } \ i = 17,...,147 \ \text{ (Model 0TE); otherwise,} \\ &EFF_{i,rescaled} = 1.0 - 1 \equiv 0 \quad \text{for } \ i = 1,...,16; \qquad \text{moreover, } \ v \sim N(0,\sigma^2). \end{aligned} \tag{22}$$

Since both Model 12TE (TEE) and the above, second-stage Tobit regression on Model 0TE's re-scaled efficiency scores were estimated by MLE techniques, it comes natural to compare the two estimation outcomes in order to check for Model 12TE's robustness. Therefore, we propose a unified Table in which both ML estimates are reported. The first columns refer to the *Z*/built-in TEE estimation of environmental effects (M12TE); the following ones report Tobit/ML estimates for the same twelve effects from second-stage analysis of Model 0TE. Comments are provided below.

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[54] Lovell (1993).

Table 3.4: TEE vs. Tobit Estimates of External Effects

Model 12TE **Built-In Environmental (*Z*) 3-step ML Estimates (Iterative) [Dependent Variable: m_u]**	**Model 0TE** **Second-Stage EFF_i Tobit/ML Estimates (Iterative) [Dependent Variable: EFF_i/Rescaled]**

Coefficient Relating to Variable...	**Parameter Estimate**	**Standard Error**	***t*-statistic**	**Coefficient Relating to Variable...**	**Parameter Estimate**	**Standard Error**	***t*-statistic**
(Constant)	*n/a*	*n/a*	*n/a*	*(Constant)*	1.14715	0.101205	11.335
DENS	-0.154229	0.039900	-3.866100	*DENS*	-0.15929	0.017285	-9.21563
INDY	-0.184793	0.094196	-1.961780	*INDY*	-0.30954	0.027088	-11.4269
THIRD	-0.284339	0.050200	-5.660420	*THIRD*	0.027401	0.021811	1.25628
AIRBT	0.094981	0.029200	3.253540	*AIRBT*	0.040857	0.00883	4.629
PTP	0.055148	0.022100	2.496420	*PTP*	0.096235	0.02354	4.08819
SOUD	-0.074541	0.065700	-1.135150	*SOUD*	0.105478	0.021889	4.81886
MOUNTD	-0.003534	0.084300	-0.041950	*MOUNTD*	-0.02625	0.024504	-1.07135
METRD	0.193281	0.372000	0.519890	*METRD*	0.225648	0.06467	3.48921
MUNID	0.172778	0.075800	2.280120	*MUNID*	0.031609	0.016541	1.91096
SEAD	-0.072725	0.069800	-1.041940	*SEAD*	-0.06747	0.018403	-3.66597
BORD	-0.189787	0.139000	-1.363830	*BORD*	-0.20747	0.033813	-6.13565
INDUSD	0.023613	0.069400	0.340150	*INDUSD*	-0.08774	0.017817	-4.92485
Log-L. Funct.	52.469			**Log-L. Funct.**	136.253		
σ–squared	0.031803	0.00521	6.104223	**σ–squared**	0.00699	0.0004326	16.1574
Iterations	55 (max: 100)			**Iterations**	5 (max: 200)		

[Note: MLE Standard Errors were computed by the TSP software using analytic second-order derivatives (Raphson-Newton Algorithm: see Maddala, 1983). Maximum number of iterations set at 200]

Since efficiency scores being regressed by Tobit/MLE lie in the $[0,+\infty)$ interval, all signs in the second regression have to be interpreted as relating to 'inefficiency' scores. In other words, a positive sign in the Tobit model would imply a *negative* effect on technical efficiency, and then on total cost minimisation. Therefore, negative signs in both regressions would imply positive effects on cost efficiency. By looking at comparative outcomes, it seems that Model 12TE provides a robust specification of environmental effects. Almost all coefficients are in agreement with each other, with a few exceptions being represented by non-significant estimates. All coefficients relating to consumer density, percentage of industrial output, percentage of overhead low-voltage cable and primary substations, and the dummy variables for mountains, metropolitan areas, municipalities, coastlines, and national

borders carry the same signs, with sometimes similar magnitudes as well. This means that only *THIRD* (the percentage of third-party works on total cost), *SOUD* (the North-South dummy), and *INDUSD* (the industrial districts dummy) are not in agreement between the two different regressions. However, such a disagreement in sign is virtually nullified by the fact that the three variables above showed statistically insignificant coefficients in either the built-in 12TE or the second-stage Tobit/ML (M0TE) models.

The above results confirm the good quality of TEE estimation *vis-à-vis* more traditional two-stage regressions of stochastically-derived efficiency scores. Among the efficiency drivers, let us once again recall consumer density, industrial output (%), third-party goods/services (%), underground low-voltage cables (%), and - possibly - borderline conditions. However, third-party works had the 'make' - instead of 'buy' - sign in the Tobit regression, with no statistical significance. The Southern dummy pointed towards higher inefficiency (on average) for Southern zones, whereas the *INDUSD* dummy gave the 'wrong' response in the built-in regression, with not even weak statistical significance, though.

Among the 'inefficiency drivers', we find overhead cables for low-voltage distribution in highly dense contexts (towns, metropolitan areas), the percentage of primary substations (with the usual caveat regarding the electricity loss minimisation dilemma), 'suspect' inefficiency effects in metropolitan areas (but see *MUNID*'s outcomes), and - finally - the presence of 'cream-skimming' municipal electric utilities in the neighbourhood. Apart from the PTP result - which does not weaken the technological assumption according to which electricity distributors should not save money on primary transformers - the above results confirm that municipal authorities did manage in 'interfering' with ENEL's local activities. The interesting aspect to be analysed now is to what extent municipally-owned electricity distributors should be allowed by the energy regulator to retain their exclusive territories within (sometimes)

highly profitable Northern and Central urban contexts. This issue is tackled by both Chapters 4 and 5, which will compare ENEL's local zones with municipal utilities by constructing a cross-sectional pooled sample, to be analysed both parametrically[55] and non-parametrically[56].

Finally, it is worth noticing that the above-outlined Tobit/ML regression of *EFFs* reported - for the first time - that the Southern dummy's (*SOUD*) coefficient was positive and statistically significant at 5%, thus highlighting lower average-cost efficiency for ENEL's Southern distributing units. This was also confirmed by our M12TE efficiency ranking (previously discussed). In other words, Southern zones were, on average, less efficient than Northern ones even after allowing for twelve more or less 'forgiving' environmental cost drivers. However, significant exceptions represented by efficient Southern units were found.

6. Conclusions

Chapter 3 analysed ENEL's local efficiency in electricity distribution by means of a stochastic frontier approach. First, a three-input, two-output translog total cost function with degree-one homogeneity imposed was estimated via the Technical Efficiency Effects (TEE) model proposed by Battese and Coelli (1995). Such a model assumes a truncated-normal distribution for the efficiency error (u), whose mean is dependent on a series of observed external effects, or 'environmental variables', which are believed to influence technical efficiency, while not being under the direct control of decision-making units (DMUs). It has been suggested[57] that incorporating environmental effects into the main stochastic frontier model - so as to centre the efficiency term's statistical (truncated) distribution on Maximum Likelihood (ML) estimates of overall external effects - is more efficient than simply

[55] Stochastic production frontier estimation: refer to Chapter 4.
[56] Output-oriented Variable Returns to Scale DEA: see Chapter 5.

regressing re-scaled efficiency scores within a second-stage estimation setting (censored regression, Tobit).

Therefore, we instrumented a translog total cost function in input prices (labour, capital, and materials), physical output, and the number of customers[58], to be estimated by TEE with both two-sided (random) and one-sided (efficiency) errors, in conjunction with an auxiliary regression of the efficiency error's mean value on twelve environmental variables (socio-economic, demographic, and geographic[59]). The econometric outcomes were computed by the dedicated software FRONTIER 4.1, which made use of a three-step estimating procedure, calculating estimated OLS in its first stage. Then, (unbiased) OLS slope coefficients[60] were used as starting values in a subsequent grid search over a different parameter space (say, γ). Parameter estimates after the grid search were finally used to reach last-stage estimated values thanks to an iterated Maximum Likelihood procedure, with the maximum number of iterations being set at 100.

Final three-step estimates for both total cost parameters and environmental effects were commented on and discussed. Moreover, standard statistics of interest were computed for the translog relationship, similarly to what happened in Chapter 2 with reference to a traditional, deterministic total cost function. In particular, outcomes relating to returns to scale, density effects, fitted cost shares, input substitution elasticities, input slacks, and dummy variable analysis were pointed out. Theoretical requirements for the cost function (monotonicity, quasi-concavity) were also checked. It is worth noticing that returns-to-scale results were much more realistic here than in Chapter 2. Overall scale economies (OSE) were computed at sample-mean values, following Panzar and Willig (1977). It was discovered that OSE were

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[57] Coelli (1996a).
[58] See Neuberg (1977); Burns and Weyman-Jones (1994a); Filippini (1994); Pollitt (1995).
[59] See Fried, Lovell, and Schmidt (1993), and the references therein.
[60] Notice that the OLS constant will be biased, as a result of the error term's decomposition.

mainly led by the number of customers, with partial Minimum Efficient Scale (MES) for physical output (GWh delivered) occurring at moderately low levels. Moreover, the (ray) AC curve[61] was found to be much more U-shaped than L-shaped (differently from Chapter 2). In all cases, returns to scale were found to be decreasing with respect to output size (analysis of second-order effects).

However, the real novelty of Chapter 3's stochastic cost frontier analysis was the possibility to compute efficiency scores (*EFFs*), constrained within fixed intervals, thanks to the "expected-value formula" for the efficiency error (u)[62]. By using exponential computations based upon the estimated expected value for u - which was assumed to have a truncated-normal distribution, with non-zero mean being centred upon environmental effects - we were then able to recover firm-specific efficiency scores, so as to build up a complete 'efficiency ranking'. The selected model (M12TE), featuring twelve environmental effects, was checked against a 'smooth' model (M0TE), which allowed for no explanatory variables other than those included in the translog total cost specification (input prices, outputs). We tried to explain why Model 12TE's efficiency outcomes should be preferred, as they are the ones which allow for non-controllable characteristics of local distributing zones. It was also noticed that Southern local units were excessively penalised by Model 0TE. Nonetheless, the average Southern unit was still less efficient than its average Northern counterpart, even after allowing for twelve environmental cost drivers (with some noticeable exceptions). Metropolitan areas were often found to be efficient 'by default'[63], whereas some Northern towns featuring municipally-owned distributors were sometimes penalised for having their city centres completely skimmed by municipal utilities.

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[61] For 'ray' Average Cost curves and, more generally, all multi-output versions of traditional cost relationships, see Baumol, Panzar, and Willig (1982).

[62] First proposed by Jondrow, Lovell, Materov, and Schmidt (1982), and subsequently generalised to panel data analysis by Battese and Coelli (1988).

Among the external effects, the main efficiency drivers were industrial output and districts, consumer density, overhead medium-voltage lines coupled with underground low-voltage cables, and third-party works (i.e., 'buy' instead of 'make'). All other variables were found to be either insignificant or cost-inefficient. In particular, it is worth noticing that PTP or 'primary' substations[64] as a proportion of total transformers were obviously found to increase total distribution cost, even though they are crucial to distributors because of their significant role in minimising electricity losses. As regards geographical/territorial dummies, the Southern effect (*SOUD*) was generally deemed insignificant, apart from the final Tobit/ML analysis, where it took the expected sign - showing a negative contribution to efficiency maximisation - with statistical significance. The mountains dummy (*MOUNTD*) was also insignificant and carried the 'wrong' sign, perhaps reflecting 'reverse causation': that is, mountain units might be more efficient simply because they have to be so in order to run mountain universal services, which would fail to be provided otherwise. While this tentative explanation is a tribute to Alpine distributors, it also has to be more seriously checked within an ENEL vs. municipalities comparative analysis, to be performed in Chapter 4.

Finally, Chapter 3 indirectly tested Model 12TE by regressing 'smooth' efficiency scores - i.e., those resulting from the non-environmental 0TE model - on the same twelve effects which entered M12TE directly, thanks to TEE-type stochastic cost frontier estimation. The basic finding was that nine out of twelve estimated coefficients were in agreement with Model 12TE's ones. The remaining three were insignificant in either M12TE's built-in estimates or in the second-stage efficiency score estimation from M0TE. By the way, recall that the second-stage regression of 'smooth' efficiency scores on external peculiarities[65] was

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[63] See also Chapter 5.

[64] Primary substations are those transforming units that deal with electricity voltage being scaled from transmission standards down to distribution ones, i.e. from high to medium voltage.

[65] Shleifer (1985); Lovell (1993); Bogetoft (1994).

performed according to the Tobit/ML censored regression model[66] being estimated thanks to the TSP/TLG computing package. Tobit analysis of estimated efficiency scores (*EFFs*) was necessary because of the left censoring problem, which ruled out the simpler OLS choice. Left censoring in Model 0TE's scores was 'felt' by the data because 16 out of 147 scores from the non-environmental model (M0TE) turned out to equal 1 (or, alternatively, zero when Tobit-rescaled). With almost 11% of scores on the censoring edge, OLS would have been unreliable because of the assumption of constant disturbance variance being automatically violated. As a consequence, efficient Tobit estimates were computed and compared to those which had been directly obtained - via TEE estimation - from M12TE. As previously outlined, the two results were largely in agreement with each other, and proved to be internally consistent to a satisfactory extent.

As regards Chapter 4, it will finally face the basic restructuring question being now addressed to ENEL. By using production data on several inputs and one relevant output (total electricity delivered, expressed in GWh), we shall pool two different cross-sectional samples of 147 ENEL's distributing zones and 37 municipally-owned electric utilities, in order to build up stochastically-derived efficiency scores and work out a mixed ranking of ENEL's zones and local utilities. The basic analytical tools to be employed are the same as those used in Chapter 3, except for the fact that a stochastic translog production frontier will be estimated, rather than a stochastic translog total cost function. Duality theory allows to do this with no difficulties. The data used have already been described in Chapter 2. Stochastic production analysis of the pooled sample will show that a 76-observation selective sample - featuring 37 municipalities plus 39 'peers' from ENEL - has to be preferred to the cumulative 184-observation (147+37) sample. This happens because it is much more sensible to compare

[66] Tobin (1958); Amemiya (1984).

municipalities with appropriate 'peers', rather than mixing them with all 147 zones from ENEL, most of which are not directly comparable to municipal authorities.

Stochastically-derived efficiency scores from the 76-observation pooled sample will be reported in detail. Comments upon mixed outcomes regarding the efficiency of municipally-owned electric utilities will be given. Finally, some tentative policy-making suggestions will follow, in view of prospective horizontal restructuring of the Italian electricity supply industry. Special attention will be paid to the possibility of merging some locally-run distributors with their surrounding (or neighbouring) ENEL zones, in order to reach for more appropriate production scales. It is worth noticing that the ownership structure of future electricity distributors is not relevant to the restructuring issue. The fact that municipalities should be either merged into ENEL's zones or kept as they are today is independent of any future economic policy choices regarding ownership transfers to be implemented for both ENEL and the so-called "Aziende Municipalizzate".

After Chapter 4's tentative policy suggestions[67], Chapter 5 will move on to a different analysis (non-parametric/DEA), whose outcomes are to be cross-checked against those resulting from stochastic frontier estimation (Chapters 3 and 4) by means of distribution-free tests[68]. Finally, Chapter 6 concludes this thesis.

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[67] Notice that some data problems were encountered with respect to Chapter 4's analysis. Pooling different cross-sections is always a difficult job. Reasons for our choice of merging 1996 ENEL data with 1994 municipal figures with no major adjustments will be extensively given in the next Chapter.

[68] As it will be clarified in Chapter 5, the NPAR1WAY procedure in SAS/STAT performs Analysis of Variance (ANOVA) on ranks and computes several statistics based upon both the empirical distribution function and certain rank scores of a response variable (in our case, an efficiency score being derived from two different computational/estimating methodologies) across a one-way classification. Most non-parametric tests are derived by examining the distribution of the rank scores of the response variable. The rank scores are simply functions of the ranks of the response variable, where the values are ranked lowest to highest. Simple linear statistics based on Wilcoxon scores, median scores, Savage scores, and van der Waerden scores may be computed. These statistics are used to test if the distribution of a variable has the same location parameter (typically, the same median) across different groups, without any *ex ante* normality assumption on population distributions. The Kolmogorov-Smirnov (K-S) statistic is also calculated, or - alternatively - the Kuiper statistics for dichotomous (i.e., categorical: 0/1) variables. These statistics are used to test whether the distribution of a variable is the same across different groups, again with no *a priori* assumptions regarding particular forms of distribution. On non-parametric statistics and testing, the reader is referred to Chapter 5 - and the references therein - which deals

Appendix: The Feasibility of Territorial Restructuring

From this Chapter - which considered a translog cost function within a stochastic frontier framework - we discovered that the main driver of scale economies for ENEL was the number of customers served within each distribution zone. By inspecting the econometric results, it is clear that energy delivered (in GWh) failed to appear as a significant explanatory variable of total distribution cost as the number of customers proved to be. Moreover, the second-order effect of energy was weakly significant at 5% (and insignificant at 1%), thus leading to dubious conclusions regarding the very existence of a minimum AC point for the Y variable. We recall from Chapter 2 - whose analysis was limited to a standard, deterministic translog equation in just one output - that the Minimum Efficient Scale for delivered electricity (Y) turned out to be severely inconsistent even with the maximum observed value in the sample[69], thus leading to the rejection of a U-shaped AC curve on empirical grounds. On the other hand, partial scale-economies[70] outcomes from Chapter 3 pointed in the direction of small energy-output sizes for exhaustion of returns to scale, which - however - were undermined by

(*a*) the low statistical significance of Y's second-order coefficient (as mentioned above);

(*b*) the presence of a second output (CUST), which much more effectively captured the presence of scale economies.

In the light of the above considerations, we chose the total number of customers (CUST) as the 'scale efficiency driver' which might be of some interest to the energy regulator when

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with rank-order tests being performed upon differently derived series (stochastic frontier vs. DEA) of unit-specific technical efficiency scores.

[69] MES = 45,320 GWh, against Y= 3,767 GWh at ENEL Rome.

[70] See Panzar and Willig (1977) for the concept of 'Overall Scale Economies'.

taking decisions about possible territorial changes to the structure of electricity distribution in Italy. The Figure below cross-plots average costs [AC(Y), AC(CUST) against output indicators (Y, CUST) by considering all possible combinations [i.e., AC(Y)⇒Y, AC(CUST)⇒CUST, AC(Y)⇒CUST, AC(CUST)⇒Y][71].

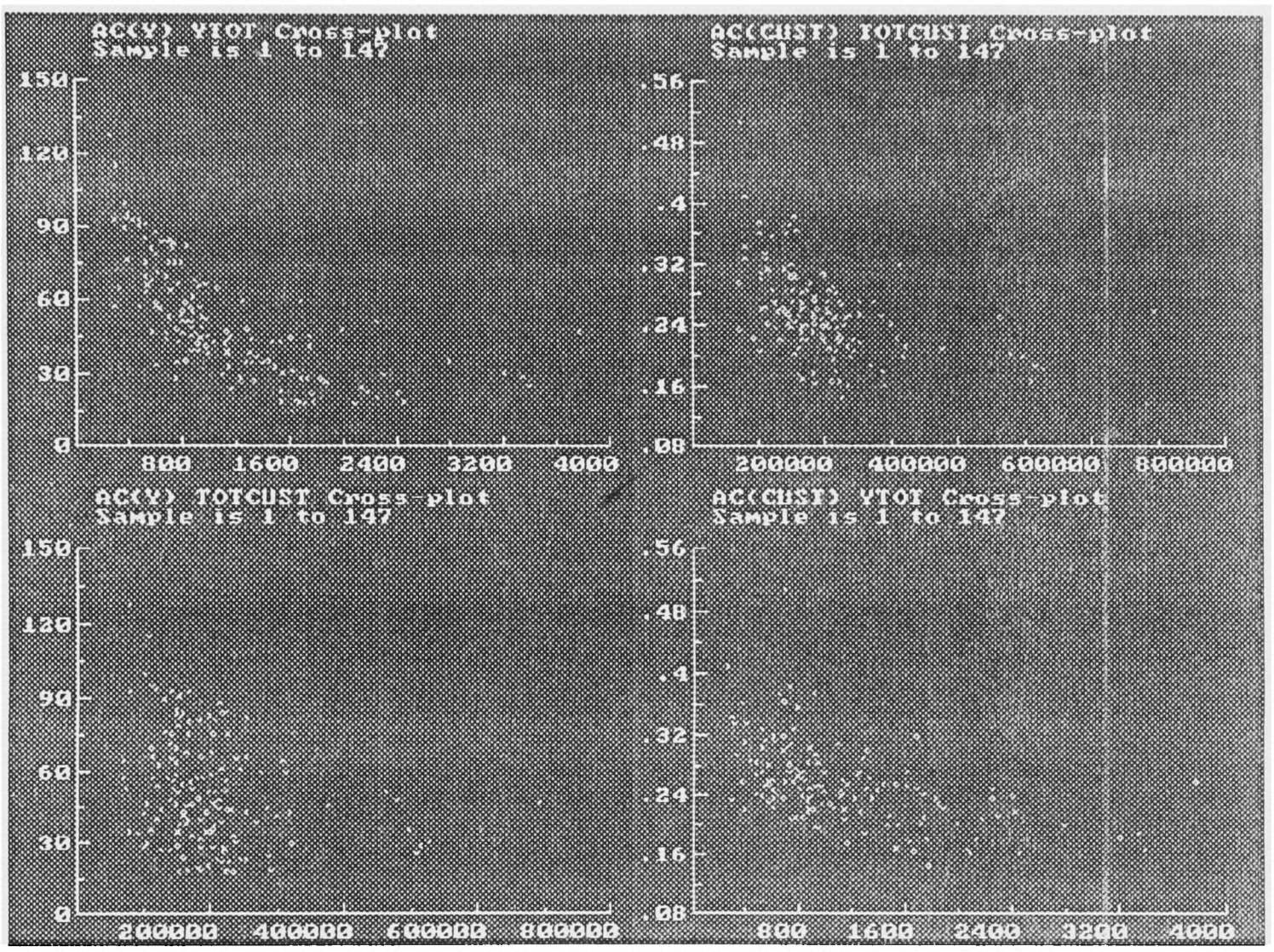


Figure 3.1: AC Cross-Plots. *[Average Costs are in million ITL per GWh, or million ITL per customer; Customers are in physical units; Energy delivered is in GWh. Business year ending 31.12.1996]*

As the diagrams above show, the presence of scale economies in the raw data is not in

[71] AC(Y) and AC(CUST) are average costs in terms of energy delivered and customers, respectively. AC is obtained as the ratio between Total Distribution Cost (TDC) and the relevant output indicator (Y, CUST).

doubt[72]. Both energy delivered and the number of customers highlight the presence of high fixed costs which spread on production 'units', thus giving rise to negatively sloped Average Cost (AC) relationships. Apart from four or five outliers (corresponding to metropolitan areas), both the AC(Y) and AC(CUST) scatters show a negatively sloped trend. The theoretical presence of a Minimum Efficient Scale (MES) is not rejected by the data. By forcing the average cost data set to follow a specific mathematical relationship (e.g., a dual total cost function), we showed that a deterministic translog approximation failed to deliver a MES(Y) value which was compatible with sample data. This is probably due to the fact that delivered energy did not prove to be a satisfactory specification for output. See below for estimation results on Y from Chapter 2.

Deterministic Translog (Ch. 2) - Estimates

Variable	Estimate	Standard Error	*t*-statistic
Y	0.32206	0.16857	**1.91059**
$0.5Y^2$	0.14709	0.0832	**1.76796**

The reader is referred to the discussions in Chapters 3 to 5 regarding the opportunity of considering alternative specifications for output. Since Neuberg (1977), several authors have adopted the number of customers (separately 'priced') as a really exogenous indicator of output within dual cost functions being applied to electricity (or gas) distributors. Estimates from this Chapter confirmed that, even in a multi-output model, customers were by far a

[72] Notice that cost curves seem to be L-shaped and that there is too little large firm data to say that the curve is upward-sloping beyond some minimum. MES could then identify a continuum of output values (flat-bottomed AC curve) rather than a unique Y^* solution.

better explanator of total distribution cost than delivered electricity was[73].

Stochastic Translog (Ch. 3) - Estimates

Variable	Estimate	Standard Error	*t*-statistic
Y	3.01455	0.988	3.05093
Y^2	0.10035	0.05278	**1.90137**
CUST	7.17963	0.614	11.6896
$CUST^2$	0.33661	0.081	4.15749

In particular, Y's second-order effect was weakly significant at 5%, and insignificant at 1%. When inspecting the possibility of territorial restructuring for ENEL's local zones, we shall therefore take customers as the relevant (exogenous) output which determines MES values.

Again from this Chapter, we have

Minimum Efficient Scale [s.t. *min* (AC)] = *CUST** (at sample-mean *Y*) = 364,687.9;

Sample-mean Value (147 observations) = $CUST_{mean}$ = 196,417.

Recalling that the total number of customers being served by ENEL during 1996 amounted to 28,660,811 units, a simulation involving identical distribution zones delivering the sample-mean value for electricity - that is, $\bar{Y}$ = 1,107 GWh - would imply the presence of n^* = 78.81 zones (the current number is 147). Moreover, as the following Table shows, the actual number of ENEL zones featuring more than 364,000 customers in 1996 were eight, with four more units still above the 300,000 threshold.

[73] The latter is almost certainly an endogenous variable to ENEL.

CUST	Unit
689,412	ROMA*
524,650	TORINO*
512,044	BOLOGNA
506,178	MILANO*
492,889	FIRENZE
475,008	GENOVA
461,261	NAPOLI
374,350	BARI
364,688	**MES**
317,981	*PADOVA*
314,446	*PALERMO (CENTRE)*
308,887	*CAGLIARI*
304,939	*TARANTO*

* Also served by a municipal electric utility (MUNI).

Table 3.5. ENEL Customers and the MES Statistic.

Notice that the above-MES units all correspond to metropolitan areas. Moreover, the only large town which is missing from the 'Big Eight' is Palermo (Sicily). This is due to the fact that Palermo's metropolitan area is split up by ENEL into two bits, with 'Palermo Ext.' (outskirts) featuring 205,890 customers.

A number of other towns might already hit the 300,000 threshold if new urban distributors were created via mergers between municipal utilities and their surrounding ENEL zones. The 'combined distribution systems' stemming from municipal unification of electricity distribution would show the following customer figures:

Towns	CUST(MUNI)	CUST(ENEL)	TOTCUST	'WINNER' (Ch. 4)
Roma	744,479	689,412	**1,433,891**	ENEL
Milano	400,940	506,178	**907,118**	ENEL
Torino	248,094	524,650	**772,744**	ENEL
Brescia	107,844	219,295	**327,139**	ENEL
Bolzano	109,533	158,614	268,147	ENEL
Verona	58,536	163,051	221,587	ENEL
Vicenza	54,526	195,175	249,701	ENEL
Modena	106,543	252,075	**358,618**	ENEL
Trieste	139,705	79,150	218,855	**MUNI**
Parma	64,747	184,043	248,790	**MUNI**
Terni	49,862	119,080	168,942	**MUNI**
Cremona	39,615	272,671	**312,286**	**MUNI**
Vercelli	25,633	100,171	125,804	**MUNI**
Sondrio	13,435	101,961	115,396	**MUNI**
	(2,441,098)	*(3,565,526)*	*(6,006,624)*	

Table 3.6. Municipal Distribution Systems (ENEL+MUNI).

Once again, the Table shows that municipalities were the 'winners' (over ENEL) in smaller towns, with ENEL being technically more efficient in larger ones. As elsewhere noticed, this might be due to either different technology, or simply to the fact that smaller towns are integrated systems with all kinds of customers being served by the same operator (the MUNI), whereas larger conurbations constitute heterogeneous sets with city centres being served by MUNIs, and (mainly industrial) outskirts being franchised to ENEL's distributors.

However, apart from Italy's main systems (Milan, Rome, Turin), the metropolitan structures of Brescia, Modena, and Cremona (Northern Italy) might still work at acceptable customer levels - provided that their local distribution systems are rationalised by unifying municipal utilities (city centres, immediate outskirts) to ENEL zones (peripheral outskirts, provincial surroundings). If one considers that only three MUNIs (again Rome, Milan, and Turin) reached acceptable customer dimensions in 1994/1996, rationalisation of municipal distribution in Italy seems now to be a policy-making priority. Perhaps, 79 ENEL zones instead of the current 147 - that is, a 46.4% reduction - might not be a feasible policy-making target. However, after considering mountain and Southern locations, it would not be unreasonable to think of at least one-third scale-efficient zones - including ENEL-systems - out of the total. For instance, 50 zones featuring 350,000 customers each would still leave more than 11,240,000 customers throughout the country, to be allocated to smaller zones (the ones which could not be restructured because of exogenous constraints), each one featuring around 120,000 customers on average. By setting a 100-zone target and adding municipal customers to ENEL's ones, we would obtain 31,181,662 customers at a national level. If at least 50 scale-efficient zones were feasible, then 17,500,000 people would be served by such units. The remaining 13,681,662 customers would be assigned to 50 scale-inefficient (i.e., too

small) distributors, each one featuring 273,633 customers on average. Obviously, the choice variable for the regulatory agency is represented by the future number of local distributors - with customers being taken as given in the short/medium run - to be franchised. In the light of the present study, such a number should float around 80 (instead of the current 147, plus 37 MUNIs) and not exceed 100 in any case - if scale efficiency is pursued as a valuable target by the policy-maker.

In other words, given the physical impossibility of rationalising the whole of Italy's electricity distribution sector, restructuring should concentrate upon urban areas, especially those currently featuring 'double' distribution systems (i.e., ENEL+MUNI). Furthermore, those towns being actually split among several ENEL zones ('Int./Ext.', 'Centre/Ext.', etc.) might be served by a single zone working at efficient customer scale. As Chapter 4 will show, municipalities proved to be technically superior to surrounding ENEL zones in the 46.15% of cases - when no mountain villages in Trentino/South Tyrol are considered. By restricting the comparison to towns featuring ENEL and MUNIs operating 'back-to-back' - i.e., not just working as neighbours in different provincial towns - six out of fourteen 'urban systems' had MUNIs outscoring ENEL in terms of technical efficiency (42.86% of cases). Again, MUNIs proved to be superior in smaller districts. Therefore, urban rationalisation should follow the usual, case-by-case approach.

The results outlined so far are summarised by the Table below.

n^* = **78.8086** zones (at CUST* = **364,688**)
Above CUST* are **8** zones.
Above CUST* are **4/5** municipal systems (ENEL+MUNI).
Actual no. of ENEL zones = **147**
Actual no. of MUNIs = **37**
78.8086/147 = **53.61%** of current ENEL zones. Reduction needed to rationalise system = **46.39%.**
Actual room for policy-making manoeuvre: unify biggest systems to get 8-10 big distributors. Unify provincial units to get some 50 zones featuring 300-350,000 customers. Rationalise remaining zones subject to exogenous (e.g., territorial, demographic, demand-based) constraints.

Table 3.7. MES Outcomes and Theoretical, Equally-Sized Optimal Zones.

CHAPTER 4

STOCHASTIC FRONTIER ANALYSIS OF ITALIAN MUNICIPAL ELECTRICITY DISTRIBUTORS, AND COMPARISON WITH ENEL'S LOCAL ZONES

1. Introduction

In this Chapter we perform a stochastic frontier analysis of Italy's municipal utilities, in order to measure their relative technical efficiency as opposed to that of a significant subset of ENEL's local zones. The analytical tool used is again the Technical Efficiency Effects (TEE) model by Battese and Coelli (1995), which was described in Chapter 3. However, due to data constraints, we shall move to a production frontier analysis in this Chapter, as no cost figures were available for municipally-owned utilities. Whereas production functions may simply be viewed as the 'primal' algebraic expressions to which 'dual' cost functions relate, input and output choices are often different, depending on data constraints. Therefore, the 'dual' correspondence between production and cost functions is obviously violated when a different input-output mix is chosen by the researcher. Owing to binding restrictions on the data, we were not able to replicate the previous translog cost functions in 'production' terms. This was mainly due to capital having different definitions in municipal figures. Moreover, the initial panel of environmental effects (the *Z*s) was incomplete because of some missing values. However, we managed to build up comprehensive models featuring from 3 up to 13 environmental variables. In the end, even though the input-output structure of the production functions being used for municipalities (hence, MUNIs) is not exactly equivalent to that of the

dual cost functions employed in the previous Chapters, the basic framework within which Chapter 4's analysis is developed will not substantially differ from the previous ones.

The real novelty of this Chapter is the tentative examination of relative efficiency for MUNIs, as compared to ENEL's zones. After ruling out the 'full' pooled sample - being made up of 184 (147+37) units - because of consistency reasons, we chose to restrict the comparison to those ENEL local zones which, owing to both geographical and economic motivations, could be regarded as 'peers' for municipalities. Basically, we singled out of the original sample those ENEL districts which either surrounded or were neighbouring units to MUNIs. By selecting 39 'peers' from ENEL's zones and adding them - after data homogenisation - to the 37 municipal units, a 76-observation cross-sectional sample was obtained for estimation of relative efficiency scores (*EFFs*). Both stochastic-frontier and DEA methods have the nice feature of producing firm-specific information regarding relative efficiency performances. As part of the methodological cross-checks to be implemented in Chapter 5 by means of non-parametric statistical tests, all the outcomes to be obtained throughout the present Chapter will be tested - together with those from Chapter 3 - against DEA-based results. In this respect, the reader is referred to the second part of Chapter 5.

The only relevant caveat to be discussed before analysing MUNIs relates to the way the pooled sample was constructed. Unfortunately, we did not manage to collect 1996 cross-sectional data for municipal authorities. The most recent year we were provided with is 1994 (business year ending 31 December). Since physical production figures were to be compared - instead of monetary units, as for cost data - we encountered no deflation problems when pooling the two cross-sections (1996 and 1994). Of course, the only problem with input-output figures relating to different years is given by technical progress. If one manages to show that technical progress in electricity distribution (at municipal levels) over the period

1994-1996 has been negligible, then input-output data for the two different cross-sections could be successfully merged in order to form a single, cross-sectional pooled sample.

So as to investigate whether 1994-to-1996 technical progress for MUNIs has been substantial, we exploited the fact that time-series data for MUNIs were available over the 1987-1994 interval. We then took a standard translog production function in one output and three inputs - which will also be used for the following work - and estimated it over the years 1987-1994, by inserting both a linear and a quadratic time trend. The symmetric translog production function was then structured as follows[1]:

$$\ln Y = \alpha_0 + \alpha_1 \ln K + 0.5\alpha_2 (\ln K)^2 + \alpha_3 \ln L_1 + 0.5\alpha_4 (\ln L_1)^2 + \alpha_5 \ln L_2 + 0.5\alpha_6 (\ln L_2)^2 +$$
$$+ \alpha_7 \ln K \ln L_1 + \alpha_8 \ln K \ln L_2 + \alpha_9 \ln L_1 \ln L_2 + \alpha_{10} t + 0.5\alpha_{11} t^2 + \varepsilon, \quad \text{where:}$$

$Y =$ physical energy distributed to customers (GWh);
$K =$ kilometres of distribution line;
$L_1 =$ number of full - time employees (end - year average);
$L_2 =$ number of (part - time) external employees (franchised works);
$t =$ a time trend (one - step);
$\varepsilon \sim N(0, \sigma^2)$ is a two - sided disturbance (with no efficiency decomposition). (1)

The insertion of a time trend into either a production or a cost function is equivalent to estimating 'disembodied' technical change. As a rule, technical change can be analysed and

[1] We did not include purchased power among our inputs, because bulk electricity is 'bought' by municipal authorities at administered prices which are periodically decided by ENEL, and then forwarded to governmental planning agencies for approval (see Chapter 1). Therefore, purchased power is a 'fixed' component of output which basically follows total distributed output (only a small fraction of output is auto-generated) and whose cost is 100% passed on to final customers, since it is deemed exogenous to MUNIs. However, we inserted a generation dummy in the main stochastic translog analysis, in order to control for the presence of auto-generating plants for some municipal distributors. Moreover, we also discarded purchased power from the pooled sample analysis, because ENEL's local zones withdraw high-voltage energy from the national grid, which is run by ENEL itself. It must be said that ENEL's internal transfer prices (unregulated until 1996) should not be trusted. By the same token, we excluded the price of 'purchased' power from our previous ENEL analyses. Filippini (1994) considers purchased power in his study of Swiss municipal distributors (Zurich). The Italian scenario - however - is such that passed-through inputs (electricity, gas, heat, phone calls) are very difficult to handle within production/cost analyses, due to the main Italian public utility firms being vertically integrated to a full extent (with some horizontal de-integration).

estimated by using production functions and associated cost relationships. One such type of technical change is a shift in the production function over time, reflecting greater efficiency in combining inputs. The efficient frontier, or the production set's frontier, is then shifted out as a result. This type of technical progress - which is easily estimable by looking at time trends - is known as 'disembodied technical change', and may be represented by the following production function:

$$y(t) = f[K(t), L(t), t], \tag{2}$$

where t is time. Time trends may be inserted in both production and cost functions, so that dy/dt and dC/dt will be the 'time effects' on output and total cost, respectively. Of course, provided that the total cost function has an intimate dual relationship with the firm's production function, the two ways of looking at disembodied technical change via time trends (t) will be completely equivalent.

Apart from disembodied technical progress - which is the easiest type to estimate - one can technically define 'neutral' (or 'Hicks-neutral') technical change as well[2]. Technical change is 'neutral' if it does not change the marginal rate of substitution between the inputs.

A major problem associated with technical change is the one regarding quality. It is easy to show that product quality may be treated as a factor which determines shifts in the production frontier. Nonetheless, it is not always easy for the investigator to insert quality in his/her production relationship. Technical progress related to quality is often referred to as 'residual' technical progress. Solow (*Review of Economics and Statistics*, 1957) expounded a simple mathematical way of isolating the 'residual' type of technical progress and measuring it[3].

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[2] See Intriligator *et al.* (1978-1994).

[3] See also Hebden (1983) for a comprehensive summary of Solow's now classic article.

Even though electricity distribution might not seem to be as constrained by particularly strong quality requirements as retail supply is, however it encounters serious quality problems (think, for instance, of network reliability needs, electricity losses in distribution, and so on).

Except for the time trend element, the above translog production function constitutes the basic analytical tool of the stochastic frontier analysis (TEE model) to be proposed in the next Sections. By estimating a non-stochastic translog relationship of the above form - with a two-sided, normally distributed disturbance term - which allowed for both a first and a second-order (one-step) time trend element, we discovered that the time trend's effect was equal to 0.01388 per year to a first-order, with only 1.4 significance (*t*-statistic), over 1987-1994. The second-order effect was negative and insignificant. This means that, adopting the 5% significance threshold, technical progress was discovered to be non-significant for Italian electric MUNIs over the time interval under consideration. Now, by looking at both 'corporate' history and the external socio-economic environment, we also found that no relevant shocks occurred for MUNIs over 1994-1996 either.

By coupling the two investigations, and also excluding deflation issues because of the physical nature of the figures involved, we decided that no significant drawbacks hindered the possibility of mixing - after allowing for unit-of-measure homogenisation - the MUNI sample (1994) with a significant subset of ENEL's units (1996). We recognise that mixing 1994 figures with 1996 ones may be rather crude, but this was in fact the only available option given informational constraints. A new analysis with 1996-97 data for both types would be needed, which is matter for future research. Finally, it must be once again stressed that we added 39 ENEL zones only to the 37 MUNIs, because of sample homogeneity reasons.

We wished to insert a discussion of the reasons for pooling physical input-output figures relating to different years in this Introduction, so as to completely direct our attention to

stochastic frontier estimation problems throughout the following Sections, which are organised as follows:

- Section 2 proposes a stochastic translog production analysis of 37 MUNIs for 1994, with computation of basic statistics and efficiency rankings;
- Section 3 will shift to the above-discussed pooled sample of 37 MUNIs plus 39 'peers' from ENEL, by outlining a final, mixed efficiency ranking[4]. The same Section puts forward some policy-making suggestions by extensively discussing comparative outcomes;
- Section 4 is both a conclusion and a link to the non-parametric analysis (DEA) to be presented in Chapter 5.

We preferred to keep this Chapter separated from Chapter 3, in order to better introduce the reader to municipal analysis. Both ENEL and municipal analyses, however, will be discussed in Chapter 5, from a different point of view. With MUNIs being already presented[5] and previously examined via stochastic production frontier estimation, we did not find any reason for separating them from the main DEA analysis of ENEL's zones: this is why Chapter 5 - differently from Chapters 3 and 4 - will provide a unified treatment of both types of firms.

2. A Stochastic Production Frontier Analysis of Italy's 37 Municipal Electricity Distributors (1994)

Similarly to the deterministic translog production function of Section 1, we instrumented a translog production frontier within a stochastic framework, by taking the same input values.

[4] A 3-environmental effects model was selected after several alternative runs.
[5] See also Chapter 1.

We refrained from taking the number of customers as our output variable, since production estimation assumes that output is endogenous. The total number of customers (*CUST*) was used in Chapter 3 because of its exogeneity within a total cost framework. Given that there are reasons to regard ENEL's energy output as 'moderately' endogenous, we took total energy delivered (GWh) as our Y dependent variable in the pooled analysis. Furthermore, we also adopted a traditional definition of output in the municipal analysis, for analogous reasons to those explained above. Moreover, we tried to regress the total number of customers as 'output', with minor success. By taking one capital and two labour inputs as exogenous variables, plus total energy delivered to final customers as the dependent variable, we constructed the following stochastic production frontier model:

$$\begin{aligned}
&\ln Y = \beta_0 + \beta_1 \ln K + \beta_2 (\ln K)^2 + \beta_3 \ln L_1 + \beta_4 (\ln L_1)^2 + \beta_5 \ln L_2 + \beta_6 (\ln L_2)^2 + \\
&+ \beta_7 \ln K \ln L_1 + \beta_8 \ln K \ln L_2 + \beta_9 \ln L_1 \ln L_2 + v + u, \quad \text{where:} \\
&Y = \text{ total energy delivered to final customers (GWh);} \\
&K = \text{ kilometres of distribution line;} \\
&L_1 = \text{ number of full - time employees (end - year average);} \\
&L_2 = \text{ number of (part - time) external employees (franchised works);} \\
&v \sim N(0,\sigma^2) \text{ is a two - sided stochastic disturbance;} \\
&u \sim N(m_i,\sigma^2) \text{ is a one - sided efficiency error } (u \leq 0) \text{ with truncated - N distribution s.t.} \\
&m_i = \delta_1 \ln THIRD + \delta_2 \ln LOSSES + \delta_3 \ln MAXD + \delta_4 \ln INDY + \delta_5 SEAD + \delta_6 METRD + \\
&+ \delta_7 SOUD + \delta_8 GEND + \delta_9 INDUSD + \delta_{10} MOUNTD.
\end{aligned} \tag{3}$$

The above variables are the same as those defined in the previous Chapters[6], with the following exceptions:

[6] Regarding the second labour variable, notice that third-party employees here are a substantial component of the production schedule, since municipal units tend to outsource substantial parts of their business by relying upon external subcontractors, sometimes working with part-time staff. On the contrary, external labour at ENEL is less important, and internal one is mostly full-time (see Chapter 2).

(*a*) *LOSSES* is electricity losses[7], expressed in GW (1 GW = 1,000 MW = 1,000,000 kW);

(*b*) *MAXD* is maximum simultaneous demand[8] in GW (peak hours);

(*c*) *SOUD* is the usual territorial dummy, with South = 1. Incidentally, we had only one municipality belonging to Southern Italy (Trani, Apulia), so that this dummy is much less relevant here than it was in the previous Chapters.

All other variables were instrumented according to the same criteria as those employed in Chapters 2 and 3. Parameter estimates were computed by using the Jondrow *et al.* (1982) measures based on Corrected Ordinary Least Squares (COLS). That is, the intercept of the model is adjusted before the residual is computed and the Jondrow *et al.*'s transformation is applied. Using COLS with Jondrow's *et al.* calculations based upon the error term decomposition generally gives rise to stark differences between the deterministic and stochastic frontier estimations, as also showed by Greene (1993b) with respect to technical efficiency analysis of airline enterprises. Once again, it is worth noticing that estimation of a production frontier - as opposed to a total cost frontier - requires a minor change in the log-likelihood function, its derivatives, and the calculation of estimates of u (in expected value). Since parameter differences between deterministic and stochastic frontiers are often substantial, a specification test for one against the other might be useful, even though no specification tests of deterministic vs. stochastic models have been developed yet, to the best of our knowledge. As basic economic results (returns to scale, returns to density, input elasticities of substitution) tend to be preserved across different models, the major difference

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[7] Electricity losses may be viewed as an input or - however - a controllable variable to be inserted in the main regression. Nonetheless, notice that losses are related to both electricity delivered and the length of distribution lines (thanks to Ohm's laws). This generates two problems: (*a*) possible double causation between Y and losses themselves (simultaneity), and (*b*) co-linearity between losses and any capital proxies involving the length of distribution lines. In the end, we preferred to view losses as a sort of environmental variable rather than an additional input.

being left is actually the more 'pessimistic' assessment produced by either half or truncated-normal models as opposed to traditional, two-sided error specifications[9].

Regarding our previous experience with deterministic analysis (Chapter 2), it must be noticed that some values being produced by deterministic estimators (consider, for instance, sample-mean returns to scale at 2.19) seemed to be implausibly large. Moreover, by using stochastic frontier methods we also tried to shift the deleterious effect of measurement error away from efficiency estimates (see also Chapter 5).

Therefore, we extended stochastic measurement to MUNIs in this Chapter because of internal consistency and implementation ease reasons. Given modern computer software, stochastic implementation is not harder than standard least squares. We once again selected a truncated normal model (TEE) because exponential and gamma specifications for the error term are still computationally unfriendly. Moreover, the numerous ancillary formulas derived by Jondrow et al. (1982) and Battese and Coelli (1988) suggest that the half/truncated model is still the most useful formulation. Random effects models on panel data might also be implementable, provided that the needed figures are made available. The real limitation we have with model TEE is that it postulates allocative efficiency *ex ante*, thus leaving efficiency scores to show technical inefficiency only. The single-equation approach is obviously inadequate for estimating both input-allocative and technical inefficiency at the same time (one has a transparent identification problem). The construction of a set of input-demand equations which incorporate allocative inefficiency and which are properly integrated within a cost or production function might solve the problem. This is matter for further research.

Turning to our previously specified model for MUNIs, it was derived from a very general, non-parsimonious specification featuring 13 environmental effects. As usual, general-to-

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[8] See Burns and Weyman-Jones (1994a).

simple considerations pushed us to refine the specification by dropping insignificant regressors. Finally, the 10-effect TEE stochastic frontier regression gave rise to the following production estimates (model labelled MUNI10):

Table 4.1: Model MUNI10: Estimation Outcomes [Dependent Variable: ln*Y*]

Coefficient Relating to Variable...	**Parameter Estimate**	**Standard Error**	***t*-statistic**
(Constant)	6.9300	0.7350	9.4200
Labour 1 (INT)	0.0435	0.0223	1.9500
$(Labour\ 1)^2$	-0.0691	0.0617	-1.1200
Capital	0.4427	0.2012	2.2000
$(Capital)^2$	-0.0498	0.0514	-0.9690
Labour 2 (EXT)	0.0831	0.0381	2.1800
$(Labour\ 2)^2$	-0.0142	0.0237	-0.5990
L_1K	0.0538	0.0834	0.6450
L_1L_2	-0.1266	0.0670	-1.8900
L_2K	0.0541	0.0316	1.7100
EXTERNAL EFFECTS			
Coefficient Relating to Variable... [Dep. Var. : m_u]	**Parameter Estimate**	**Standard Error**	***t*-statistic**
THIRD	0.07120	0.03520	2.02600
LOSSES	0.20200	0.11091	1.82133
MAXD	-0.24900	0.18500	-1.34595
INDY	0.35200	0.13000	2.69970
SEAD	0.32100	0.42500	0.75526
METRD	-0.31500	0.57900	-0.54440
SOUD	-0.47500	0.95800	-0.49610
GEND	0.32100	0.13300	2.40890
INDUSD	0.61300	0.32800	1.86890
MOUNTD	0.55400	0.34901	1.58734
σ*–squared*	0.02950	0.00923	3.19329
γ *(Grid Search)*	0.61900	0.12400	4.99580
Log-L. Function	7.65E+07		
LR Test of the One-Sided Error[10]	0.51001E+02		
Number of Iterations	39 (max: 100)		
Number of Time Periods	1		
Total Number of Observations	37		

[9] Nonetheless, Chapter 5 will show that DEA outcomes with respect to, e.g., firm-specific inefficiencies may often be more 'pessimistic' than those displayed by stochastic frontier analyses.

[10] Mixed Chi-square distribution.

The above-displayed estimates suggest that the stochastic production function is well-behaved (first-order input effects are positive, with negative second-order effects reflecting decreasing marginal returns), and that some environmental variables have statistically significant coefficients. The estimation strategy was again devised according to a three-step procedure using initial OLS slope coefficients as starting values of a grid search being performed on the γ parameter space, to get final (unbiased) starting values which were utilised for Maximum Likelihood estimation of both the 'betas' (production function coefficients) and 'deltas' (auxiliary regression coefficients, or environmental effects). The efficiency error is now a non-positive one, reflecting erroneous shifts below the efficient production frontier. The *u*s' distribution is still a truncated normal one, with (fitted) mean resulting from the auxiliary regression on external effects[11]. Finally, computation was worked out by using the FRONTIER 4.1 package for stochastic frontier estimation.

As regards parameter estimates, it is worth noticing that external labour was more productive for MUNIs, thus suggesting that 'buy' instead of 'make' might be an interesting management option so as to maximise output[12]. Capital intensity of electricity distribution is confirmed by the close relationship between output and kilometres of distribution line (which, once again, were our proxy for the physical quantity of capital). Finally, all second-order effects for the three inputs were negative - thus suggesting decreasing marginal returns - even though none of them was statistically significant at 5%. Looking at environmental effects, the following variables only were found to make a statistically significant contribution to output maximisation for the 37 MUNIs in our 1994 cross-section:

[11] See Chapter 3 for further details.
[12] Within a cost frontier framework, the 'buy' result was also found for ENEL's zones in the previous analyses.

(*a*) third-party works (expressed in terms of percentage of external materials cost on total distribution cost) were found to increase output, in accordance with the finding relating to external labour in the main translog production function ('make' or 'buy' issue);

(*b*) there was also a positive relationship between losses and output, which is intuitive (reverse causation should be underlined: larger/smaller output determines larger/smaller losses);

(*c*) the percentage of industrial output on the total also (intuitively) increased global output, as industrial supplies are generally much larger than domestic/residential ones;

(*d*) the generation dummy showed a positive effect of internal power stations on delivered output; *GEND* for municipal units was set at 1 for those MUNIs featuring auto-generating plants, and zero otherwise. Differently from what was found in the total cost analysis, the presence of internal generation did affect the dependent variable. This is - however - intuitive, since internally generated electricity is directly transferred from MUNIs to final customers, thus being immediately classified as 'output'. Moreover, internal energy has a 'right of way' over ENEL's transferred output (because of costs), so that the positive relationship between internally generated output and final delivered energy is easily understood;

(*e*) finally, the *INDUSD* dummy (relating to industrial districts) was found to have a positive impact on GWh delivered. Once again, this result was expected, as more industrialised towns also show stronger demand for (especially) medium-voltage electricity, to be devoted to industrial usage.

We also tried to compute some statistics of interest stemming from the above stochastic production model. Empirical researchers in production economics do prefer total cost functions as they easily deal with returns to scale, input substitution elasticities, own-price and

cross-price demand elasticities, and so on. The only immediate statistic which can be calculated from estimated production functions is, according to theory, the one relating to returns to scale. For a standard (log) Cobb-Douglas function with *i* inputs, returns to scale are given by

$$RTS_{C-D} = \sum_{i=1}^{n} \alpha_i, \quad \text{where the } \alpha\text{s are input parameters.} \tag{4}$$

The expression above may be easily generalised to the translog case by considering partial log-derivatives of total output with respect to each of the inputs (being evaluated at the expansion point), such that sample-mean RTS will be computed as

$$RTS_{translog} = \sum_{i=1}^{n} \left(\frac{\partial \ln Y}{\partial \ln x_i} \right), \quad \text{where the } x\text{s are inputs.} \tag{5}$$

Notice that the above expression is the standard one for RTS, giving rise to dual measures such as those proposed by Hanoch (1975), and extensively utilised by empirical researchers within total cost analyses[13]. By calculating the above expression at the Taylor's series expansion point we found that, for the 1994 cross-sectional sample of 37 Italian electric MUNIs, scale economies were present with *RTS* = 1.013. This value is not as large as that found for ENEL's zones within a total (translog) cost analysis, which equalled 1.5 at the sample's mean. However, the two values are not directly comparable because of the different regressors being used. Thanks to duality theory, RTS measures from both production and cost functions must yield the same outcomes provided that inputs and output(s) are the same, and

[13] Hanoch's measure was also used in Chapters 2 and 3.

that dual functions are correctly derived from primal relationships according to theoretical lemmas and identities (Shephard, Roy). However, if one either changes the model's specification, or uses different data, no direct comparability between RTS estimates will be possible any more. We actually altered the model because of data constraints, by considering capital, internal labour, and external labour (instead of materials) as inputs in the current production analysis, thus differentiating it from the previous total cost context.

Even though the production RTS measure of 1.013 (sample mean) is not comparable to that derived from total cost analysis because of different model specification, its own validity as a separate statistic is not in doubt. Slight economies of scale were found at sample-mean values, meaning that the AC curve should be U-shaped, with MES occurring at sample-consistent points (not far from the average *Y*). Such a result was expected, given similar outcomes for sizewise comparable ENEL zones. However, production functions are not so flexible as to let returns to scale react to output changes. In order to compute the 'extent' of scale economies with respect to output, we would have needed a total cost function. Nonetheless, this had to be ruled out at the outset because of data restrictions on MUNIs. We shall analyse RTS again in this Chapter, with special reference to the 'pooled' sample (ENEL, MUNIs) being devised later on.

The MUNI analysis now concentrates upon *EFF* scores for the 37 municipal utilities in our 1994 cross-section. As pointed out in Chapter 3, a few minor changes in log-likelihood functions allow the computer to shift from cost to production function estimation and *vice versa*, with efficiency scores being worked out by *u*'s (Jondrow) expected value being inserted in the following formula:

$$EFF_i = \exp(u_i) \in (0,1]. \qquad (6)$$

Notice that we now have a stochastic production frontier - so that u is non-positive - and the dependent variable is expressed in natural logarithms. Hence, the efficiency score formula to be used by the computer program will once again be the exponential one. As a result of the production (translog) function being estimated - with no 0.5 scaling of quadratic terms - reported efficiency scores will lie within the (0,1] interval. Input-allocative efficiency is imposed *ex ante* by the TEE specification. Of course, those MUNIs featuring higher scores will be technically more efficient, and *vice versa*. We shall not perform any second-stage Tobit analysis of *EFFs* in this Chapter, thus sticking to the environmental results stemming from the TEE model 'MUNI10' (previously displayed). The following ranking of municipalities - resulting from the above-discussed production analysis - concludes this Section.

Table 4.2: Model MUNI10: Estimated Efficiency Scores (*EFFs*)

MUNIs[14]	EFF_i	RANKING
Roma	0.987	1
Vercelli	0.987	1
Torino	0.986	3
Parma	0.984	4
Soresina (CR)	0.984	4
Cremona	0.983	6
Milano	0.981	7
Terni	0.981	7
Voghera (PV)	0.978	9
Vicenza	0.976	10
Trani (BA)	0.973	11
Seregno (MI)	0.973	11
Brescia	0.969	13
Modena	0.968	14
Verona	0.966	15
Trieste	0.966	15
Imola (BO)	0.946	17

[14] Acronyms in brackets (e.g., CR = Cremona, PV = Pavia, BA = Bari, and so on) indicate provinces. When no province is given, the MUNI directly relates to the province's main town (e.g., Rome, Vercelli, Turin, Parma, etc.).

Sanremo (IM)	0.876	18
Selvino (BG)	0.809	19
Sondrio	0.772	20
Average Unit	**0.754**	-
Riva del Garda (TN)	0.719	21
Tolentino	0.709	22
Tirano (SO)	0.697	23
Osimo (AN)	0.606	24
Brunico (BZ)	0.601	25
Rovereto (TN)	0.573	26
Bolzano	0.569	27
Rep. S. Marino	0.563	28
Vigo di Cadore (BL)	0.529	29
Bressanone (BZ)	0.492	30
Primiero (TN)	0.467	31
Mezzolombardo (TN)	0.46	32
Gattinara (VC)	0.431	33
Tione (TN)	0.427	34
Levico Terme (TN)	0.39	35
Silandro (BZ)	0.323	36
Laces (BZ)	0.294	37

The first suggestion stemming from the outcomes above is that the first 16 units (more than 96% technically efficient) are made up of 12 town-based MUNIs, i.e. municipal utilities serving urban contexts (or 'capoluoghi di provincia'), plus one semi-urban distributor (Voghera) and one from the Milanese hinterland (Seregno). The remaining two units among the most efficient ones were two MUNIs from smaller - but by no means rural - centres (Soresina, Trani). Also notice that the only Southern electric MUNI, i.e. Trani in Apulia (Adriatic coast), was found among the best firms, with 97.3% technical efficiency.

If one looks at the remaining MUNIs - showing less than 95% efficiency - mainly rural and/or mountain utilities will be found, apart from only two main towns, which - however - run electricity services in the mountains (Sondrio, 77.2% efficient, is located in Northern Lombardy, not far from the Swiss border, whereas Bolzano, 56.9% efficient, is in South Tyrol, bordering Austria). Almost all other units are mountain distributors, with South Tyrolian units prevailing: from Brunico down to Laces, 10 MUNIs out of 13 are from North-

Eastern mountain villages. Mountain electricity distribution is provided on social grounds, meaning that the lowest efficiency scores ($EFF < 0.6$) cannot be taken as really comparable to town-based ones, even after allowing for environmental variables[15]. For example, Laces's 29.4% efficiency score comes as a direct consequence of the fact that no electricity distribution at all would be provided for that Tyrolian mountain village in the absence of subsidies being raised out of general taxation policies. To sum up, almost all MUNIs featuring more than 95% technical efficiency were urban ones, while all municipalities with less than 55% scores came from mountain districts in the Alps - facing scattered population, as well as 'extreme' landscape conditions.

Before switching to the 'pooled' analysis, a final word should be spent on the interpretation of (0,1] *EFFs*. Differently from DEA scores (either input or output-oriented), efficiency figures derived from stochastic frontier estimation are not clearly interpretable. As Chapter 5 will show, DEA's *EFFs* may be viewed as either input-reducing or output-augmenting scores, thus providing the investigator with straightforward policy-making implications. On the contrary, stochastic frontier *EFFs* (which are estimated, not computed) give only technical efficiency outcomes[16] and often assume, as in TEE, that input-allocative efficiency is given *a priori*. Both of these drawbacks (interpretation of *EFFs*, and efficiency decomposition) are not present in DEA, which is capable of parting (in)efficiency into several bits, ranging from input-allocative to scale, congestion, and 'purely technical' components[17]. On the other hand, the most serious limitation of DEA is that it does not allow for measurement error, thus attributing all deviations away from optimality to 'inefficiency' (*tout court*). This is why,

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[15] Incidentally, customer density was not inserted among environmental effects, since it had been deemed insignificant in a previous regression on 13 Z variables.
[16] Stochastic frontiers do not support input/output orientation, contrary to DEA: see Seiford and Thrall (1990).
[17] See Fare et al. (1985, 1994).

ceteris paribus, stochastic frontier outcomes are more 'forgiving' than DEA results towards observed DMUs. This, however, will be discussed in detail in Chapter 5.

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. Reasons for the 1994-1996 mixed cross-section have already been given in Section 1. 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[18];

(*d*) insignificance of most environmental effects when examining the homogeneous pooled sample (instead of the dishomogeneous 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[19].

As a result of the remarks outlined in both Section 1 and this Section, we turned to estimate 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.

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[18] Recall that - as shown in Chapter 3 - there is a positive relationship between differentiation of firm-specific scores and the number of *relevant Z* effects being included in the model's specification.

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):

$$\ln Y = \gamma_0 + \gamma_1 \ln K + \gamma_2 (\ln K)^2 + \gamma_3 \ln L + \gamma_4 (\ln L)^2 + \gamma_5 \ln K \ln L + v + u, \quad \text{where:}$$
$Y =$ total energy delivered to final customers (GWh);
$K =$ kilometres of distribution line;
$L =$ number of full - time employees (end - year average); (7)
$v \sim N(0, \sigma^2)$ is a two - sided stochastic disturbance;
$u \sim N(m_i, \sigma^2)$ is a one - sided efficiency error ($u \leq 0$) with truncated - N distribution s.t.
$m_i = \delta_1 \ln DENS + \delta_2 GEND + \delta_3 MUNID.$

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 4.3: Pooled Sample (37 MUNIs, 39 ENEL): SFM3 Estimation Outcomes [Dependent Variable: ln*Y*]

Coefficient Relating to Variable...	Parameter Estimate	Standard Error	*t*-statistic
(Constant)	6.14266	0.55300	11.10440
Labour	0.24248	0.12190	1.98941

[19] 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*).

(Labour)^2	-0.10112	0.06520	-1.56516
Capital	0.61358	0.29200	2.10298
(Capital)^2	-0.10551	0.05290	-I.99557
L×K	0.21803	0.11100	1.97300

EXTERNAL EFFECTS *[Dep. Var.: m_u]*			
Coefficient Relating to Variable...	**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
σ-*squared*	0.116000	0.032200	3.612626
γ *(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 all the previous total cost analyses[20], 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[21] 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).

Returns to scale for the above analysis were calculated - at sample-mean values - following the usual formula, and turned out to equal

$$RTS_{pooled} = \frac{\partial \ln Y}{\partial \ln K} + \frac{\partial \ln Y}{\partial \ln L} = 1.063 > 1 \text{ (sample - mean value).} \qquad (8)$$

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[20] See Chapters 2 and 3.

[21] These are unilaterally priced: see Chapter 1.

Recall that RTS for the 37-MUNI sample equalled, at sample-mean values, 1.013 > 1. Therefore, slight scale economies were found at the Taylor's series expansion point. This does not make a big difference *vis-à-vis* the sample-mean value obtained in the pooled analysis. Once again, as pointed out earlier in this Chapter, the RTS outcomes being computed from the present functions and those previously calculated in Chapters 2 and 3 are not directly comparable in magnitude. However, they are in agreement on the fact that scale economies are present at the sample's mean for both ENEL's zones and MUNIs.

Given that the two estimated values for RTS are quite similar (1.063 - 1.013 = 0.05), the two samples (37, 37+39) being analysed in the present Chapter show some convergence on scale economies. In both cases, the scale economies result implies a U-shaped AC curve, with MES being not far from the average unit's *Y* level. Slight economies of scale originate from the fact that urban distributors had a strong weight in the pooled sample. This suggests that scale economies are certainly not exhausted in mountain/rural contexts, even though the largest MUNIs might already be working at cost-minimising levels. However, the size dispute will be re-examined in detail when looking at the pooled ranking (ENEL/MUNIs) which is proposed below[22].

Table 4.4: Pooled Sample (37 MUNIs, 39 ENEL): SFM3 Efficiency Ranking

MUNI/ENEL	EFF (0/1)	RANKING
Soresina	0.990	1
Selvino	0.990	1
MONZA	0.990	1
MILANO	0.977	4
Terni	0.976	5
CORSICO	0.975	6
Parma	0.946	7
Vigo di Cadore	0.937	8

[22] Block capitals in the Table identify ENEL's zones (e.g., MILANO), whereas MUNIs are in lower-case letters (e.g., Soresina, Selvino, and so on). Also notice that an alternative strategy for analysis would have been to perform a non-parametric test of the null hypothesis that ENEL zones and MUNIs are equally efficient in technical terms. This approach will be adopted later on in the thesis (see Chapter 5).

MELZO	0.936	9
BOVISIO	0.899	10
TORINO	0.886	11
MILANO EXT.	0.862	12
BUSTO A.	0.855	13
BERGAMO EXT.	0.855	13
BOLOGNA	0.850	15
LECCO	0.797	16
Vercelli	0.752	17
MODENA	0.744	18
ROMA	0.744	18
LODI	0.721	20
IMPERIA	0.717	21
ANCONA	0.712	22
VERONA SUD	0.707	23
BRESCIA	0.706	24
VICENZA	0.693	25
VERONA NORD	0.692	26
SALO'	0.687	27
Cremona	0.685	28
PARMA	0.683	29
BASSANO	0.666	30
Trani	0.664	31
MONOPOLI	0.663	32
Gattinara	0.662	33
PESARO	0.660	34
VIGEVANO	0.658	35
RIMINI	0.642	36
TRENTO	0.633	37
VERBANIA	0.620	38
Average Unit	*0.619*	-
MACERATA	0.619	39
Seregno	0.610	40
Trieste	0.608	41
Sondrio	0.605	42
Tirano	0.599	43
CREMONA	0.569	44
BIELLA	0.560	45
SONDRIO	0.556	46
BELLUNO	0.552	47
Voghera	0.548	48
Vicenza	0.547	49
Milano	0.537	50
BRENO	0.533	51
Riva del Garda	0.511	52
Roma	0.495	53
TRIESTE	0.481	54
Torino	0.476	55
Tolentino	0.471	56
Sanremo	0.468	57
Tione	0.462	58
Brunico	0.448	59

Imola	0.440	60
VERCELLI	0.435	61
TERNI	0.433	62
Modena	0.432	63
Brescia	0.418	64
Mezzolombardo	0.412	65
Osimo	0.405	66
Verona	0.344	67
BOLZANO	0.334	68
Silandro	0.328	69
Primiero	0.324	70
Rep. S. Marino	0.297	71
Bressanone	0.295	72
Levico Terme	0.293	73
Rovereto	0.288	74
Bolzano	0.241	75
Laces	0.226	76

By looking at the first ten units in the ranking, one finds that five of them are MUNIs. Moreover, there are some rural/mountain distributors (Vigo di Cadore, Selvino). Efficiency in relative terms shows that MUNIs are not systematically outperformed by ENEL zones. Even though some municipal distributors are not efficient when compared to other MUNIs, sometimes they manage to come out as winners *vis-à-vis* their ENEL peers (Vigo di Cadore). Furthermore, urban operators (Terni, Parma) won against their ENEL counterparts in the pooled sample, thus confirming that the MUNIs' efficiency issue has to be handled on a strict case-by-case basis. Among those local units which have high efficiency scores (say, higher than sample-mean $EFF = 61.9\%$), ENEL zones dominate MUNIs (76% ENEL), but this is not a correct evaluation of relative efficiency. First, ENEL's peers outnumber MUNIs in the pooled sample (39 against 37), as several MUNIs were allowed to have more than one ENEL peer. Secondly, given environmental peculiarities, each MUNI must be compared to its peer(s), and not to all ENEL zones in the sample[23]. By doing so, even some mountain MUNI

[23] In fact, this is the basic reason why a 76-observation pooled sample was adopted, instead of the global 147+37 sample.

districts might turn out to be technically efficient[24] as opposed to their direct ENEL counterparts.

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

Table 4.5: MUNIs and their ENEL Peers (SFM3): Winners/Losers[25]

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
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., MONZA	ENEL
Vercelli	VERCELLI	**MUNI**
Rep. S. Marino	RIMINI, PESARO	ENEL
Riva del Garda	SALO', TRENTO	ENEL
Osimo	ANCONA	ENEL
Sondrio	SONDRIO	**MUNI**

[24] Recall that TEE imposes input-allocative efficiency *ex ante*, so that reported efficiency scores (*EFFs*) only relate to technical (input-minimisation/output-maximisation) efficiency for a given, optimising input mix. See Battese and Coelli (1995), and Coelli (1996a).

[25] Also refer to the map at the end of this thesis.

Levico Terme	TRENTO	ENEL
Soresina	CREMONA, LODI	**MUNI**
Tirano	SONDRIO, LECCO	**MUNI**
Gattinara	VERCELLI, BIELLA, VERBANIA	**MUNI**
Mezzolombardo	TRENTO	ENEL
Selvino	BERGAMO EXT., BRENO	**MUNI**
Vigo di Cadore	BELLUNO, BASSANO	**MUNI**

It is clear from the Table above that 13 out of 37 MUNIs outperformed their ENEL counterparts. 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 *vis-à-vis* 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[26] 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

[26] DEA computes efficiency scores - instead of estimating them - and eliminates model specification problems (at some cost: see Chapter 5).

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 the only Southern municipality[27] not only fared better than its ENEL counterpart (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. All the caveats which should be kept in mind while looking at the above results are clarified in the next Section, which concludes Chapter 4. Some of the drawbacks encountered here will be overcome in Chapter 5, thanks to the DEA approach. Other ones will be left in any case, due to *ex ante* data limitations. A link between the two analyses of Chapters 4 and 5 is also provided below.

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

Table 4.6: MUNI/ENEL Efficiency Comparison (SFM3): Statistics of Interest

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

Comments: ENEL fares better in metropolitan contexts, but MUNIs do better in Lombardy, smaller towns, and (sometimes) in the mountains.

4. Conclusions

This Chapter was aimed at analysing relative efficiency for 37 municipal electric utilities (MUNIs) in Italy and their 'peers' from ENEL. First, a stochastic production frontier model was estimated according to the TEE specification proposed by Battese and Coelli (1995). Estimation of a translog total cost function was hindered by the unavailability of reliable data on costs. We then opted for a stochastic translog production frontier in three inputs plus two disturbance elements, the first one accounting for random noise (v, a two-sided error), and the second one intended to capture inefficiency effects (u, a one-sided error with truncated-normal distribution). The first sample was a 37-unit cross-section of Italian electric MUNIs for the business year 1994. Separate figures for the distribution business were obtained and utilised (MUNIs sometimes do generation, and always do electricity supply). Estimation of the MUNI cross-section revealed a well-behaved stochastic translog relationship in all inputs (which, incidentally, were labour, capital, and third-party labour for external goods and services). A ranking based on *EFF* scores was also displayed.

By looking at the first main efficiency ranking relating to the 37 MUNIs only, one discovers that the insertion of some environmental effects to allow for local peculiarities did not suffice to rescue mountain distributors (mainly located in the North-Eastern Alpine region

of Trentino/South Tyrol) from their status of 'low performers' in the league. The best MUNIs were generally located in metropolitan areas (with Rome, Turin, and Milan all featuring more than 98% efficiency) and in medium-sized urban contexts[28]. The remainder was made up of rural and/or mountain distributors - which often run the electricity service within public subsidy schemes - except for the mountain semi-urban districts of Sondrio (Northern Lombardy) and Bolzano (South Tyrol)[29].

From the first cross-sectional analysis of 37 MUNIs for 1994, the first impression is that at least some locally-owned electricity distributors might have outperformed their ENEL neighbours. To test this, we built up a pooled sample of 37 MUNIs and 39 'peers' (ENEL zones), being selected among neighbouring and/or surrounding local units administered by the national monopolist. Reasons were given for the choice of merging two cross-sections (37+39) relating to different business years. Moreover, we also explained why a 76-observation pooled sample had to be preferred to a complete 184-observation cross-section, featuring all ENEL units and not only the MUNIs' appropriate 'peers'[30]. By taking the restricted (76-obs.) pooled sample into account, a stochastic production function in two inputs and three environmental effects was estimated according to the TEE model. The model was kept as parsimonious as possible because of the auto-imposed homogeneity of the pooled sample, which gave us the chance of dropping several insignificant environmental variables, so as to have a larger number of degrees of freedom for estimation. Outcomes from the parsimonious model showed that the translog production function was well-behaved in both inputs (capital, labour). Moreover, environmental effects on the efficiency error (u) - and

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[28] Vercelli, Parma, Cremona, Terni, Vicenza, Brescia, Modena, Verona, and Trieste all featured higher than 96.5% efficiency records.

[29] Notice that efficiency scores deal with *relative* efficiency (i.e., given all firms in the sample). Obviously, the most efficient units in the current sample would not necessarily retain their status within a different sample context.

hence on output *Y*, the main equation's dependent variable - had a plausible economic interpretation. We also explained why physical energy delivered (GWh) was chosen as the endogenous variable, rather than the (exogenous) total number of customers which had been extensively utilised in Chapter 3.

Finally, stochastic production frontier estimation originated its usual 'nice' output made up of efficiency scores, which were ordered for the whole sample, so as to give rise to a ranking. The pooled efficiency ranking showed that more than 35% of MUNIs managed to outperform their ENEL peers, and that a further 46% of them also managed to outscore their ENEL counterparts outside Trentino/South Tyrol's mountain villages (which suffer from a particularly hard external environment). Finally - as shown in one of the above Tables - when Lombardy only is taken into account[31], MUNIs outscored their ENEL peers in 5 out of 9 direct comparisons (corresponding to a 55.6% ratio). MUNIs were found to be particularly strong within medium-sized urban contexts, and semi-urban centres in the North (especially Lombardy). On the contrary, ENEL's zones were found to dominate MUNIs within metropolitan areas (Rome, Milan, Turin). South Tyrolian villages did badly in terms of technical efficiency, this being mainly due to their peculiar environmental situation. Finally, the only Southern MUNI in our sample (Trani, from the Adriatic region of Apulia) slightly outscored its ENEL counterpart, and managed to join the first group - the one including all DMUs which were found to outperform the 'average' firm - thus demonstrating that municipal firms in the South should not necessarily do worse than ENEL's zones serving the same territories. However, given that Trani was the only Southern MUNI in the sample, such

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[30] 'Peer' is the standard word used in the DEA literature, meaning that every decision-making unit is being compared to one or more 'equivalent' firms in the current sample.

[31] Lombardy is the most populated region in Italy, distributing around 40 TWh (1 TWh = 1,000 GWh) of energy out of 165 TWh being globally absorbed every year by Italy's electricity customers.

a conclusion cannot be generalised, since statistical inference in such a situation is obviously impossible to make.

Regarding the metropolitan dominance of ENEL zones upon local MUNIs, and - more generally - all the above results, it is worth recalling that stochastic frontier methods constrain all DMUs to have the same technology, for which a specific functional form (more or less generalisable, e.g. a translog) is devised. This might turn out to be an incorrect assumption each time structurally different DMUs are examined. For instance, ENEL zones might have different distributing technologies from local MUNIs. If a non-parametric approach - which does not constrain technology within any specific functional form, and computes efficiency scores rather than estimating them - is to be used, this will be the case for Data Envelopment Analysis (DEA)[32].

To conclude, a number of caveats must be mentioned with special reference to the stochastic frontier analysis being carried out in Chapter 4. They are quickly listed below:

(*a*) when pooling the two sub-samples (37, 39), we used two cross-sections from different years (1994, 1996). Even though we had no monetary values, technical progress might have influenced the MUNIs' efficiency performance over the time interval 1994-1996. We ran a separate regression on a time series for MUNIs (1987-1994), and discovered that the time trend's coefficient was not significantly different from zero. We then extrapolated no significant technical progress from 1994 to 1996, too, in the absence of any relevant exogenous shocks over that period. However, the imperfect 1994-1996 pooling still remains a drawback of the current analysis;

[32] See next Chapter.

(*b*) since ENEL and MUNIs serve different zones, even face-to-face matching of MUNIs and their peers suffers from (partial) lack of comparability. When MUNIs and ENEL zones are found serving the 'same' town (e.g., Milan), it should be always kept in mind that MUNIs are generally allowed to deliver electricity within city centres, with their ENEL 'peer' (e.g., ENEL Milan) serving the outskirts and peripheral industrial districts. Since metropolitan areas generally feature industrial zones in their outskirts, ENEL's units will be more likely to serve the vast majority of metropolitan industrial consumers. On the contrary, medium-sized industrial towns have their MUNIs serving both domestic and industrial demand, which is generally located not far from city centres. Such a difference between metropolitan zones and urban areas might explain why ENEL systematically outperformed MUNIs in Rome, Milan, and Turin, whereas the majority of medium-sized towns in Lombardy were served with relative success by their own municipal utilities. The concept gets clearer if one considers that AEM, the Milanese MUNI, does not serve the large industrial area surrounding Milan (which is operated by ENEL), whereas Parma, Trieste, Vercelli, Cremona, Sondrio, and so on, are wholly served by MUNIs - which are also in charge of electricity distribution to outskirts and industrial estates;

(*c*) as regards ENEL 'peers', we tried to stick to objectivity in choosing the closest proxies for given MUNIs (surrounding zones, neighbouring units), so as to make the pooled analysis as realistic and plausible as it could be, given the constraints outlined sub point (*b*);

(*d*) the main suggestion stemming from the above discussion is that the ENEL vs. MUNIs dispute can be hardly generalised. As shown by the comparative analysis, ENEL zones won in some cases, whereas MUNIs outscored ENEL in others. Apart from comparability problems, we found that MUNIs did better in medium-sized towns, in Lombardy, and (sometimes) in the mountains, whereas ENEL won in metropolitan areas. Furthermore, no inference about

Southern trends could be made, because only one unit in our sample was from the South of Italy. Given that generalisation is not possible, no one can say whether ENEL's zones are right in asking for mergers with MUNIs on microeconomic efficiency grounds. In some cases, it appears that a better policy-making choice would be to allow MUNIs to expand beyond municipal borders, at the expense of ENEL. The returns to scale results pointed out that only slight increasing RTS (weakly > 1) were found for the average firm in the sample. However, average values are of limited utility. Firm-specific statistics will finally be obtained in Chapter 5, thanks to the disaggregation provided by DEA. Let alone RTS results, all merger proposals between ENEL zones and MUNIs should be appraised by looking at the fact that MUNIs are very heterogeneous as regards efficiency levels. Therefore, ENEL might not be wrong when claiming higher efficiency in some contexts, but MUNIs could be right as well when pointing out that they are sometimes more efficient than ENEL itself (in technical terms). What must be said in the end is that, according to the mixed outcomes resulting from the present analysis, the ENEL/MUNI dispute should be sorted out on a strict case-by-case basis, because generalisation is by no means feasible.

The Chapter concludes by considering that at least part of the above-mentioned caveats might be overcome thanks to the use of a different, non-econometric technique. Data Envelopment Analysis (DEA) originates from the classic productive efficiency literature[33] and adopts linear programming as its main computing tool. First proposed in the late Seventies, DEA is now widely used in efficiency measurement by both Management Science (MS) and Industrial Organisation (IO) researchers. Its non-econometric nature - while giving rise to a new set of drawbacks - is however capable of improving upon some aspects of stochastic

[33] Koopmans (1951), Farrell (1957).

frontier estimation, and stimulates the investigator to cross-check the two methodologies[34]. A 'ceteris paribus' (same data set) methodological cross-check will be performed in Chapter 5.

[34] Pollitt (1993).

CHAPTER 5

EFFICIENCY ANALYSIS OF ELECTRICITY DISTRIBUTION IN ITALY: A NON-PARAMETRIC APPROACH

1. Introduction

This Chapter is concerned with technical efficiency analysis of Italy's local electricity distributors (both ENEL and municipally-owned). Data Envelopment Analysis (DEA) will be used in order to obtain relative efficiency outcomes and compare efficiency scores with the previous econometric results (Chapters 3 and 4), according to the 'methodological cross-checking' approach. Rank-order (non-parametric) tests will be used in order to test statistical agreement among different efficiency series. Relative - not absolute - efficiency will obviously be considered. The efficiency analysis will deal with both ENEL zones and MUNIs. Moreover, ENEL/MUNI comparisons will be made thanks to a pooled cross-sectional sample, so as to provide a non-parametric alternative to the stochastic production frontier analysis carried out in Chapter 4.

The Chapter is organised as follows. Section 2 is a comprehensive overview of Koopmans-Farrell efficiency measurement, and DEA. Section 3 is a brief literature survey of DEA in both public utilities and other enterprises. Section 3.1 offers a comparison between DEA and Stochastic Frontier Estimation. Section 4/4.1 provides a variable returns to scale (VRS), input/output-oriented DEA optimisation investigating microeconomic efficiency of 147 ENEL local zones (business year 1996, same data set as in Chapters 2 and 3). Section 4.2 is a

VRS DEA of 37 municipal utilities for 1994 (same data set as in Chapter 4). Section 4.3 analyses a pooled sample of 37 MUNIs and 39 ENEL's 'peers', thus establishing a transparent connection with Chapter 4's comparative analysis. Section 4.4 is a supplementary ENEL-MUNI (DEA-only) analysis.

All the above Sections also implement methodological cross-checking by comparing econometric (stochastic frontier) outcomes with non-parametric (OR/DEA) results. Section 5 tries to quantify the 'cost' of ENEL's technical inefficiency in monetary terms, whereas Section 6 proposes a supplementary analysis of frontier-efficient units thanks to the 'peer count' approach. Finally, Section 7 concludes and paves the way to Chapter 6, which outlines future research strands.

2. Microeconomic Efficiency Measurement and DEA: a Theoretical Summary

This Section outlines a number of commonly used efficiency measures and discusses how they may be calculated relative to an efficient technology, which is generally represented by some frontier function. Frontiers have been estimated using many different techniques over the past forty years. The two principal methods[1] are the following:

(*a*) Stochastic Frontier Estimation (SFE), which was used in Chapters 3 and 4;

(*b*) Data Envelopment Analysis (DEA), which is the focus of this Chapter.

The two methodologies involve econometric and mathematical programming methods, respectively. The discussion in this Section provides a brief introduction to modern efficiency

[1] See Pollitt (1995).

measurement. A more detailed treatment is provided by Fare, Grosskopf, and Lovell (1985, 1994), and Fried, Lovell, and Schmidt (1993). An interesting overview of DEA is in Seiford and Thrall (1990), whereas the two basic DEA models being developed in the late Seventies and early Eighties - to which most applied papers still refer - are those by Charnes, Cooper, and Rhodes (1978) for constant returns to scale (CRS) DEA, and by Banker, Charnes, and Cooper (1982, 1984) for variable returns to scale (VRS) DEA. A new perspective on DEA in principal-agent theory terms has recently been provided by Bogetoft (1994).

Modern efficiency measurement begins with Farrell (1957), who drew upon the work of Debreu (1951) and Koopmans (1951), to define a simple measure of firm efficiency which could account for multiple inputs, and easily generalise to multiple outputs. He claimed that the efficiency of a firm consists of two components:

(*a*) technical efficiency, which reflects the ability of a firm to obtain maximal output from a given set of inputs, and

(*b*) input-allocative efficiency, which reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices.

These two measures are then combined to provide a measure of total economic efficiency[2]. The following discussion begins with Farrell's original ideas, which were illustrated by the author in input-input space and hence had an input-saving focus (i.e., they assumed that firms should minimise input usage for a given set of outputs). These are usually termed input-orientated measures, as opposed to output-maximising (or output-orientated) ones, which assume that firms maximise output(s) for a given set of inputs.

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[2] Some of Farrell's terminology differed from the current one. He used the term *price efficiency* instead of 'input-allocative' efficiency, and the term *overall efficiency* instead of 'economic' efficiency.

Farrell (1957) illustrated his ideas by using a simple example involving firms which utilise two inputs (to make up the input vector, **X**) to produce a single output (**Y**), under the assumption of constant returns to scale (CRS)[3]. Knowledge of the unit isoquant of the fully efficient firm[4], represented by SS' in Figure 1, permits the measurement of technical efficiency. If a given firm uses quantities of inputs, defined by point P, to produce a unit of output, technical inefficiency for that firm is represented by the distance QP, i.e. the amount by which all inputs could be proportionally reduced without a reduction in output. This is usually expressed by the ratio QP/OP, which represents the percentage by which all inputs could be reduced. The technical efficiency level (TE) of a firm is most commonly measured by the ratio

$$TE_i = OQ/OP, \qquad (1)$$

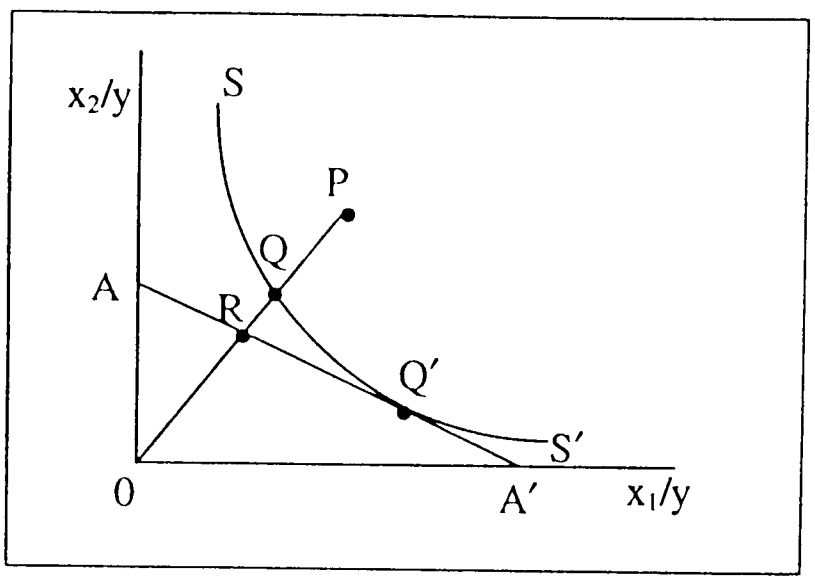
which is equal to one minus QP/OP. It will take a value between zero and one, and hence provides an indicator of the degree of technical (in)efficiency of the firm. A value of one indicates that the firm is fully technically efficient. For example, point Q is technically efficient because it lies on the efficient unit isoquant.

[3] The CRS assumption simplifies the analysis by allowing the use of unit isoquants. Furthermore, Farrell also discussed the extension of his method so as to accommodate more than two inputs, multiple outputs, and non-constant returns to scale.

[4] The production function of the fully efficient firm is not known in practice, and thus must be estimated from observations on a sample of firms in the industry concerned. In this Chapter, DEA is utilised to estimate the efficient production, or 'best-practice', frontier.

Figure 1

Technical and Allocative Efficiencies



Source: Coelli (1996b).

If the input price ratio, represented by the line AA' in Figure 1, is also known, allocative efficiency may also be calculated. The allocative efficiency level (AE) of the firm[5] operating at point P is defined by the ratio

$$AE_i = OR/OQ, \qquad (2)$$

since the distance RQ represents the reduction in production costs that would occur if production were to take place at the allocatively (and technically) efficient point Q', instead of

[5] More generally, data points are for 'decision-making units' (DMUs), which can also be branches of a single company.

the technically efficient, but allocatively inefficient, point Q[6]. To sum up, the total economic efficiency level (EE) for the *i*-th decision-making unit will be defined as

$$EE_i = OR/OP, \tag{3}$$

where the distance RP can also be interpreted in terms of a cost reduction. Notice that the product of technical and allocative efficiency provides the overall economic efficiency level (multiplicatively separable), which is also known as 'Farrell efficiency':

$$TE_i \cdot AE_i = \frac{OQ}{OP} \cdot \frac{OR}{OQ} = \frac{OR}{OP} \equiv EE_i. \tag{4}$$

Notice that all measures are bounded by zero and one, and that overall (Farrell) efficiency has the nice property of multiplicative separability into input-allocative and technical efficiencies. Separability may also be exploited in order to decompose technical efficiency into scale, congestion, and 'purely technical' efficiency, as in Fare et al. (1985). These efficiency measures assume that the production function of the fully efficient, or 'best-practice', firm is known. However, this is rarely the case, so that the best-practice unit isoquant must be estimated from sample data. Farrell suggested the use of either

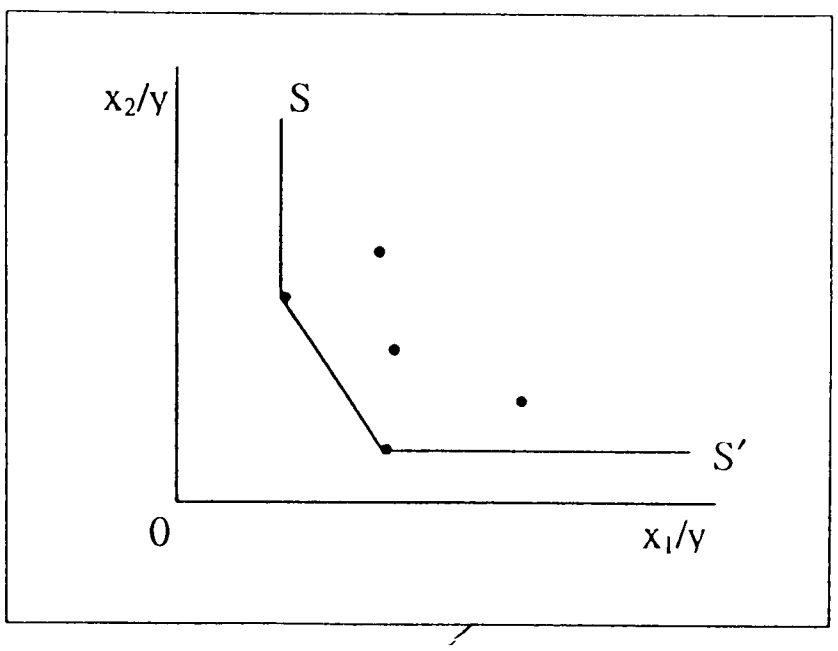
(*a*) a non-parametric piecewise-linear convex isoquant constructed such that no observed point should lie to the left or below it (refer to Figure 2), or

[6] One could illustrate this by drawing two isocost lines through Q and Q'. Irrespective of the slope of these two parallel lines (which is determined by the input price ratio, or relative price), the ratio RQ/OQ would represent the percentage reduction in costs associated with movement from Q to Q'.

(*b*) a parametric function, such as the Cobb-Douglas, CES, generalised Leontief (Diewert), or translog[7] forms being fitted to the data, again such that no observed point should lie to the left or below it.

Figure 2

Piecewise Linear Convex Isoquant



Source: Coelli (1996b).

Farrell provided an illustration of his methods using agricultural data for the 48 continental states of the US. The radial nature of Farrell's geometric efficiency measure makes it particularly appealing, given its multiplicative separability property. However, radial measures do encounter consistency problems whenever input reduction has to be measured along segments which are parallel to one of the axes. In those cases, 'input slacks' are found, and alternative, non-radial efficiency measures should be used[8].

---

[7] Translog functional forms were first introduced by Christensen, Jorgenson, and Lau (1971, 1973). Using Monte Carlo simulations, Guilkey, Lovell, and Sickles (1983) compare three flexible functional forms translog, generalised Leontief (Diewert), and generalised Cobb-Douglas - and conclude that the translog form performs at least as well as the other two and "[...] provides a dependable approximation to reality, provided that reality is not too complex" (IER, page 614).

[8] See Fare et al. (1985, 1994) on the 'Russell' measure of microeconomic efficiency.

If one wishes to know by how much output quantities can be proportionally expanded without altering the input quantities being used, then an 'output-orientated' measure must be introduced. The difference between the output and input-orientated measures can be illustrated by using a simple example involving one input and one output. This is depicted in Figure 3a, where we have a decreasing returns to scale technology represented by $f(x)$, and an inefficient firm operating at point P. The Farrell input-orientated measure of TE is AB/AP, while the output-oriented measure of TE is CP/CD. The output and input-oriented measures will only provide equivalent technical efficiency values when constant returns to scale (CRS) are assumed, but will be unequal when either increasing or decreasing returns to scale are encountered[9].

The case where production involves two outputs (making up the output vector **Y**), a single input (say, x), and constant returns to scale is depicted in Figure 4, where the line ZZ' is the unit production possibility curve, and point A corresponds to an inefficient DMU. Notice that the inefficient point (A) lies below the curve in this case, because ZZ' represents the upper bound of production possibilities.

[9] Fare and Lovell (1978).

Figure 3

Input- and Output-Orientated Technical Efficiency Measures and Returns to Scale

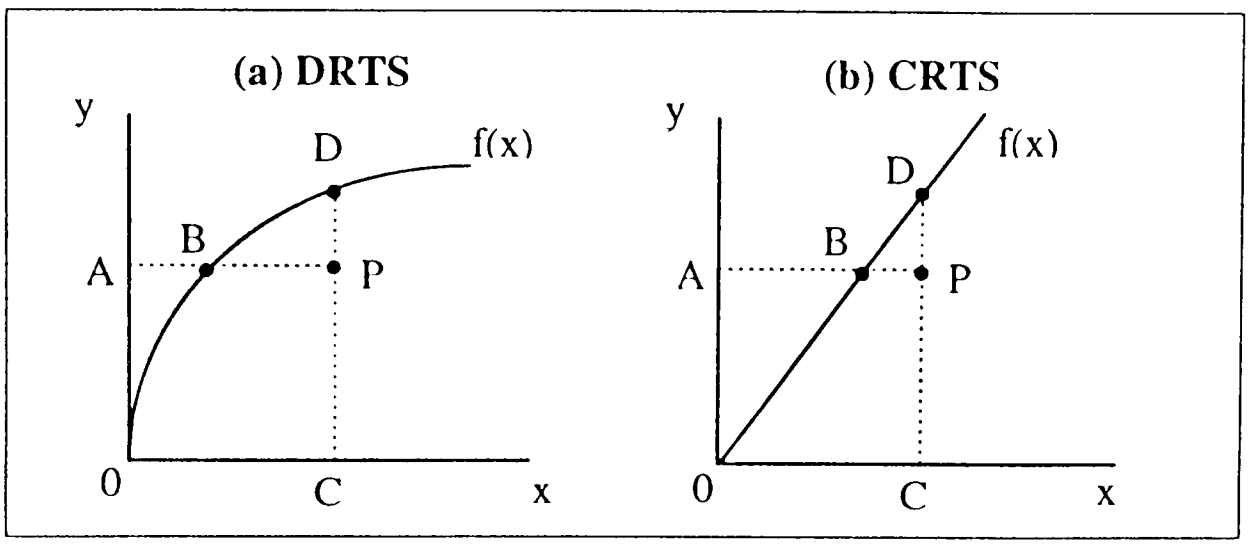
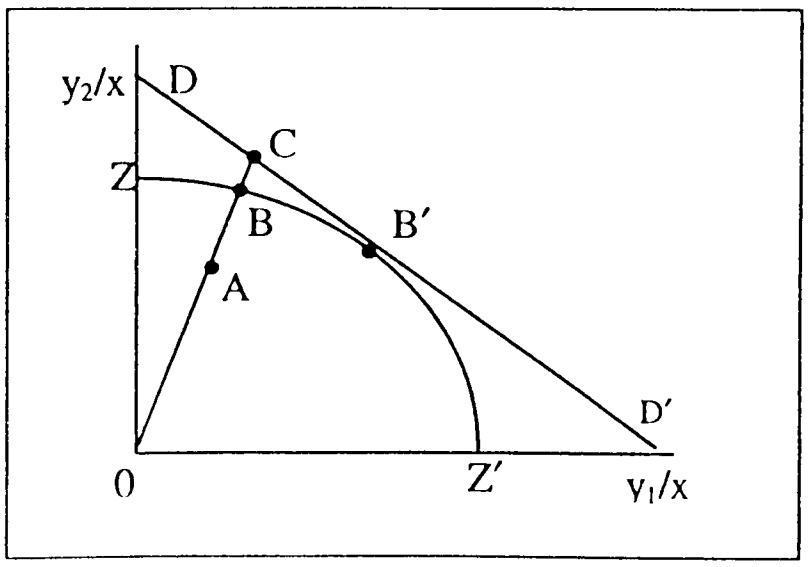


Figure 4

Technical and Allocative Efficiencies from an Output Orientation



Source: Coelli (1996b).

The Farrell output-oriented efficiency measures are defined as follows. In Figure 4 above, the AB distance represents technical inefficiency (that is, the amount by which outputs could be increased without requiring extra inputs). Hence, a measure of output-oriented technical efficiency will be the following ratio:

$$\text{TE } (\textit{output}) = \text{OA/OB}. \tag{5}$$

If we have price information, then we can draw the isorevenue line DD', and define allocative efficiency to be equal to

$$\text{AE } (\textit{output}) = \text{OB/OC}. \tag{6}$$

Output-oriented allocative efficiency (AE) has now a revenue-increasing interpretation, which is similar to the cost-reducing interpretation of allocative inefficiency in the input-oriented case. Furthermore, one may define overall output-oriented economic efficiency as the product of TE and AE (again, notice multiplicative separability), that is

$$EE_{output} = \frac{OA}{OC} = \frac{OA}{OB} \cdot \frac{OB}{OC} = TE_{output} \cdot AE_{output}. \tag{7}$$

Again, all of these three measures are bounded by zero and one. Before we jump to more detailed decompositions of technical efficiency[10] and to the theoretical treatment of DEA[11], two quick points should be made regarding the six efficiency measures which were previously defined:

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[10] See Fare et al. (1985).

(*a*) all the above efficiency measures are computed along a ray from the origin of axes to the observed production point. Hence, they hold the relative proportions of inputs (or outputs) constant. One advantage of these radial efficiency measures is that they are invariant to the choice of measurement units. A non-radial measure, such as the shortest distance from the production point to the production surface, may be argued for, but this measure will not be invariant to the units of measurement being chosen. Changing the units of measurement in this case could result in the identification of a different 'nearest' point. This issue will be tackled when we come to consider the treatment of 'input slacks' (or 'excesses') in DEA;

(*b*) the Farrell input and output-oriented technical efficiency measures may be shown to be equal to the input and output distance functions discussed in Shephard[12] (1970). This observation becomes important when one considers the use of DEA methods in calculating Malmquist indices of Total Factor Productivity (TFP) change[13].

Fare, Grosskopf, and Logan (1983) analysed the efficiency of a sample of Illinois electric utilities. They decomposed global economic efficiency (EE) into three further measures:

$$EE = AE \cdot TE = AE \cdot (SE \cdot CE \cdot PTE), \tag{8}$$

where AE = input-allocative efficiency, SE = scale efficiency, CE = congestion efficiency, and PTE = purely technical efficiency. The calculation of these three measures is illustrated in Figure 5. Technical inefficiency is decomposed into three further multiplicative elements.

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[11] Charnes, Cooper, and Rhodes (1978) is the seminal paper.
[12] For more on this, see Lovell (1993).

Scale efficiency (*SE*) relates to the fact that the DMU might not operate at optimal scale. If one assumes that an 'ideal' unit isoquant for CRS may be drawn, then the radial distance between such isoquant and the 'real' (VRS) one will give a measure for 'scale inefficiency' - that is, inefficiency stemming from the firm operating on a non-flat region of the AC curve, where returns to scale are either increasing (IRS) or decreasing (DRS). Whereas scale efficiency assumes that the initial CRS assumption of Charnes, Cooper, and Rhodes (1978) is dropped, congestion efficiency (*CE*) may be computed provided that the assumption of strong (i.e., free) disposability of inputs is ignored by the linear program. This allows the unit isoquant to bend backwards, indicating that as the quantity of one input (say, *K*) is increased, the output produced falls. Finally, purely technical (in)efficiency (*PTE*) is residually defined as the measure of how much inefficiency is solely due to merely technical gap between the DMU under consideration and the best-practice DMU, or best-practice 'peer', to which the current unit is being compared. In other words, PTE is 'pure' inefficiency after that both scale (VRS/CRS) and congestion inefficiencies have been extracted from the global *TE* (technical efficiency) measure. All *SE*, *CE*, and *PTE* are bounded by zero and one, and multiplicatively recover the *TE* measure, so that *PTE* may be computed residually, after knowing *TE*, *CE*, and *SE*.

[13] Refer to Forsund and Kittelsen (1997) for Norwegian electricity distribution over the Eighties and Nineties. Burns and Weyman-Jones (1994b) provide an empirical application to regional electricity distributors in England and Wales.

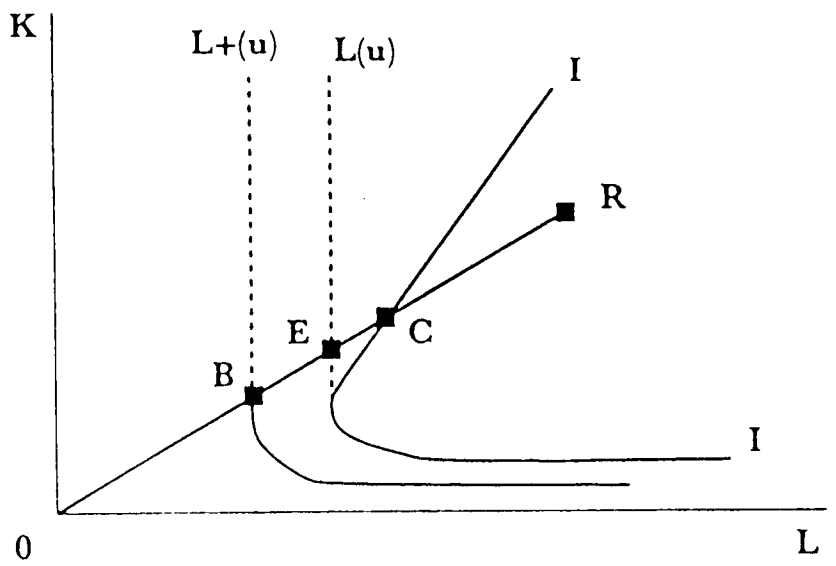


Figure 5: Purely Technical, Congestion, and Scale Measures of Technical Efficiency. *Source: Pollitt (1995).*

In Figure 5 - drawn in (K, L) space - the above efficiency measures are

$SE = OB/OE;\ CE = OE/OC;\ PTE = OC/OR$, so that (9)

$$TE = SE \cdot CE \cdot PTE = \frac{OB}{OE} \cdot \frac{OE}{OC} \cdot \frac{OC}{OR} = \frac{OB}{OR} \in (0,1]. \quad (10)$$

Whereas congestion inefficiency originates from the fact that **C** falls on a backward bending section of the **II** isoquant, so that inputs are congesting, scale inefficiency is due to the fact that, in the long run, DMUs in competitive equilibrium should be operating at a minimum of the U-shaped AC curve. Therefore, the DMU under examination in the short run might adjust its scale and produce its current output level with fewer inputs. The 'best-practice' unit isoquant **L+(u)**, where all efficient 'peers' are located, is the relevant isoquant

for comparison as it incorporates the twin, 'ideal' assumptions of strong (free) input disposability (leading to CE = 1) and constant returns to scale (leading to SE = 1). It is obvious that, under the above assumptions, both scale and congestion inefficiencies will disappear, thus making TE ≡ PTE, and EE = AE · PTE. The details of the linear programs required for the above three measures of technical efficiency (SE, CE, and PTE) are given in Fare et al. (1985, 1994), and Pollitt (1995). It is also possible to identify whether a DMU showing scale inefficiency is exhibiting constant, increasing, or decreasing returns to scale, and thus classify it as CRS, IRS, or DRS. Modern DEA computer packages are able to compute the above efficiency measures for each DMU in the sample, and also tell whether DMUs are operating on the decreasing (IRS), flat (CRS), or increasing (DRS) region of the U-shaped average cost curve.

Data Envelopment Analysis (DEA) is the non-parametric mathematical programming approach to frontier estimation. The discussion of DEA models being presented here is brief, with relatively little technical detail[14]. The piecewise linear convex hull approach to frontier estimation, proposed by Farrell (1957), was considered by only a handful of authors in the two decades following Farrell's paper. Authors such as Boles (1966) and Afriat (1972) suggested mathematical programming methods which could achieve the task, but their method did not receive wide attention until a paper by Charnes, Cooper, and Rhodes (CCR, 1978) inserted Afriat's methodology within a standard operations research framework, and coined the term 'Data Envelopment Analysis' (DEA). Since then, there have been a large number of papers extending and applying the DEA methodology. CCR proposed a model which had an input orientation and assumed constant returns to scale (CRS). Subsequent papers have considered alternative sets of assumptions, such as Banker, Charnes, and Cooper (BCC,

1984), who proposed a variable returns to scale (VRS) model. The following discussion of DEA begins with a description of the input-oriented CRS model (CCR), because this model was the first one being widely applied to real-world data.

The CCR (CRS) model will be introduced by first defining some notation. Assume that there is data on K inputs and M outputs for each of N firms (or DMUs, as they are often called in the DEA literature[15]). For the i-th DMU, these are represented by the vectors $\mathbf{x}_i$ and $\mathbf{y}_i$, respectively. The $K \times N$ input matrix, $\mathbf{X}$, and the $M \times N$ output matrix, $\mathbf{Y}$, represent the data of all N DMUs. The purpose of DEA is to construct a non-parametric envelopment frontier over the data points, such that all observed points lie either on or below the production frontier. For the simple example of an industry where one output is produced using two inputs, it can be visualised as a number of intersecting planes forming a tight fitting cover over a scatter of points within a three-dimensional space. Given the CRS assumption by CCR (1978), this can also be represented by a unit isoquant in input/input space (refer to Figure 2). The best way to introduce DEA's linear programs - which, incidentally, are numerically solved by means of Dantzig's (1963) 'simplex' method - is via the 'ratio' form. For each DMU, we aim at obtaining a measure of the ratio of all outputs over all inputs, such as $\mathbf{u'y/v'x}$, where $\mathbf{u}$ is an $M \times 1$ vector of output weights, and $\mathbf{v}$ is a $K \times 1$ vector of input weights. In order to select 'optimal' weights, we specify the following mathematical programming problem:

---

[14] More detailed reviews of the methodology are presented by Seiford and Thrall (1990), Lovell (1993), Ali and Seiford (1993), Lovell (1994), Charnes et al. (1994, 1995), Pollitt (1993, 1995), and Seiford (1996). Theoretical perspectives on DEA are also outlined, within a principal-agent relationship, by Bogetoft (1994).

[15] DMU, or 'decision-making unit', is a more appropriate term than 'firm' when, for example, a bank is studying the performance of its branches, an education district is examining the performance of its schools, or an electricity firm is analysing the relative efficiency of its distributing units (after allowing for 'environmental' variables: see Lovell, 1993).

$$\max_{\mathbf{u},\mathbf{v}} (\mathbf{u}'\mathbf{y}_i / \mathbf{v}'\mathbf{x}_i), \text{ subject to}$$
$$\mathbf{u}'\mathbf{y}_j / \mathbf{v}'\mathbf{x}_j \leq \mathbf{1}, \quad j = 1,2,3,\ldots,N, \quad \text{and} \tag{11}$$
$$\mathbf{u}, \mathbf{v} \geq \mathbf{0}.$$

This involves finding values for **u** and **v**, such that the efficiency measure for the *i*-th DMU is maximised, subject to the constraint that all efficiency measures must be less than or equal to one (efficiency score normalisation to **(0,1]**). One problem with this particular ratio formulation is that it has an infinite number of solutions. This is because if (**u***, **v***) is a solution, then all proportional vectors (α**u***, α**v***) will be solutions, with $\alpha \in \Re^{\oplus}$. To avoid this, one may impose the multiplying constraint **v'x** = **1** on the CRS linear program (CCR, 1978), so as to obtain the following form:

$$\max_{\mu,\nu} (\mu'\mathbf{y}_i), \quad \text{subject to}$$
$$\nu'\mathbf{x}_i = \mathbf{1},$$
$$\mu'\mathbf{y}_j - \nu'\mathbf{x}_j \leq \mathbf{0}, \quad j = 1,2,3,\ldots,N, \quad \text{and} \tag{12}$$
$$\mu, \nu \geq \mathbf{0},$$

where the notation change from **u** and **v** to μ and ν reflects the transformation. This form is known as the 'multiplier' form of the linear programming problem. Using duality in linear programming, one can derive an equivalent 'envelopment' form of this problem, which is given by the following expressions:

$$\min_{\theta,\lambda} \theta, \quad \text{subject to}$$
$$-\mathbf{y}_i + \mathbf{Y}\lambda \geq \mathbf{0},$$
$$\theta\mathbf{x}_i - \mathbf{X}\lambda \geq \mathbf{0}, \tag{13}$$
$$\lambda \geq \mathbf{0}, \quad \text{and}$$
$$\sum \mathbf{y}_i = \mathbf{Y}; \quad \sum \mathbf{x}_i = \mathbf{X}.$$

With respect to the above minimisation problem (a dual one), θ is a scalar (a radial, composite distance function) and λ is a $N \times 1$ vector of constants (weights). This envelopment form involves fewer constraints than the multiplier form, as $K+M < N+1$, and hence is the preferred form to solve. The forms defined by the multiplier problem (the 'primal' one) were introduced here for expository purposes only. They will not be used again in the remainder of this Section. The multiplier form has, however, been estimated in a number of studies. The μ and ν weights can also be interpreted as normalised shadow prices.

Turning to the envelopment problem, the value of θ being obtained from the minimisation process will be the efficiency score (*EFF*) for the *i*-th decision-making unit, and will be bounded by zero and one. Geometrically, it will be a hyperspatial distance function of the Farrell type, measuring the distance between the examined DMU and its peer(s) on the efficient, or 'best-practice', isoquant. Efficient-frontier benchmarks are computed by DEA itself, being made up of those DMUs for which is $EFF \equiv 1$. Efficiency scores might be either input or output-orientated (see the discussion above). As Burns and Weyman-Jones (1994b) notice, model orientation is not particularly relevant - as efficiency outcomes will be exactly the same for CRS DEA, and very similar for VRS DEA - whereas the choice of outputs and inputs is generally crucial for obtaining plausible results[16]. The obtained minimised value (θ) is a relative efficiency score (in the sense of Farrell), and will then satisfy $\theta \leq 1$, with a value of 1 indicating a point on the efficient frontier (the 'best-practice' unit isoquant) and hence a technically efficient DMU, according to the Farrell definition[17]. Notice that the linear programming problem must be solved *N* times, once for each DMU in the sample. A specific value of $EFF = \theta$ is then obtained for each DMU.

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[16] See Section 4.

The piecewise linear form of the non-parametric frontier in DEA can cause a few difficulties in efficiency measurement. Problems arise because of the sections of the piecewise linear frontier which run parallel to the axes (refer to Figure 2): this does not occur in most parametric functions (look at Figure 1). To illustrate this, consider Figure 6, where the DMUs using input combinations C and D are the two efficient DMUs which define the best-practice frontier, whereas DMUs A and B are relatively inefficient (when compared to C and D). The Farrell (1957) measure of technical efficiency gives the efficiency of DMUs A and B as OA'/OA and OB'/OB, respectively. However, it is questionable as to whether point A' is really an efficient point, since one could reduce the amount of input x_2 being used (by the amount CA'), and still produce the same output. This is known as 'input slack', or 'input excess', in the literature. When one considers a case involving more inputs and/or multiple outputs, the diagrams will no longer be as simple, and the possibility of the related concept of 'output slack' also occurs. Thus, it could be argued that both the Farrell measure of technical efficiency (that is, θ) and any non-zero input or output slacks should be reported, so as to provide a comprehensive and accurate indication of technical efficiency for each DMU in the DEA run[18]. Notice that, for the *i*-th DMU, output slacks will be equal to zero only if

$$\begin{aligned} &\mathbf{Y}\lambda - \mathbf{y}_i = \mathbf{0}, \text{ while input slacks will equal zero only if} \\ &\theta\mathbf{x}_i - \mathbf{X}\lambda = \mathbf{0} \quad \text{(for the given optimal values of } \theta \text{ and } \lambda\text{).} \end{aligned} \tag{14}$$

---

[17] The 'Koopmans' definition is more stringent.

[18] As noticed earlier, Koopmans's (1951) definition of technical efficiency was stricter than Farrell's (1957) definition. The former is equivalent to stating that a firm is only technically efficient if it operates on the frontier and if - simultaneously - all associated non-radial slacks (excesses) equal zero. The 'Russell' efficiency measure incorporates Koopmans slacks (i.e., non-radial contractions towards efficiency) and is therefore a non-radial, units-dependent measure.

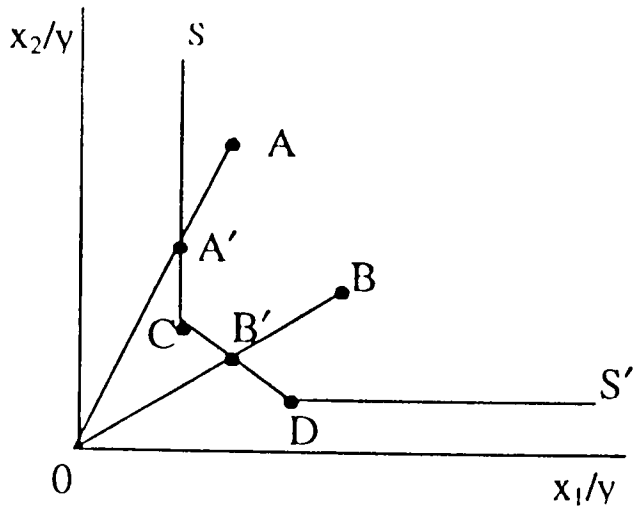


Figure 6

Efficiency Measurement and Input Slacks

Source: Coelli (1996b).

In Figure 6, the input slack associated with point A' is CA' (for input 2). In those cases which feature more inputs and outputs - so that more than three dimensions are involved - the identification of the 'nearest' efficient frontier point (such as C), and hence the subsequent calculation of slacks, is not a trivial task. Some authors[19] have suggested the solution of a second-stage linear programming problem, so as to shift to an efficient frontier point by *maximising* the sum of slacks required to move from an inefficient point to a 'best-practice' one. However, there are two major problems associated with this second-stage linear program. The first, and most obvious, problem is that the sum of slacks is maximised rather than minimised: hence, it will identify nót the nearest efficient point, but the *farthest* efficient point. The second major problem associated with the above, second-stage approach is that it is not invariant to units of measurement. Charnes, Cooper, Rousseau, and Semple (1987) suggested a unit-invariant model, which introduced an arbitrary weighting procedure for the input/output slacks.

As a result of the above problem, many studies simply solve the first-stage linear program for the values of Farrell's radial technical efficiency measures (θ), and ignore slacks completely. Other studies report both the Farrell radial technical efficiency scores and the residual slacks, which may be calculated as non-zero vector algebraic sums as in the above **Y**, **X** formulas. However, this approach is not without problems, either because these residual slacks may not always provide all (Koopmans) slacks, or because they may not always

identify the nearest (Koopmans) efficient point for each DMU. Computer packages (Warwick DEA, DEAP) generally give the user three choices regarding the treatment of slacks:

(*a*) one-stage DEA, in which the main linear program is solved, with I/O slacks being calculated residually;

(*b*) two-stage DEA, where two linear programs are run, with slacks being calculated numerically, and independently of the θs;

(*c*) multi-stage DEA, where a sequence of radial linear programmes is solved, in order to identify the efficient 'projected' point on the best-practice isoquant.

The multi-stage DEA method is more computationally demanding than the other two options[20]. However, the benefits of the approach sub (*c*) are that it identifies those efficient projected points whose input and output mixes are as similar as possible to those of the inefficient points[21]; moreover, multi-stage DEA is also units-invariant. To conclude on slacks, it must be noted that, if an infinite sample size were available, and/or an alternative frontier construction method were used - so as to involve a smooth function surface - the slack issue would vanish completely, as we would not have any frontier regions to be parallel to any of the axes. In addition to this observation, it also seems quite reasonable to accept the argument of Ferrier and Lovell (1990), according to whom slacks may essentially be viewed as allocative inefficiency, resulting from the DMU failing to choose its optimal input mix, given input relative prices. Therefore, analyses of technical efficiency can reasonably concentrate upon the radial efficiency scores provided in first-stage DEA (one linear program only for

---

[19] See Ali and Seiford (1993).
[20] Coelli (1997).
[21] Efficient projected points are input/output linear combinations of 'peers', or 'reference DMUs'.

each DMU), whereas if one is looking for allocative efficiency, too, and for Koopmans-efficient projected points, then it would be the case for either two-stage or multi-stage DEA.

As regards some simple examples of both constant returns to scale (CRS) and variable returns to scale (VRS) DEA, the interested reader is referred to Ali and Seiford (1993), and Coelli (1996b). On CRS DEA, it must be said that the CRS assumption is only appropriate when all DMUs in the sample are operating at an optimal scale (i.e. MES, the one corresponding to the flat portion of the long-run Average Cost curve). Imperfect competition, constraints on finance, etc., may cause a DMU to be not operating at optimal scale. Banker, Charnes, and Cooper (BCC, 1984) suggested an extension of the CRS DEA model, in order to account for variable returns to scale (VRS). The use of the CRS specification when not all DMUs are operating at optimal scale will result in technical efficiency measures being 'jammed' by scale effects. On the contrary, the use of VRS DEA (as in BCC) will permit the calculation of technical efficiency scores which are multiplicatively separable according to 'purely technical' and 'scale' (CRS vs. VRS) components. Moreover, congestion inefficiency might also be allowed for. Formally, the CRS linear programming problem may be easily modified - in order to accommodate VRS - by adding a 'convexity constraint', which turns the linear production hull into a 'convex hull' featuring non-constant returns to scale. With the convexity constraint imposed, the VRS DEA linear program runs as follows:

$$
\begin{aligned}
&\min_{\theta,\lambda} \theta, \quad \text{subject to} \\
&-\mathbf{y}_i + \mathbf{Y}\lambda \geq \mathbf{0}, \\
&\theta\mathbf{x}_i - \mathbf{X}\lambda \geq \mathbf{0}, \\
&(\mathbf{N1})'\lambda = \mathbf{1}, \\
&\lambda \geq \mathbf{0},
\end{aligned}
\tag{15}
$$

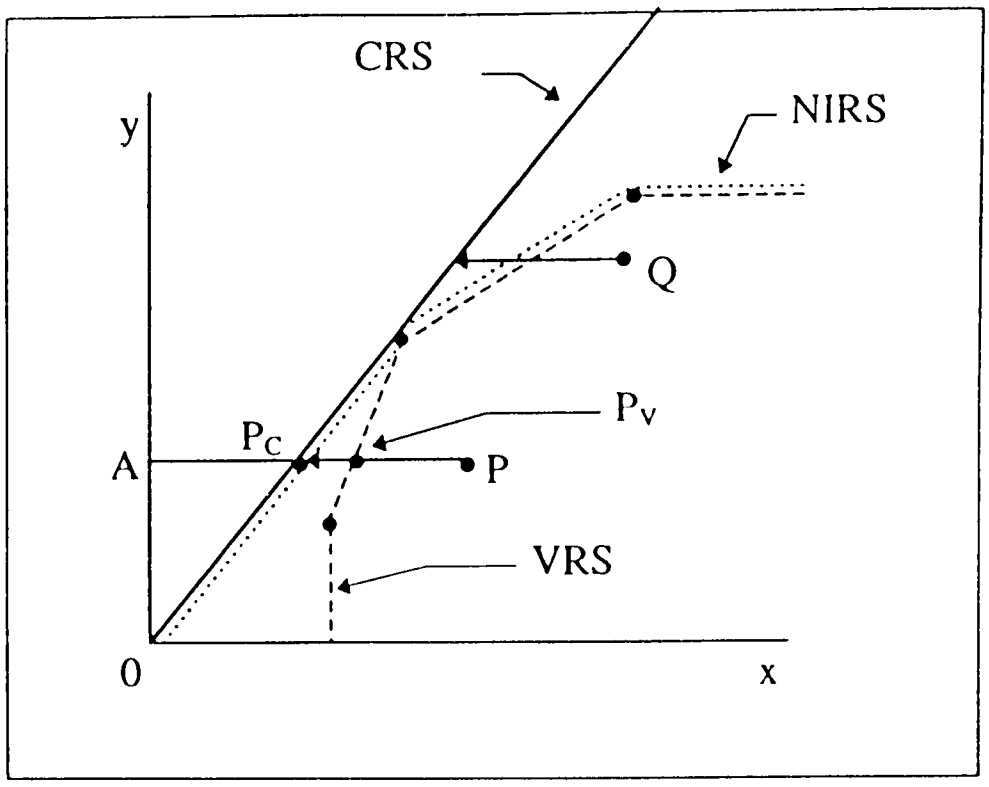
where **N1** is a $N \times 1$ vector of ones. This approach gives origin to a convex hull of intersecting (hyper)planes which, ceteris paribus, envelopes the data points more tightly than the CRS conical hull does, and thus provides technical efficiency scores which are greater than (or equal to) those obtained via the CRS model. The 'tighter envelope' property will then deliver (ceteris paribus) a higher number of 'best-practice' DMUs, which would have been excluded from the CRS DEA conical hull (see Figure 7 below, which clarifies the difference between the CRS conical hull, and the VRS convex hull). The VRS (BCC) specification has been the most commonly used DEA option in the recent literature (public utilities, non-profit organisations, branched enterprises, and so on). VRS DEA will be utilised in the present Chapter, too.

As mentioned earlier, many studies have decomposed the technical efficiency (TE) scores being obtained from CRS DEA into two elements, one due to scale inefficiency (SE) and one due to 'purely technical' inefficiency (PTE)[22]. This is practically implemented by conducting both a CRS and a VRS DEA simultaneously upon the same data set. If there is a difference in the two TE scores for a particular DMU, this will indicate that the DMU has scale inefficiency, and that the partial SE score ($SE \leq 1$) may be calculated from the (multiplicative) difference between the VRS TE score and the CRS TE score. Figure 7 below attempts to illustrate this.

[22] Fare, Grosskopf, and Lovell (1994).

Figure 7

Calculation of Scale Economies in DEA



Source: Coelli (1996b).

In Figure 7, we have a one-input, one-output example with both CRS and VRS DEA best-practice production frontiers. Under CRS, the input-oriented technical efficiency measure of point P is given by the horizontal distance PP_C, while under VRS technical efficiency would only be PP_V. The difference between these two, i.e. P_CP_V, is put down to scale inefficiency. One can also express the above ideas in ratio efficiency measures, as:

$$\begin{aligned} TE_{CRS} &= AP_C / AP; \\ TE_{VRS} &= AP_V / AP; \\ SE &= AP_C / AP_V . \end{aligned} \qquad (16)$$

Notice that all the above measures relate to input-oriented DEA. If one is considering relative efficiency within public utilities which are compelled to deliver a fixed amount of output while minimising their input usage, input-oriented DEA will be the right choice. On the contrary, if one assumes that output is endogenous whereas inputs are not (this might be the case with ENEL), then output-maximisation for a given amount of inputs should be sought, and hence output-oriented DEA ought to be chosen. However, even if VRS DEA is utilised, differences between the two orientations are generally negligible, whereas the choice of inputs, outputs, and environmental variables (in econometric terms, one would say 'model

specification') is the real cornerstone for successful DEA outcomes. Notice also that all of the above measures are, as usual, bounded by zero and one. We also note that

$$TE_{CRS} = TE_{VRS} \cdot SE, \quad \text{and that}$$
$$SE \leq 1 \Rightarrow TE_{VRS} \geq TE_{CRS}, \quad \text{meaning that VRS } EFFs \text{ are generally higher than CRS } EFFs. \tag{17}$$

The above result confirms that the VRS DEA convex hull envelops the data scatter more tightly than the CRS conical hull does, as Figure 7 above tries to show. In diagrammatic terms, the VRS/CRS relationship for the *TE* scores is justified by the fact that

$$\frac{AP_C}{AP} = \frac{AP_V}{AP} \cdot \frac{AP_C}{AP_V} = PTE \cdot SE = TE_{VRS} \cdot SE = TE_{CRS}. \qquad \text{[Fig. 7]} \tag{18}$$

That is, the CRS technical efficiency measure is decomposed into 'purely' technical efficiency (*PTE*) and scale efficiency (*SE*). A shortcoming of this measure of scale efficiency is that its value does not indicate whether the DMU is operating in an area of either increasing or decreasing returns to scale (IRS, DRS). However, this may be easily determined by instructing the computer to run an additional DEA linear problem with non-increasing returns to scale (NIRS) imposed. This can be done via the previous, VRS DEA model by substituting the convexity restriction with the looser *non-concavity* constraint, which determines the NIRS contour as a less tight data envelopment than the VRS one. This is because non-increasing returns to scale feature a region of constant returns (see Figure 7) and do not encompass all 'extreme' DMUs in the scatter, thus incorporating fewer best-practice units in the frontier than those encompassed by the VRS DEA contour, but more frontier DMUs than those embraced by the CRS DEA envelope. NIRS is then an intermediate contour between CRS and VRS

DEA, and provides - ceteris paribus - higher TE scores than CRS, but lower scores than VRS. The NIRS DEA linear program is an auxiliary optimisation of VRS DEA with the non-concavity constraint imposed, and runs as follows:

$$
\begin{aligned}
&\min_{\theta,\lambda} \theta, \quad \text{subject to} \\
&-\mathbf{y}_i + \mathbf{Y}\lambda \geq \mathbf{0}, \\
&\theta\mathbf{x}_i - \mathbf{X}\lambda \geq \mathbf{0}, \\
&(\mathbf{N1})'\lambda \leq \mathbf{1}, \\
&\lambda \geq \mathbf{0}.
\end{aligned} \tag{19}
$$

The NIRS DEA frontier is also plotted in Figure 7. The nature of scale inefficiencies (i.e., those stemming from the examined DMU working at either increasing or decreasing returns to scale on the *AC* curve) for a particular unit may then be determined by seeing whether the NIRS TE score is equal to the VRS TE score or not. If they are unequal - as is the case for point P in Figure 7 - then increasing returns to scale exist for that DMU, because the VRS frontier is closer to point P than the NIRS contour is, thus spotting that NIRS does not encompass P as well as VRS does. By a residual reasoning, if it is not the case for non-increasing returns to scale, *increasing* returns will be accepted. On the other hand, if NIRS TE and VRS TE scores are equal - as is the case for point Q in Figure 7 - this will mean that the NIRS and VRS contours coincide (i.e., they are the same efficient frontier), so that non-increasing returns *and* variable returns to scale simultaneously apply: that is, decreasing returns to scale apply. An example of this VRS/NIRS approach (now provided by almost all DEA computing packages) being adopted for the analysis of international air carriers is given by the Australian Bureau of Industry and Energy (BIE, 1994)[23].

[23] Some examples of VRS/NIRS DEA are also provided by Ali and Seiford (1993).

Regarding input and output orientations, it must be emphasised that, in the preceding input-oriented models, the methodology identified technical inefficiency as a proportional reduction in input usage (for a given output), in percentage terms. For example, TE = 89% meant that the DMU could have produced the same output(s) by using 11% fewer inputs. Input-oriented DEA is then also known as 'input-saving' DEA. Notice the clearer and straightforward interpretation of DEA efficiency scores, as opposed to stochastic frontier *EFFs*[24]. Input-oriented DEA directly stems from Farrell's (1957) input-based measure of technical inefficiency. However, as previously discussed, it is also possible to measure technical inefficiency as a proportional increase in output, for a given set of inputs. The two measures provide the same values under CRS, but become unequal when VRS is assumed. Given that linear programming cannot suffer from such statistical problems as simultaneous equation bias, the choice of an appropriate 'orientation' is not as crucial as it is in the econometric estimation case. In many studies, the analysts have tended to select input-orientated models because many DMUs have particular fixed (or regulated) schedules[25], hence input quantities appear to be the primary decision variables. Nevertheless, this argument may not be as strong in other industries.

It might be the case that, in some sectors, DMUs are given a fixed quantity of resources[26], and asked to produce as much output as possible. In this case, output-oriented DEA would be more appropriate. Essentially, one should select DEA's orientation according to which quantities (either inputs or outputs) the DMU's managers have most control over. However, in many instances one observes that the choice of orientation will have only minor influences

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[24] See Chapters 3 and 4.

[25] Consider, for instance, electricity generation as treated by Nerlove's (1963) seminal econometric paper.

[26] If they are publicly-owned and/or hold Demsetz-type (1968) franchises, DMUs will receive public subsidies on a regular basis, being ultimately financed by taxpayers.

upon the final efficiency scores being obtained[27], because the identification of which inputs and outputs should be included in the DEA frontier's construction is much more influential upon the final outcomes than either input or output orientation is.

Output orientation implies that technical efficiency scores will express output-maximisation possibilities for a given bundle of production factors. Therefore, scores will say by how much output might be increased for given inputs. For instance, output $TE = 1.21$ implies that the DMU under examination might have produced 21% more output out of its input endowment[28]. Of course, both input and output-oriented efficiency scores are worth one for those DMUs that are located on the efficient, or best-practice, frontier. From a mathematical programming point of view, output-oriented DEA models are very similar to their input-oriented counterparts. Consider the example of the following output-orientated VRS DEA problem:

$$
\begin{aligned}
&\max_{\phi,\lambda} \phi, \quad \text{subject to} \\
&-\phi \mathbf{y}_i + \mathbf{Y}\lambda \geq \mathbf{0}, \\
&\mathbf{x}_i - \mathbf{X}\lambda \geq \mathbf{0}, \\
&(\mathbf{N1})'\lambda = \mathbf{1}, \\
&\lambda \geq \mathbf{0}, \quad 1 \leq \phi < (+\infty).
\end{aligned}
\tag{20}
$$

Of course, $(\phi - 1) \geq 0$ will be the proportional increase in output(s) that could be achieved by the *i*-th DMU, with input quantities being held constant[29]. Notice that $1/\phi$ defines a TE score which varies between zero and one, so that (0,1] normalisation is easily achieved for subsequent comparison work, second-stage econometrics, and so on. A two-output example of an output-orientated DEA could be represented by a piecewise-linear production possibilities

[27] See Coelli and Perelman (1996).
[28] It must be noticed that, once again, DEA scores are more easily interpretable than stochastic-frontier *EFFs*.
[29] An output-oriented CRS model is defined in a similar way, but is not presented here for the sake of brevity.

curve, whose interpretation is analogous to that of the input-output DEA frontiers which were previously discussed. Output-orientated DEA is really a 'dual' representation of input-orientated DEA, unless VRS DEA is assumed. We shall not treat it in detail, as this would be a partial duplication of the above discussion. The interested reader is referred to Coelli (1996b), among others. The only point that should be stressed in any case is that the output and input-orientated models will estimate exactly the same frontier and therefore, by definition, will identify the same set of best-practice DMUs. Only the efficiency measures associated with the inefficient (i.e., off-frontier) DMUs may differ between the two methods, and - however - only when VRS DEA is utilised. Under CRS DEA, even relative (in)efficiency scores (the TEs) will provide the beholding investigator with exactly the same information for both input-orientated and output-orientated DEA.

3. DEA: A Brief Literature Survey

Seiford (1990) describes a brief history of DEA through its relevant literature. Surveys of DEA appeared in Charnes and Cooper (1985), and Seiford and Thrall (1990). Banker, Charnes, and Cooper (1984) first introduced VRS DEA. Discrete, or 'categorical', variables were treated by Banker and Morey (1986) within a study of fast-food outlets in the United States. 'Environmental' variables were introduced by the same authors[30], thus paving the way to the most advanced DEA specification, i.e. the one featuring both controllable and non-controllable (or non-discretionary) effects. To get beyond the piecewise-linear nature of DEA

[30] With reference to fast-food restaurants, environmental effects in Banker and Morey are: age of store, advertising expenditures allocated to store by headquarters, presence/absence of drive-in window, and location in urban versus rural areas.

best-practice frontiers, some researchers have also attempted to model non-linear segments along the frontier[31].

By its very nature, DEA is useful in evaluating relative efficiency across branched firms (hence, decision-making units - rather than 'firms' - make up data points in DEA samples). Therefore, it has been successfully applied to bank branches in several countries[32], to courts[33], education districts[34], hospitals[35], municipalities[36], post offices[37], refuse collection[38], and urban transport[39]. Among UK studies, it should be recalled that Thanassoulis, Dyson, and Foster (1987) analysed the efficiency of the rate collection function of metropolitan district councils. Norman and Stoker (1991) considered seven UK efficiency studies using DEA, including a comparison of the efficiency of UK water companies, plus analyses of a national building society (branched).

Obviously, DEA lends itself - within a Management Science (MS) perspective - to efficiency analysis of non-profit organisations, as it does not necessarily require input/output prices to be successfully computed. However, DEA's flexibility is such that every branched firm - or even groups of homogeneous firms - can be analysed. Public utilities provide a typical example of internally branched, comparable units whose relative efficiency might be evaluated by means of environmentally-corrected DEA programs. Private-sector decision-making units which were analysed by DEA include coal[40], water[41], farming[42], UK building societies[43], gas[44], and electricity[45].

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[31] See Charnes, Cooper, Seiford, and Stutz (1982).
[32] Parkan (1987); Tulkens and Vanden Eeckaut (1990); Berg, Forsund, and Jansen (1991).
[33] Jamar and Tulkens (1990); Forsund and Kittelsen (1992).
[34] Charnes, Cooper, and Rhodes (1981); Fare, Grosskopf, and Lovell (1989); Lovell, Walters, and Wood (1990).
[35] Banker, Das, and Datar (1989); Grosskopf and Valdmanis (1987).
[36] Vanden Eeckaut, Tulkens, and Jamar (1992); Charnes, Cooper, and Li (1989).
[37] Deprins (1983); Deprins, Simar, and Tulkens (1984); Tulkens (1986).
[38] Cubbin, Domberger, and Meadowcroft (1987); Burgat and Jeanrenaud (1990).
[39] Thiry and Tulkens (1992); Chang and Kao (1992).
[40] Byrnes et al. (1984, 1988).
[41] Byrnes (1985).

With special regard to the effects of ownership on performance, Alchian (1965) noticed that the basic difference between publicly and privately-owned utilities should be primarily identified with the high costs which public ownership imposes upon the transfer of property rights as opposed to private ownership. This happens because 'public' stockholders face no market for their 'shares' in the publicly-owned company, whereas private shareholders can much more easily trade their property rights. Alchian reckons that public stockholders may - as taxpayers - 'sell' their shares in public firms by moving out of their tax areas, but this seems to be a far-fetched way of justifying the existence of tradable rights with regard to publicly-owned firms. Over the same years, Leibenstein (1966) introduced the concept of 'X-inefficiency'. Furthermore, Leibenstein and Maital (1992) noticed that efficiency measures provided by DEA - with special reference to technical efficiency decomposition - are consistent with the notion of X-inefficiency, and can contribute to help the investigator when it comes to separate different components of X-inefficiency. With reference to public vs. private efficiency effects, it should be recalled that most public/private comparisons are conducted using regulated utility data, because public and private firms sometimes simultaneously compete in these industries (especially in the US), and because regulatory agencies have direct access to data. As regards public vs. private DEA/non-DEA efficiency comparisons, comprehensive surveys are provided by De Alessi (1980), Pestieau and Tulkens (1990), and by Pollitt (1995). The Pestieau-Tulkens article crucially notices that such comparisons should be narrowly based on the criterion of *technical* efficiency, which is the only objective being shared by both types of producers[46], and also the only objective which is

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[42] Grabowski and Pasurka (1988).
[43] Button and Weyman-Jones (1992).
[44] Price and Weyman-Jones (1993).
[45] Fare et al. (1983, 1989); Hausman and Neufeld (1991); Forsund and Kittelsen (1997); Burns and Weyman-Jones (1994b); Pollitt (1995); Kittelsen (1993, 1996).
[46] Assuming that public concerns do not go for X-inefficiency.

not in conflict with other goals of the public producer. For example, input-allocative efficiency in publicly-owned firms might be influenced by the fact that input mixes are often biased by political process factors (overmanning, short-run capital strategies, excessive third-party subcontracting, and so on). Moreover, our previous stochastic frontier analysis[47] postulated *ex ante* allocative efficiency, so that methodological cross-checking will take place on the basis of 'purely technical' efficiency (*PTE*) only.

When different DMUs are compared (e.g., publicly-owned versus privately-owned ones), environmental effects will be just part of the analytic framework. Apart from 'non-discretionary' variables, the methodology itself does make a difference within the analysis of several, non-homogeneous DMUs. As Lovell (1993, pg. 7) notices, "[...] If the question is whether producers in one category outperform producers in another category, then OLS with dummy variables will do just fine. However, dummy variable techniques categorise producers prior to estimation, and frontier techniques do not. Thus, frontier techniques can be more informative, since they can show which producers in one category outperform which producers in another category. Moreover, since the categories can be defined after estimation, they can be selected so as to maximise the performance differential, and thereby to refine the original hypothesised categorisation". Alternatively, dummy variable (econometric) techniques might be used in order to *ex post* 'explain' efficiency scores, e.g. within a Tobit-type estimation[48], as shown by Moroney and Lovell (1991), who used this technique in order to compare the performance of groups of planned and market economies.

Among the DEA studies which more closely relate to the topics being examined within this thesis, it is worth recalling that Pollitt (1996) used Fare *et al.*'s (1985) methods so as to compare the productive efficiency of 78 nuclear power stations operating in Canada, Japan,

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[47] See Chapters 3 and 4.
[48] See also Chapter 3.

the US, the UK, and South Africa in 1989. His study found no significant difference between privately and publicly-owned generators in the sample, but ignored crucial costs which are connected to nuclear generation (e.g., those regarding decommissioning expenses). Hjalmarsson and Veiderpass (1992a) analysed the efficiency of a sample of 285 electricity distribution utilities operating in Sweden in 1985, finding no significant effect of ownership or service area (meaning that some environmental variables were not relevant) upon measured technical efficiency, although rural utilities tended to exhibit higher scale inefficiency. In a subsequent study (1992b), the same authors also examined 289 Swedish electricity distribution companies over the period 1970-1986, by utilising Malmquist productivity measures to be based upon DEA technical efficiency scores. Once again, they found no significant differences in efficiency due to ownership, thus confirming that ownership *per se* might not be as crucial for economic efficiency as could market structure[49].

Energy industries have been recently analysed by DEA to a large extent. Together with electricity, gas has been examined as well. Price and Weyman-Jones (1993) investigated input-output data from the regional divisions - or Area Boards - of British Gas over the period 1977-78 to 1991, and found evidence of significant increases in productivity growth starting from 1983 (three years before privatisation). Privatisation effects might be jammed by other, systematic factors which add changes to the picture and tend to insert noise into the calculations. In order to really evaluate privatisation effects as a 'stand-alone' event, one should build up a 'counterfactual' scenario, similarly to the ones being devised by Galal et al. (1994), and by Newbery and Pollitt (1997). More recent DEA studies on electricity distribution include Burns and Weyman-Jones (1994b), Pollitt (1995), and Forsund and Kittelsen (1997).

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[49] Vickers and Yarrow (1988).

Burns and Weyman-Jones (1994b) use mathematical programming (DEA) techniques to construct measures of relative efficiency and productivity growth within a multiple input, multiple output model of UK electricity distributors before and after privatisation (which took place in 1990). They found that, although the privatised Regional Electricity Companies (RECs) of England and Wales are now more efficient than before divestiture, this productivity growth simply continues a long-term historical trend, starting at least in the early Seventies. The authors were unable to reject the hypothesis that privatisation has not added any further increment to efficiency. The explanation provided is that initial price regulation for distributors was too generous (1990-1994), in that it severely underestimated the industry's underlying productivity growth. Different performances were also found for different RECs since privatisation.

Pollitt (1995) proposed a DEA model for electricity distribution, featuring the number of employees, transformers, and kilometres of distribution line among inputs, and the total number of customers[50], residential/non-residential sales, service area, and maximum simultaneous demand among outputs. Following Huettner and Landon (1977), the author also considered the share of residential sales in total sales (1 – *INDY*), overhead and underground distribution lines, transformer capacity, wage cost per employee, and a couple of dummy variables (one for ownership, and one for US/UK differentiation). The model was, however, kept parsimonious, by recalling the fact that - ceteris paribus - 'fatter' DEA specifications will tend to smooth out all efficiency scores, thus attributing 100% technical efficiency to an implausible number of sampled DMUs. Pollitt used both econometric and DEA methods, in order to cross-check his final efficiency outcomes by means of statistical testing. His analysis also embraced electricity generation and transmission. With special regard to both electricity

[50] See Neuberg (1977).

transmission and distribution, the author's major finding was that, working on a 1990 US/UK cross-section, it was not possible to reject the null hypothesis according to which publicly-owned and privately-owned electricity transmission/distribution systems exhibited no statistically significant difference in technical/cost efficiency. Apart from DEA, OLS cost functions were also estimated for transmission and distribution, and these provided further cross-checking of DEA results. There still were a large number of 100% efficient units left, as a result of multiple outputs featuring in the author's final DEA specification[51].

Pollitt's regression results for the US and UK suggested that, once environmental variables are incorporated into the cost function, there appears to be no role for ownership in determining costs. Moreover, together the DEA and OLS results suggested that there was no evidence of the fact that the British Area Boards/RECs were performing poorly, as compared to US electricity distribution utilities, prior to privatisation (that is, before 1990). Comparisons between publicly and privately-owned firm-specific efficiency scores were made possible thanks to distribution-free statistical tests (Wilcoxon, Savage)[52].

Finally, Forsund and Kittelsen (1997) analyse local electricity distribution in Norway by DEA. Combination of stochastic frontier and DEA methods leads the authors to discover that optimal scale for electricity distributors is smaller than the average observed scale[53]. Widespread inefficiency is found across DMUs, and the authors suggest to alter the current structure of local electricity distribution in Norway, as part of the reform programme which the Norwegian ESI has been undergoing over the last few years[54]. Environmental (non-

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[51] As Pollitt (1995) notices, efficiency scores of 100% do not imply that there is no scope for higher efficiency, because all efficiency measures are *relative* to other DMUs in the sample, and not absolute. As one is constrained within his/her collected data, it is obvious that 100% DEA scores will provide no information for best-practice (frontier-efficient) DMUs on how they may reduce inputs for a given output, or - alternatively - increase output for a given input mix.

[52] Such tests are clarified by Lehmann (1975) and Byrnes (1985).

[53] This finding is consistent with some of Chapter 3's results on MES for ENEL zones, at least with respect to physical delivered energy (*Y/GWh*).

[54] See Chapter 1.

discretionary) variables are also considered, given their crucial importance for electricity distribution within the Norwegian territory, which couples very low population density with jagged coastlines (fjords), a mountain landscape, and - sometimes - permanently iced regions. Forsund and Kittelsen's results are very useful in interpreting DEA outcomes from the current analysis, as we shall clarify later on.

3.1 A Comparison Between DEA and Stochastic Frontier Estimation

We conclude this Section by quickly sketching the main pros and cons which should be taken into consideration when comparing DEA efficiency results with those previously discussed in Chapters 3 and 4 (stochastic frontier analysis). In order for methodological cross-checking to be fully understood, the following differences between DEA and Stochastic Frontier Estimation (SFE) must be kept in mind:

(*a*) the DEA technique does not require the specification of a functional form for the production function. Such flexible functional forms as the translog definitely improve the situation, but are not able to clarify how different components of efficiency might be separated within SFE. As noticed in the previous Chapters, stochastic frontier methods are generally unable to effectively distinguish between input-allocative and technical efficiency. Battese and Coelli's (1995) 'Technical Efficiency Effects' model, for instance, sorts out the problem by simply assuming that allocative efficiency is *ex ante* perfect (AE ≡ 1), thus ascribing all deviations from best-practice efficiency to technical effects (apart from random noise, of course). In general, SFE encounters serious problems with input-allocative efficiency computations;

(*b*) the DEA technique is non-stochastic[55] and does not take errors (random noise, measurement error) into consideration, unlike the SFE technique. Empirical work always involves some degree of measurement error, data handling errors, stochastic shocks, *et similia*. On the other hand, the ability of SFE to handle errors only comes at the expense of

[55] Some researchers have tried to develop a stochastic version of DEA (see Land, Lovell, and Thore, 1988, and Lovell, 1993), but those models are by no means complete, and require massive data information regarding expected values, variance-covariance matrices, probability levels, and so on. Stochastic DEA would solve the

either the imposition of a functional form for the errors themselves[56], or the use of panel data[57];

(*c*) DEA scores are heavily affected by specification and variable selection errors. On the contrary, SFE frontiers give rise to standard errors and *t*-values for each of the parameters (e.g., in a translog total cost function). It is also true that sophisticated sensitivity analysis of DEA scores might be a possible solution to this problem, but it would be indeed complex and time-consuming;

(*d*) from a computational point of view, differences between DEA and SFE are now negligible, as a consequence of modern computing power. SFE involves econometric estimation of either a production or a cost function (plus share equations, if feasible), whereas DEA implies a separate linear program for each DMU in the sample. The most recent DEA software is capable of accommodating thousands of simultaneous linear problems automatically, so that computer programming skills are no more essential;

(*e*) DEA allows easy extension to multiple outputs in a production frontier context, and can also accommodate non-discretionary variables into the analysis in a direct way. On the contrary, SFE may only be extended to multiple outputs within a cost frontier setting[58]. However, an excessive number of outputs (or inputs) in DEA will rapidly give rise to an excessive number of best-practice DMUs. This may result in a tighter constraint on the number of inputs/outputs which can be inserted in DEA - as opposed to SFE - without saturating the model[59].

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main methodological problem with Data Envelopment Analysis, and is therefore worth investigating to a larger extent in the future.

[56] See Jondrow, Lovell, Materov, and Schmidt (1982), and Greene (1993b).

[57] See Burns and Weyman-Jones (1994a), and Chapter 3.

[58] E.g., the multi-output translog total cost function presented in Chapter 3.

[59] On the 'parsimony' requirement for DEA, see Ferrier and Lovell (1990).

Some applied studies used real-world data, so as to compare practical outcomes for both SFE and DEA (hospital efficiency, electricity, oil enterprises). The general conclusion was that the form of the production function (for SFE) and the input/output choice (for DEA) are much more important than the measurement technique[60]. Since DEA treats random noise as inefficiency, DEA scores will be - ceteris paribus - lower than SFE ones. In fact, SFE separates inefficiency from random noise, whereas DEA penalises DMUs by attributing measurement error and/or exogenous shocks to inefficiency. Of course, DEA scores would be *higher* (ceteris paribus) than SFE ones if positive exogenous shocks/noises were incorporated into technical (in)efficiency. Wagstaff (1989) uses signed-rank tests in order to implement methodological cross-checking, as does Pollitt (1995). Ferrier and Lovell (1990) used DEA and SFE on panel data for US banking. They found that the DEA frontier was more flexible than a translog SFE frontier, and that correlation between the technical efficiency scores (TE, *EFFs*) generated by the two methodologies was not statistically significant according to signed-rank tests. Weyman-Jones (1992) examined cost efficiency in electricity distribution (UK) by using DEA and SFE, and found that SFE showed relatively little inefficiency as compared with DEA (again, because of the different treatment of random noise under DEA). Finally, Burns and Weyman-Jones (1994a, 1994b) found that both SFE and DEA analyses showed irrelevant privatisation effects upon the Regional Electricity Companies of England and Wales, probably owing to the fact that initial regulation of the RECs had been so loose that no significant efficiency enhancement was stimulated over the first years following divestiture (1990-1994).

As Pollitt (1995, pg. 85) notices: "[...] Comparative studies suggest that the SFE efficiency scores will, in general, be higher than the non-stochastic methodologies would suggest.

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[60] See, for instance: Banker, Conrad, and Strauss (1986); Kopp and Smith (1980).

Choice of functional form for the production function would seem to be an important factor in determining the value and the accuracy of efficiency scores. [*omissis*] If this author was to have to judge about the relative merits of the techniques, he would favour DEA over SFE for practical application because of the relative ease of extension to allocative efficiency, multiple outputs and environmental variables, and the lack of restrictive distributional assumptions and complex likelihood functions". Such a view should now be tested against our real ENEL/MUNI data, which next Sections investigate by means of a non-econometric methodology that *calculates* efficiency scores, instead of estimating them. The data will be 'encompassed' by a VRS DEA non-stochastic frontier, which sets production/cost relationships completely free from any *ex ante* functional structure. Distribution-free DEA will then be compared with parametric SFE in order to cross-check the two methodologies, thanks to both parametric and rank-order testing. The remainder of this Chapter is organised according to the Table below.

Table 5.1: Chapter 5: Plan of Empirical Analysis

$$\begin{cases}\text{VRS (Input / Output) DEA on 147 ENEL Zones (1996)}\\ \text{VRS (Output) DEA on 37 MUNIs (1994)}\end{cases} \Rightarrow \text{Cross - Checking with SFE Results}$$

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$$\begin{cases}\{\text{VRS DEA (Output) on a Pooled Sample (76 - obs.)} \Rightarrow \text{Cross - Checking and Rank - Order Tests}\\ \{\text{VRS DEA (Output) on Two Separate Sub - Samples (31 + 31 obs.)} \Rightarrow \text{Internal Cross - Checking}\end{cases}$$

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$$\{\text{Second - Stage Tobit Analysis of DEA Efficiency Scores against Environmental Variables}$$
$$\Rightarrow \text{Final Policy - Making Suggestions.}$$

4. Data Envelopment Analysis (VRS DEA) of Local Electricity Distributors in Italy

As discussed above, VRS DEA is highly sensitive to measurement error, which is treated as 'inefficiency' due to the non-stochastic nature of this methodology. This means that outliers will be crucial in determining the best-practice efficient frontier. More precisely, outliers *will* make up the frontier. Apart from the measurement error issue - which might be sorted out by either adopting 'stochastic' DEA, or by upgrading the data set to a panel - the non-parametric methodology suffers from 'efficiency score smoothing', which takes place when the model features too many inputs and/or outputs[61]. In the absence of panel data, the best strategy is to keep the production/cost model as parsimonious as possible. Inflated inefficiency scores resulting from (negative) random shocks being erroneously attributed to the DMU's cost performance cannot be avoided when one has single-year data only. As regards the returns to scale assumption, a CRS model for ENEL's local zones should be ruled out. Since the *ex ante* assumption is that of a U-shaped average cost curve with returns to scale being generally non-constant (either IRS or DRS), a VRS DEA approach will be adopted in our case.

Finally, as regards the model's orientation - which does matter in VRS DEA - we chose to adopt output orientation throughout most (but not all) of the following empirical work. This might appear to be a non-traditional choice for a public utility investigation. However, recalling the discussion in Chapter 3 on output endogeneity at ENEL, once again we emphasise that the Italian electricity monopolist - differently from American-style utilities - is not compelled to provide customers with whatever quantities they desire. The really exogenous output component for ENEL is given by the number of customers being served,

not by physical energy (GWh) delivered. Then, we often chose to view *Y*/GWh as a maximisable quantity for a given set of inputs (Models DEA1Y2), and hence opted for an output-oriented VRS DEA framework (with input-oriented cross-checks in the ENEL study only). However, we also considered *TOTCUST* (total customers) as an alternative measure for output[62] and ran a separate output-oriented VRS DEA (Models DEA1C2), with physical energy-output being taken as exogenously given, plus 'maximisable' customers. Cost-minimising DEA was not performed, as price data was not sufficiently 'clean' to enter a non-stochastic linear programming procedure. We shall also assume strong (that is, free) input disposability, so that Congestion Efficiency (CE) ≡ 1. This constraint might be somewhat unrealistic (especially at ENEL) and could be lifted within more sophisticated analyses featuring weak input disposability[63].

By using the Warwick DEA dedicated software, we obtained computed (not estimated) values for the technical efficiency indicator, which are multiplicatively separable from non-technical efficiency scores. It is worth recalling that comparisons with efficiency scores (*EFFs*) derived from the TEE stochastic-frontier model will thus be straightforward, because TEE postulates allocative efficiency *ex ante*[64]. Therefore, if one wishes to compare (estimated) *EFFs* with (computed) θs from DEA, allocative efficiency (*AE*) must be constrained to equal 100%. Moreover, recall that radial DEA is typically not immune from the 'slacks' problem. Following Ferrier and Lovell (1990), input slacks may be regarded as a form of input-allocative inefficiency, resulting from the firm's failure in achieving the optimal factor mix, given input relative prices. We shall follow this view, and consider slacks as a manifestation

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[61] A rough 'rule of thumb' would be to add inputs to outputs and work with a number of observations equalling at least that sum times three. This would ensure minimum discrimination, with not too many DMUs featuring 100% efficiency.

[62] Neuberg (1977); Huettner and Landon (1977).

[63] See Fare et al. (1994) for a theoretical treatment.

[64] See Chapters 3 and 4.

of allocative inefficiency. Finally, 'peers', or best-practice 'twins', will be identified by the computer package according to their technological proximity to each examined DMU. In other words, DEA's mathematical implementation is such that - by the very nature of the underlying optimisation procedure - each unit will be translated into a linear combination of best-practice DMUs with similar input-output levels, being 100% efficient. Those optimising DMUs are taken as 'peers', or reference units, for the DMU under consideration. Therefore, DEA provides an 'ideal' DMU, or 'projected point', resulting from linear combinations of peers, to which the inefficient unit must refer if it wishes to improve on itself towards full efficiency.

The above, theoretical remarks will be better understood by practically running a VRS DEA linear program. First, we start by analysing the most general DEA model being applied to the 147 ENEL zones for the business year ending 31 December 1996[65]. Its more general form involves two outputs (energy delivered, total customers), three inputs (kilometres of line, full-time employees at end-year, and the total amount of transformers), plus a number of second-stage environmental variables - most of which were, unfortunately, instrumented as dummies - to be kept separate for the sake of discrimination among examined decision-making units. The most general DEA23 model for ENEL's local distributors (1996) would run as follows:

$\Rightarrow$

[65] Refer to Chapter 2 for data description.

Table 5.2: Start-up DEA Model for ENEL (1996)

Outputs	**Inputs**	**Input Prices(*)**	**Non-Discretionary[66] Variables(**)**
Total Energy Delivered (**Y**)	Labour (**LAB**)	Labour Price (p_l)	**INDY**
Total Number of Customers (**TOTCUST**)	Capital Proxy 1 (Lines, **LIN**)	Capital Price (p_k)	**INDCUST**
	Capital Proxy 2 (Transformers, **TRANS**)	Materials Price (p_m)	**INDLINES**
	Capital Proxy 3 (Nominal Power of Substations, **POW**)		**DENS**
			THIRDS
			AIRMT
			AIRBT
			PTPFRC
			SEADUM
			MOUNTDUM
			METRDUM
			MUNIDUM
			BORDUM
			GENERDUM
			INDUSDUM
			SOUD

(*) Dropped from DEA.

(**) Subsequently examined thanks to a second-stage econometric analysis (Tobit).

The power of substations is - at least theoretically - the best proxy for productive capacity, and thus for capital. Defining capital as an index of productive capacity is consistent with the idea of 'nominal power' declared by ENEL for each of its distributing zones. Following some other studies, we tried to run an output-oriented, VRS DEA optimisation featuring power (in kW) - rather than distribution lines - as a capital proxy, and found that the discrimination level among different DMUs was unsatisfactory, with efficiency scores ranging from 0.84 to 1 (spread = 0.16). We also tried to consider kilometres of line and nominal power together, which obviously increased the number of 100% efficient units, leaving the lowest scores at around 85% (spread = 15% only). Such outcomes were not compatible with a sufficient level of discrimination among differently efficient DMUs, especially in view of prospective statistical comparisons between DEA and SFE scores. We therefore dropped the third capital proxy. Since nominal power has been traditionally utilised by other authors, such a strategy must be qualified. Working with cross-sectional figures entails estimating, by definition, short-run technological (production, cost) relationships. Capital - and even labour to some extent - can be regarded as a fixed factor in the short run. Purchased energy would be the only variable input for a distributing utility over the short term, but ENEL did not even include internal energy transfer prices within its 1996 production-transmission-distribution accounts. Kilometres of line are also quasi-fixed in the short run, but their susceptibility to change (e.g., in response to the need for new connections) is higher as opposed to that of transforming power. Therefore, under the binding constraint represented by the cross-sectional analysis being carried out here, kilometres of line appeared to be 'less constant' capital indicators than nominal power levels

[66] This is the DEA counterpart of 'environmental variables'. The two expressions are, however, fully interchangeable.

did, thus leading to more significant results and less smooth efficiency score series. Of course, nominal power should be preferred within time-series/panel data analyses, which - however - were made impossible in this thesis because of ENEL's centralised and integrated accounting structure prior to 1996.

The variables above are exactly the same as those defined in the previous Chapters. We remind the reader of the facts that physical output (i.e., delivered energy) is expressed in GWh, the total number of customers is in physical units, and labour corresponds to full-time equivalent employees at end-year (*N,* or *LAB*). Finally, capital is approximated by either kilometres of distribution line, or by the total number of transformers - including both primary and secondary substations/capacitors, so as to enlarge the concept of 'transformer' in such a way to make it represent capital (instead of a loose proxy for services/materials). As regards input prices,

- the labour price was computed as the ratio of labour costs to *N*;
- the price of capital was made equal to capital costs divided by kilometres of line;
- finally, the price of materials was roughly proxied by the ratio of third-party costs to transformers.

Non-discretionary variables have the usual meaning:

- *INDY*, *INDCUST*, and *INDLINES* capture the presence of industrial deliveries (as opposed to residential ones);
- *DENS* is consumer density (i.e., number of customers divided by areas served);
- *THIRDS* is third-party cost's fraction in total distribution cost;

- *AIRMT* and *AIRBT* capture the presence of overhead lines (as opposed to underground cables) on total medium and low-voltage lines;
- *PTPFRC* is the percentage of primary transformers (depending on the transmission network, and on high-voltage access points) on total substations.

All remaining environmental variables are dummies, and reflect non-discretionary conditions which the DMU cannot directly control. Namely,

- *SEADUM* = 1 for coastline zones;
- *MOUNTDUM* = 1 for mountains;
- *METRDUM* = 1 for metropolitan areas (according to Law no. 142/1990);
- *MUNIDUM* = 1 for zones which either encompass or lie beside a municipally-owned electricity distributor (MUNI);
- *BORDUM* = 1 for zones at Italy's national borders;
- *GENERDUM* = 1 for zones which also feature ENEL-owned power stations within their borders;
- *INDUSDUM* = 1 for industrial districts;
- *SOUD* = 1 for Southern distributing zones.

In the discussion provided above, the need for parsimonious DEA models was stressed because of the efficiency scores' "smoothing" problem. As a first step towards parsimony, we dropped input prices, whose 'proxy' nature could well be accepted in econometric analysis, yet it would have created problems in deterministic DEA[67].

[67] In particular, the materials price had been constructed starting from a very crude proxy, to be used as a mere normaliser in the previous, translog deterministic and stochastic analyses of Chapters 2 and 3.

Thus, after dropping input prices, we were left with a first, VRS input/output DEA specification consisting of two outputs (*Y*, *TOTCUST*), three inputs (*LINES*, *LAB, TRANS*), and 16 non-discretionary variables (the ones outlined above). As Lovell (1993, pg. 53) noticed: "[...] The only general guideline I have to offer is that variables under the control of the decision-maker during the time period under consideration belong in the first stage. Variables over which the decision-maker has no control during the time period under consideration belong in the second stage". In this respect, the first-best strategy would have been to run a single DEA program in two stages, featuring non-discretionary effects in the second stage - separately from the main input/output mix, which would have been given absolute priority in the first optimisation step. That is, environmental variables would have entered the optimisation problem as constraints only - not as arguments of the objective function. This is in line with the 'fast-food' example by Banker and Morey (1986).

Regrettably, inserting environmental variables in the DEA problem would have jeopardised the level of discrimination between 'good' and 'bad' DMUs to a remarkable extent. Therefore, after trying a two-stage DEA with environmental effects featuring in the second stage, we decided that a 'slim', parsimonious model in inputs and outputs only should have been preferred after all. Environmental effects were then confined to a separate, second-stage Tobit estimation. The Tobit approach is a second-best solution, but the significance of efficiency score series was prioritised in the current analysis because of the need for statistical comparability between DEA-derived scores and stochastic frontier ones.

The following Subsections are intended to comment upon DEA outcomes, to perform statistical tests *vis-à-vis* stochastic-frontier scores stemming from the analyses reported in Chapters 3 and 4, and - finally - to examine non-discretionary variables by means of second-stage Tobit estimation. To sum up,

(*a*) Subsection 4.1 is on ENEL;

(*b*) Subsection 4.2 is on MUNIs;

(*c*) Subsection 4.3 examines the 1994-1996 pooled sample (already seen in Chapter 4);

(*d*) Subsection 4.4 tries a different comparison (a more direct one) between MUNIs and ENEL's local zones, by exploiting DEA's flexibility;

(*e*) finally, Sections 5 and 6 touch different issues stemming from DEA calculations, whereas Section 7 concludes.

4.1 DEA Outcomes on ENEL's Local Units (1996) with Statistical Comparisons and Second-Stage Tobit Analysis of Reported Efficiency Scores

As explained in Chapter 3, the basic, American-style assumption regarding exogeneity of output does not hold for ENEL's 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 on ENEL (cross-section for 1996). This gave rise to models DEA22OUT and DEA23OUT, featuring two outputs (electricity, customers) plus two inputs (labour, capital/lines), and two outputs (*idem*) plus three inputs (labour, capital/lines, transformers), respectively. The best units according to these two output-oriented models (which also postulated Variable Returns to Scale, or VRS) were Aosta, Bergamo, Bologna, Bovisio (Milan), Milan, Monza (Milan), Corsico (Milan), followed by the usual series of Northern and Lombard small units. Generally speaking, the

comments made on stochastic-frontier results (Chapter 3) are still valid after DEA. The Table in the Appendix clearly shows that the efficient units under SFE had their results confirmed in the vast majority of cases.

Together with really efficient units, however, we also found in DEA some local distributors which were put on the best-practice frontier by the linear program simply because they had no other DMUs to be compared to. These are the 'outliers' of the sample (either too large or too small units, lying away from the scatter's centre) and must be treated very carefully when commenting upon DEA efficiency scores. Since DEA is not based on central tendencies (as statistical procedures are), it examines best (and worst) practice tendencies and constructs the efficient isoquant accordingly. This means that the best-practice frontier will include, among other units, also those DMUs which operate at 'weird' levels of input/output, e.g. turning out extremely large/small amounts of output when compared to sample-mean values. Typically, this is the case with large conurbations on one side, and small rural villages on the other. Those zones which DEA puts on the frontier, and which are not comparable to any other DMUs in the available sample, are deemed 'efficient by default'. Nothing special can be really said of such units. Examples from this analysis are Milan, Rome, Naples, and Palermo. The only chance of separating a really efficient large town from a 'default' efficient one is to check its DEA score against that obtained by means of another methodology[68]. Stochastic Frontier Estimation (SFE) outcomes are of great help and show that the value of '1' cannot always be replicated by those units once they are re-appraised within a statistical/econometric setting. However, the general impression stemming from DEA outcomes - as compared to SFE results - is that some statistical testing might be useful in spotting significant similarities among the different efficiency score series under examination.

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[68] See also Chapter 6.

For instance, we found no real improvement in Southern scores after running DEA. The main reason for this finding is that environmental variables were confined to a second-stage Tobit estimation because of the arguments outlined in Section 4. This obviously penalised the bulk of less-favoured Southern ENEL distributors (apart from metropolitan ones such as Naples, Palermo, Catania, and Bari), and suggested that our judgement should be suspended until a full Tobit analysis of scores is carried out. Generally speaking, output-orientated DEA confirmed that the most efficient ENEL units in Italy are those around Milan (Lombardy), plus some interesting small towns (Aosta, in the North-West, Venice, in the North-East, and Prato, near Florence) which are either exploiting favourable environments (e.g., Prato; Venice's harbour), or are enjoying an efficient public utility service tradition (Aosta), or - finally - are simply experiencing good management.

DEA Tables: See Numerical Appendix.

Whereas Southern efficiency should only be appraised after running Tobit estimation, statistical tests on the extent of 'agreement' among different series may be performed now, so as to check whether Stochastic Frontier Estimation (SFE) and Data Envelopment Analysis (DEA) really provide the investigator, starting from an identical data set, with the same kind of information. Of course, such an issue should be addressed on a case-by-case basis. As Pollitt (1995) recalls, SFE scores are generally higher (ceteris paribus) because DEA - which is a deterministic procedure - includes measurement error within the inefficiency measure, whereas SFE separates the random element according to two components (one for inefficiency, the other one for noise). Nonetheless, once rank-order tests are performed, it could be discovered that, in overall terms, SFE and DEA results do not reject each other on

the basis of differences in their location parameters (medians). Before stating that SFE and DEA report different outcomes simply because they result from alternative data treatment procedures, some comparisons should be made. This is what the following Tables attempt to do. First, in order to make comparisons between DEA and SFE-generated scores more sensible, we re-ran both DEA22 and DEA23 models with an input orientation (hence: DEA22IN, DEA23IN). This gets closer to the econometric idea of (translog) cost minimisation, and introduces two further DEA efficiency score series to be tested against SFE ones. Finally, the two SFE models to be examined are M0TE (no environmental effects) and M12TE (twelve external effects) from Chapter 3.

The first test to be performed is the general Kolmogorov-Smirnov one, which investigates normality and uniformity of distribution functions for the populations from which our efficiency score samples were extracted. K-S test results (Chi-Square statistic used) are reported - together with all other outcomes - in the Tables below, and are commented on in the subsequent paragraphs.

Table 5.3: ENEL: Non-Parametric and Parametric Tests

Descriptive Statistics

Models	N	Mean	Std. Deviation	Minimum	Maximum
DEA22IN	147	.6989	.1554	0.42	1.00
DEA23IN	147	.7553	.1419	0.49	1.00
M0TE	147	.7537	.1440	0.5	1.00
M12TE	147	.7939	.1287	0.48	.99
DEA22OUT	147	.6905	.1592	0.37	1.00
DEA23OUT	147	.7359	.1517	0.44	1.00

One-Sample Kolmogorov-Smirnov Test

	DEA22IN	DEA23IN	M0TE	M12TE	DEA22OUT	DEA23OUT
K-S Z (Normal)	1.329	1.857	0.889	0.904	1.307	1.421
Z Prob (2-tailed)	0.059	0.03	0.408	0.388	0.066	0.035
K-S Z (Uniform)	1.621	1.548	1.32	2.346	1.519	1.526
Z Prob (2-tailed)	0.01	0.017	0.061	0	0.02	0.019

Parametric Paired-Samples *t*-tests

Pairs/Values	DEA22IN-M0TE	DEA22IN-M12TE	DEA22OUT-M0TE	DEA22OUT-M12TE
t-value	-6.054	-11.5	-6.282	-11.017
Deg. Freed.	146	146	146	146
t-prob	0	0	0	0

Non-Parametric Tests

Tests		DEA23IN-M0TE	DEA23OUT-M0TE	DEA23IN-M12TE	DEA23OUT-M12TE
Wilcoxon (SR)	Z-value	-0.184	-2.196	-4.639	-6.652
	Z-prob	0.854	0.028	0	0
Sign	Z-value	-0.426	-1.958	-3.134	-5.609
	Z-prob	0.67	0.05	0.002	0
McNemar	n/a	n/a	n/a	n/a	n/a

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

Tests		DEA23IN-M0TE	DEA23OUT-M0TE	DEA23IN-M12TE	DEA23OUT-M12TE
t-value		0.174	-1.997	-4.767	-7.022
Deg. Freed.		146	146	146	146
t-prob		0.862	0.048	0	0

K Related-Samples Tests

Tests		Friedman	Kendall's W	Cochrane
Chi-Sq. Value		226.577	226.577	n/a
Deg. Freed.		5	5	n/a
Chi-Sq. Prob		0	0	n/a

First, from the Table of descriptive statistics it appears that stochastic frontier methods generally lead to higher (on average) scores, other things being equal. This is because DEA does not cater for any stochastic elements, thus attributing all noise to inefficiency. The

problem is obviously limited by inserting more inputs or outputs in the DEA model, which will increase non-comparability among 'peer' units, and push the average efficiency score up at the expense of locating too many DMUs on the efficient frontier, thus blurring the overall picture of discrimination across units.

The one-sample Kolmogorov-Smirnov test is used to investigate whether the sample is consistent with a specified distribution function or not. The version that was used in this work tests whether the sample of efficiency scores from different methodologies is consistent with either a normal or a uniform distribution function (or with both). At a 5% significance level, the K-S test fails to reject the null hypothesis according to which the efficiency score series from models DEA22IN, M0TE, M12TE, and DEA22OUT are consistent with a normal distribution. Moreover, the test also fails to reject the null about uniformity for M0TE, which then has a 'well-behaved' distribution (both normal and uniform). In the light of the above results, it was possible to perform some parametric paired-samples *t*-tests, together with the more general - but somewhat less powerful - rank-order procedures. Precisely, models DEA22IN and DEA22OUT were tested against their SFE counterparts by means of standard paired-samples *t*-tests (which rely on the assumption of normality, if not uniformity). The *t*-probability value of around zero indicates strong rejection of the null hypothesis that the matched efficiency score series came from populations featuring identical distribution functions in terms of means[69]. This is consistent with the stylised fact according to which statistical/econometric methods and linear programming ones generally fail to deliver the same numerical outcomes (ceteris paribus) because of the different nature of the basic hypotheses involved. In particular, linear programming being non-stochastic and

[69] Means are the central parameters being tested by paired-samples parametric procedures.

concentrating upon best-practice units instead of central tendencies (as statistical methods do by definition) are assumed to be the main reasons for the discrepancies spotted by our *t*-tests.

However, as the following results will show, the above considerations should in no way be taken as generalisable propositions. As a consequence of the results obtained from the initial Kolmogorov-Smirnov tests, we carried out non-parametric testing procedures on the matches represented by models DEA23IN/OUT and M0/M12TE. Computed *Z* values for the resulting Wilcoxon tests tell us that statistical agreement between different matching pairs[70] is accepted for the pair DEA23IN-M0TE only. The consistency hypothesis for all other comparisons turned out to be rejected at a 5% significance level. A second non-parametric test was also used: this is known as the Sign Test, and utilises a strict subset of the information gathered by Wilcoxon. Basically, Sign examines the ranks of differences between each 'matched pair' resulting from the two samples, without weighting that by the magnitude of each difference (which is done by Wilcoxon's Signed-Rank test). This will result in the Sign Test being more general than Wilcoxon - which assumes symmetry for the ranks' distribution function - but also less powerful (since it uses less information), meaning that - ceteris paribus - it will tend to accept H_0 more frequently. The Sign Test's outcomes, then, fully confirm those obtained by means of Wilcoxon - that is, the couple of models DEA23IN-M0TE once again provides the investigator, from a statistical point of view, with the same kind of information about differences in efficiency levels among ENEL units. On the other hand, statistical agreement is not found for any of the remaining matched efficiency series[71].

It is interesting to notice that, from a theoretical viewpoint, models DEA23IN and M0TE are in fact very similar because both of them, simultaneously,

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[70] The common 'location parameter' is assumed to be the median. Means are not examined by distribution-free tests.

[71] The McNemar test was not implemented because it assumes the presence of dichotomous variables, which is not compatible with our data.

(*a*) consider three inputs and two outputs in their specification;

(*b*) regard outputs as exogenous (the two outputs entered a translog cost specification - as exogenous determinants of normalised total distribution cost - in M0TE, whereas they were held fixed during optimisation in DEA23IN, an input-orientated DEA model);

(*c*) feature no environmental variables at all, thus being 'pure' input/output specifications.

Therefore, the above result points in the direction of a possible reconciliation between SFE and DEA, provided that the models examined are reciprocally consistent and show analogous economic features. Once again, it must be stressed that model specification in both econometric and linear programming methods is crucial for obtaining reliable outcomes. Rather than trying to use alternative stochastic frontier techniques (e.g., by assuming gamma or exponential distribution functions for the efficiency error term) or different DEA orientations (input, output, both input and output, two-stage, multi-stage, etc.), one would better concentrate upon the choice of inputs, outputs, and environmental variables in order to achieve plausible results in terms of efficiency scores. It is not by chance that the most similar models being compared by the above tests were in statistical agreement with each other, whereas all remaining comparisons faced strong rejection of the null hypothesis of concordance.

Given that both M0TE and M12TE series were found by Kolmogorov-Smirnov to be consistent with normality, we also ran standard paired-samples *t*-tests to see whether the above outcomes with respect to the couple DEA23IN-M0TE are robust. As the Additional Cross-Checking Table shows, parametric tests fully confirmed that the latter pair of models were internally consistent even in terms of means, whereas all other matches were more or

less strongly rejected[72]. Again, parametric outcomes confirm that DEA and SFE may well reach similar conclusions (ceteris paribus), provided that the models being compared are consistent in terms of specification.

Finally - for the sake of completeness - we carried out general, related-samples non-parametric procedures, testing the null hypothesis of concordance among all samples. Not surprisingly, both Friedman and Kendall's W tests categorically rejected any global agreement among the six efficiency score series being examined with respect to ENEL's local distributing units[73].

To keep DEA models as parsimonious as possible, we excluded all environmental variables from the linear optimisation problems and confined them to a second-stage Tobit estimation, whose features have already been introduced in Chapter 3. The environmental effects used here are exactly defined as those employed in the previous Chapters. Only two new variables were introduced in the Tobit estimation, following data upgrading, but they did not turn out to be particularly significant in the end (RURALCST is the percentage of customers living in rural areas on total customers, and RURALIN is the percentage of rural distribution lines on total lines[74]). Tobit analysis is very useful in spotting significant external effects, which could be used by the electricity regulator to re-classify efficiency scores according to non-controllable inputs and outputs. This might improve the situation of Southern ENEL units, which were only in the number of ten within the first group of 50 efficient units (that is, 20%) according to the Table of average scores[75]. It would perhaps be possible to grant more generous efficiency targets to those Southern, Central, and Alpine

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[72] Precisely, DEA23OUT-M0TE faced weak acceptance in Sign, weak rejection in the parametric *t*-test, and strong rejection in Wilcoxon. The other two matches were rejected with no uncertainties.

[73] Again, the Cochrane test was not implemented because it assumes the presence of dichotomous variables.

[74] 'Rural areas' are imperfectly defined by ENEL on the basis of population, rather than density. Zones featuring more than 30,000 customers are deemed 'urban'. All other zones are either labelled 'rural' (less than 10,000

distributors facing particularly severe external circumstances - in terms of rural customers, low population density, geographical constraints, presence of municipal utilities skimming city centres, and the like. We first ran a Tobit estimation with all effects, and then refined it by dropping insignificant efficiency drivers. As an endogenous variable, we took the DEA score for the two input-minimising DEA models (namely, DEA22IN, DEA23IN) - which seemed to be more reliable after statistical testing against SFE outcomes - and Tobit-regressed its transformed values against the external variables which were previously outlined (Section 4). The transformation of DEA22/23IN's scores was needed for the sake of 'left censoring'. Basically, 0-1 scores were converted to the $[1,+\infty)$ interval by taking their reciprocal values, and then shifted back to $[0,+\infty)$ so as to conform with the left censoring requirement. Therefore, efficiency scores of zero would now mean that the DMU under consideration is fully efficient, whereas high scores would mean that it is progressively becoming less efficient. This implies that positive estimated coefficients will indicate a negative effect on efficiency maximisation, whilst negative estimated coefficients will entail a positive contribution to efficiency maximisation. The second Tobit run being performed - according to a general-to-simple methodology - provided the results which are reported in the following Tables[76].

Table 5.4: ENEL: Second-Stage Tobit Analysis of DEA Efficiency Scores (Two Runs)

Run 1

Available on request.

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customers), or 'semi-urban' ($10{,}000 \leq TOTCUST \leq 30{,}000$). This follows from Italy's official statistical categorisations (ISTAT).

[75] Notice that more than 30% of ENEL distributing units are located in the South of Italy.

[76] The first run is available as a file, together with other DEA Tables. It was impossible to report all numerical results in the main text.

Run 2

DEPENDENT VARIABLE: DEA22A[77]

LOG-LIKELIHOOD FUNCTION	-13.2485
NUMBER OF OBSERVATIONS	147
NUMBER OF POSITIVE OBSERVATIONS	135
PERCENT OF POSITIVE OBSERVATIONS	0.918367

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	-0.02385	0.080528	-0.29613
SEADUM	0.072292	0.048612	1.48713
INDUSDUM	-0.18872	0.048023	-3.92978
AIRBT	0.242772	0.181608	1.33679
PTPFRC	0.972671	0.196956	4.93852
RURALCST	3.69E-03	1.16E-03	3.17734
SIGMA	0.248664	0.015257	16.2981

DEPENDENTVARIABLE: DEA23A

LOG-LIKELIHOOD FUNCTION	18.6176
NUMBER OF OBSERVATIONS	147
NUMBER OF POSITIVE OBSERVATIONS	131
PERCENT OF POSITIVE OBSERVATIONS	0.891156

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	-0.13358	0.111891	-1.19379
MUNIDUM	-0.06365	0.045695	-1.39289
INDUSDUM	-0.13384	0.036801	-3.63678
GENERDUM	0.070565	0.033545	2.10363
AIRBT	0.288556	0.135711	2.12625
INDLINES	0.421175	0.359524	1.17148
PTPFRC	1.08563	0.138464	7.8405
SIGMA	0.190275	0.011916	15.9686

Standard Errors computed from analytic second derivatives (Newton)

After dropping insignificant effects, we saw that the first model (DEA22A, input-orientated) featured the industrial zone dummy (INDUSDUM), the percentage of primary substations (PTPFRC), and the percentage of rural customers (RURALCST) as the efficiency drivers. It was found that industrial zones do matter in boosting technical efficiency (defined as input minimisation for given outputs), whereas primary substations increase capital usage

[77] All dependent variables in the Tobit analysis are re-scaled efficiency scores - lying within the $[0,+\infty)$ interval - stemming from corresponding DEA models with two or more inputs. The 'A' suffix means that scores have been inverted and re-scaled for the sake of left censoring (Tobit). For instance, DEA22A is a re-scaled DEA score in two inputs and two outputs; DEA1CA is a re-scaled DEA score with consumers as output and the usual

and thus depress technical efficiency. However, as noticed earlier, primary substations are the ones which scale down electricity voltage to distribution-compatible levels, thus enhancing security and minimising electricity losses. Therefore, even though electricity loss minimisation was not explicitly considered by our models, recall that it is generally prioritised by distribution utilities, so that PTPFRC's effects upon efficiency should be taken *cum grano salis*. Finally, rural customers had a small yet very significant (negative) effect upon efficiency, which is in line with expectations regarding the negative influence of a certain category of customers on distribution efficiency. The small magnitude of the latter effect, however, shows that industrial areas are much more influential on efficiency (in a positive sense) than rural customers are (in a negative sense), thus leading the regulator to constrain Northern distributors more tightly, without necessarily being too much generous to Southern and mountain units on the other hand.

By examining the second regression on DEA23IN - stemming from the three-input model - we noticed that the industrial area dummy still pointed towards efficiency enhancement, whereas the presence of generation facilities in the district was negative for efficiency. The latter result also appeared in our previous analysis (Chapter 3), and may be interpreted as an indicator of costs being shifted by ENEL from its generating arm to the distribution business (connection costs, etc.). In fact, some electricity by-passes the national transmission grid, and is directly conveyed to the distribution network - after being scaled down in voltage at the outset - from power stations located within the distribution area. This might worsen the distributing unit's efficiency record, by charging on its own accounts the physical use of interconnectors, more powerful transformers, and so on. The internal transfer price issue within ENEL is obviously one of the most important challenges to the energy regulator, as

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two inputs; DEA1YA is a re-scaled DEA score with physical energy (GWh) as output and (K, L) as inputs, and so on.

part of the broader question represented by ENEL's prospective 100% accounting separation. It is interesting to notice that PTPFRC turned out to be significant in DEA23IN, i.e. in the model where transformers are present (they had been excluded from DEA22IN). Of course, primary transformers inflate capital usage, and this may explain their negative effect on input-minimising technical efficiency in the short run. Similarly, the generation dummy - which is also linked to the transformers variable - popped up as a significant effect in DEA23IN, but not in DEA22IN, where transformers (as an input) had been completely ignored.

The three-input regression also showed that efficiency requires underground cables for low-voltage distribution (look at the AIRBT effect), since low-voltage energy is better carried via underground links in city centres and crowded districts. This is a standard result and confirms our previous, econometric findings. Finally, the effect of PTPFRC has already been explained: here it will suffice to notice that, as a result of transformers being inserted as an input, PTPFRC's significance was much higher for DEA23IN than for the two-input model. Nonetheless, the obvious correlation between TRANS and PTPFRC should not appear to be the only reason for PTPFRC's high significance: indeed, DEA22IN's outcomes just show that PTPFRC is *per se* a crucial explanatory variable.

The next Subsection deals with DEA results on municipal units (MUNIs).

4.2 DEA Outcomes on Municipal Units (1994) with Statistical Comparisons and Second-Stage Tobit Analysis of Reported Efficiency Scores

We took a 1994 cross-section of 37 municipal electricity distribution companies (production data) and ran three output-orientated VRS DEA programs: DEA22 (two outputs and two inputs, exactly as defined before), DEA1C2 (total customers as output, plus two

inputs, i.e. kilometres of line and full-time equivalent employees at end year), and DEA1Y2 (electricity delivered as output, plus the two usual inputs). We did so because

(*a*) we lacked data on a possible third input (transformers, or whatever);

(*b*) the model could not be congested by external variables as a consequence of the limited sample size;

(*c*) the stochastic frontier series with which DEA results were to be compared came from production function analysis (with *Y* being energy delivered), so output-orientated DEA was preferred. Single-output analysis was provided for the sake of completeness and comparability.

DEA outcomes (efficiency score series) were compared with scores stemming from the MUNI10 model (see Chapter 4). This model was a translog production function featuring electricity as output and internal employees, third-party employees (often belonging to controlled municipal enterprises), and kilometres of distribution line as inputs. Furthermore, MUNI10 contained ten environmental effects to correct the estimate of the efficiency error term (*u*) in stochastic frontier analysis[78]. All efficiency scores were normalised to the (0,1] interval before being statistically compared. MUNI Tables in the Appendix report efficiency scores from the three DEA models, as compared to the ones estimated via MUNI10. A sum of scores is also provided, separately for each municipality[79].

DEA Tables: See Numerical Appendix.

[78] Battese and Coelli (1995).

[79] We did not compute geometric means because we were just interested in the ordering not in the absolute values of mean efficiency scores.

It appears from the comparative Table that, generally speaking, DEA outcomes tend to confirm stochastic frontier results. Apart from a few exceptions (very small units as Mezzolombardo and Selvino in mountain districts, for example), non-outlier units were ranked by the two methodologies in a similar fashion. This obviously called for paired-samples statistical testing. First of all, Kolmogorov-Smirnov tests revealed that the two one-output DEA series were compatible with normality assumptions, whereas normality was rejected for DEA22(OUT) and MUNI10. This led to parametric paired-samples *t*-tests being performed, together with rank-order ones, for two out of three of the matched series. Matches DEA1C2-MUNI10 and DEA1Y2-MUNI10 were tested via both parametric (*t*) and non-parametric (Wilcoxon, Sign) procedures. Test outcomes confirm that statistical agreement is found between both the one-output DEA series and the MUNI10 one. Both parametric and non-parametric test results show this. In particular, strong agreement is spotted between DEA1Y2 and MUNI10, which makes sense if one recalls that MUNI10 scores come from a production function (compatible with output-orientated DEA) featuring energy delivered as *Y* (just as in DEA1Y2). However, even DEA1C2-MUNI10 proved to be a successful comparison - albeit to a lesser extent - whereas DEA22(OUT)-MUNI10 failed both (non-parametric) tests, meaning that two-output DEA scores could not be deemed compatible with one-output, production frontier ones. This also appears to be a sensible result.

Finally, K related-samples tests (Friedman, Kendall's W) strongly reject the null hypothesis according to which, with no normality assumptions, the four samples examined above come from populations with identical distribution functions, thus accepting the alternative hypothesis that at least two of the above samples differ with respect to their location parameters (medians).

Table 5.5: MUNIs: Non-Parametric and Parametric Tests

Descriptive Statistics

Models	N	Mean	Std. Deviation	Minimum	Maximum
DEA1C2	37	0.734541	.234521	0.2659	1.00
DEA1Y2	37	0.753484	.222724	0.3245	1.00
DEA22	37	0.849319	.184928	0.399	1.00
MUNI10	37	0.753919	.238080	0.294	.987

One-Sample Kolmogorov-Smirnov Test

	DEA1C2	DEA1Y2	DEA22	MUNI10
K-S Z (Normal)	1.025	0.982	1.368	1.518
Z Prob (2-tailed)	0.244	0.290	0.047	0.020
K-S Z (Uniform)	1.808	1.723	2.630	2.446
Z Prob (2-tailed)	0.003	0.005	0.000	0.000

Parametric Paired-Samples *t*-tests

Pairs/Values	DEA1C2-MUNI10	DEA1Y2-MUNI10
t-value	-0.708	-0.010
Deg. Freed.	36	36
t-prob	0.484	0.992

Non-Parametric Tests

Tests		DEA1C2-MUNI10	DEA1Y2-MUNI10	DEA22-MUNI10
Wilcoxon (SR)	Z-value	-1.622	-0.023	-3.040
	Z-prob	0.105	0.982	0.002
Sign	Z-value	-0.658	-0.658	-3.288
	Z-prob	0.511	0.511	0.001
McNemar	n/a	n/a	n/a	n/a

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

Not appropriate.

K Related-Samples Tests

Tests		Friedman	Kendall's W	Cochrane
Chi-Sq. Value		25.912	25.912	n/a
Deg. Freed.		3	3	n/a
Chi-Sq. Prob		0.000	0.000	n/a

We now move to second-stage Tobit analysis of efficiency scores for models DEA22, DEA1C2, and DEA1Y2. Scores were inverted and shifted to the [0,+∞) interval, in order to comply with Tobit's left censoring requirement. Interpretation of coefficient signs is then still in the sense of higher efficiency with negative coefficients and vice versa. Run 2 of Tobit dropped all insignificant environmental variables and re-estimated the three models with surviving variables only. DEA22 performed badly even in the second-stage Tobit regression, thus confirming that one-output models fit underlying figures much better than a double-output specification does. Since no environmental effects were significant in DEA22, we shifted to a second Tobit run with models DEA1C2 and DEA1Y2 only. External-effect outcomes for DEA1C2 highlight INDY, MOUNTDUM, and SEADUM as the (in)efficiency drivers. The positive sign of INDY's coefficient is *prima facie* embarrassing, but can be easily explained by recalling that DEA1C2 maximised total customers for given inputs. By doing so, the model obviously 'felt' the percentage of industrial output as something hindering maximisation of customers, since industrial output is notoriously directed towards a limited number of users (as compared to residential ones). The 'tricky' objective function of DEA1C2 then explains why industrial output was seen as inefficiency-enhancing in that model: therefore, one should take INDY's sign rather carefully after noticing this. *A fortiori*, INDY's sign was 'regular' for DEA1Y2's scores, thus showing that (energy-maximising) efficiency levels were actually boosted as a result of growing percentages of industrial users on the total. Going back to model DEA1C2, both mountain and sea dummies turned out to be efficiency handicaps for municipalities, thus implying that customer-maximising efficiency scores are indeed depressed by both mountain and coastline locations. The most obvious explanation to this is that, given Italy's high mountains and jagged coastlines, efficiency maximisation - in

terms of total customers - is obviously better achieved in plains (such as the Po Valley) and metropolitan contexts, rather than in coastal and Alpine ones. Of course, such big seaside towns as Genoa, Naples, Palermo, Bari, Venice-Marghera-Mestre, and Trieste will be exceptions. Nonetheless, Trieste only has a municipal electric utility, whereas all other big towns are run by ENEL. Other MUNIs operating on the coastline are Sanremo and Trani (two small towns). Alpine villages, on the other hand, are obviously in need for state/regional subsidies, and should not be subject to (yardstick) regulation at all.

Shifting to second-stage Tobit analysis of DEA1Y2 scores, INDY's coefficient recovered the 'right' sign (as an efficiency driver), and the industrial area dummy also showed positive contribution to (energy-maximising) technical efficiency. All remaining coefficients did not survive a second Tobit run. These results are standard, and point in the obvious direction of higher technical efficiency within industrial districts where the percentage of industrial output - i.e., delivered energy - is higher (e.g., Lombardy, Emilia, parts of Piedmont, parts of the North-East).

Table 5.6: MUNIs: Second-Stage Tobit Analysis of DEA Efficiency Scores (Two Runs)

Run 1

Available on request.

Run 2

DEPENDENTVARIABLE: DEA1CA

LOG-LIKELIHOOD FUNCTION	-23.433
NUMBER OF OBSERVATIONS	37
NUMBER OF POSITIVE OBSERVATIONS	26
PERCENT OF POSITIVE OBSERVATIONS	0.702703

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	-1.13906	0.281136	-4.05163
INDY	2.70954	0.525967	5.15153
MOUNTDUM	0.901357	0.208964	4.31345
SEADUM	1.04701	0.36406	2.87592
BORDUM	0.274018	0.240127	1.14114

INDCUST	-9.44572	6.04403	-1.56282
SIGMA	0.470008	0.066973	7.01788

DEPENDENTVARIABLE: DEA1YA

LOG-LIKELIHOOD FUNCTION	-29.2352
NUMBER OF OBSERVATIONS	37
NUMBER OF POSITIVE OBSERVATIONS	28
PERCENT OF POSITIVE OBSERVATIONS	0.756757

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	1.15409	0.260888	4.42369
INDY	-1.37776	0.558307	-2.46775
METRDUM	-0.13463	0.408637	-0.32947
SEADUM	0.174155	0.300453	0.57964
INDUSDUM	-0.54626	0.200873	-2.71942
SIGMA	0.536273	0.074083	7.23882

Standard Errors computed from analytic second derivatives (Newton). Low values of the log-likelihood function partially depend on the fact that MLE is a large-sample estimation method. Apart from the main ENEL analysis, all remaining samples are not particularly large.

The next Subsection deals with the same DEA models as those used for the municipal analysis, now being applied to a pooled sample (1994-1996) of ENEL units and MUNIs. Comparisons between SFE and DEA scores will also be made.

4.3 DEA Outcomes from a MUNI-ENEL Pooled Sample (1994-1996) with Statistical Comparisons and Second-Stage Tobit Analysis of Reported Efficiency Scores

We instrumented the same models (DEA22OUT, DEA1C2, DEA1Y2) for the pooled sample already examined in Chapter 4. Output orientation was again selected, so as to look for consistency with stochastic-frontier estimation outcomes on the same 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 Tables in the Appendix provide usual comparisons of scores for the three DEA models and model

SFM3, developed in Chapter 4 and featuring three environmental variables only[80]. Aggregated scores from all models (with no weighting) are reported in the second Table.

DEA Tables: See Numerical Appendix.

In terms of notation, recall that the reported Tables feature 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 Chapter 4 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 counterparts 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 Subsection. Statistical agreement between SFM3 and one of the DEA models would call for a further, final comparative analysis of efficiency of MUNIs and ENEL units, which is outlined in the next Subsection. At a first glance, the towns that even in DEA had their municipality

[80] The reason for this is found in the nature of the pooled sample itself: for an explanation, see Chapter 4.

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 the usual battery of descriptive statistics and comparison tests, which will be commented on in detail throughout the following paragraphs.

Table 5.7: 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 DEA1C2-SFM3 and DEA22OUT-SFM3. On the contrary, statistical agreement between DEA1Y2 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 Chapter 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 Chapter 4's 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.

Before moving to a supplementary analysis of MUNIs and corresponding ENEL zones in DEA terms[81], 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.

We now conclude by examining the usual two-run Tobit analysis of DEA efficiency scores for the 1994-1996 ENEL/MUNI pooled sample. Estimates from the second run only are reported in the Tables below.

Table 5.8: Pooled Sample: Second-Stage Tobit Analysis of DEA Efficiency Scores (Two Runs)

Run 1

Available on request.

Run 2

DEPENDENTVARIABLE: DEA22A

LOG-LIKELIHOOD FUNCTION	-62.7711
NUMBER OF OBSERVATIONS	76
NUMBER OF POSITIVE OBSERVATIONS	60
PERCENT OF POSITIVE OBSERVATIONS	0.789474

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	-0.28744	0.263357	-1.09143
INDY	1.682	0.471723	3.56566
BORDUM	0.43286	0.169889	2.5479
INDUSDUM	-0.66527	0.146472	-4.54197
MUNIDUM	0.560813	0.143062	3.92007
SIGMA	0.564182	0.052867	10.6718

[81] See next Subsection.

DEPENDENTVARIABLE: DEA1CA

LOG-LIKELIHOOD FUNCTION	-55.2635
NUMBER OF OBSERVATIONS	76
NUMBER OF POSITIVE OBSERVATIONS	64
PERCENT OF POSITIVE OBSERVATIONS	0.842105

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	-0.75357	0.235429	-3.20082
INDY	2.90911	0.421795	6.89698
BORDUM	0.394292	0.151104	2.60941
INDUSDUM	-0.74775	0.129629	-5.7684
MUNIDUM	0.757121	0.126689	5.97624
SIGMA	0.502151	0.045029	11.1517

DEPENDENTVARIABLE: DEA1YA

LOG-LIKELIHOOD FUNCTION	-99.5394
NUMBER OF OBSERVATIONS	76
NUMBER OF POSITIVE OBSERVATIONS	64
PERCENT OF POSITIVE OBSERVATIONS	0.842105

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	2.18409	0.453973	4.81106
DENS	-5.86E-04	2.84E-04	-2.06567
INDY	-1.88934	0.834031	-2.26531
INDUSDUM	-0.9483	0.260627	-3.63853
MUNIDUM	0.880182	0.256096	3.43692
SIGMA	0.967701	0.087669	11.0381

Standard Errors computed from analytic second derivatives (Newton)

After dropping insignificant external variables, the second-stage Tobit analysis of efficiency scores was left with three small regressions of 'inverted' efficiency scores from models DEA22OUT, DEA1C2, and DEA1Y2. The two-output, two input model for the pooled sample again showed that the percentage of industrial customers had a 'wrong' influence on efficiency maximisation. However, the presence of total customers as a maximisable output in the objective function triggered the perverse effect of INDY on efficiency, since larger industrial output entails more industrial customers as a percentage of the total, and hence implies a smaller overall amount of electricity users (provided that capacity constraints are binding). The border dummy (BORDUM) suggests a negative effect of borderline territories on efficiency. This again must be taken carefully, because the pooled

sample was made up of several North-Eastern rural and mountain distributors, mostly located in the neighbourhood of the Alpine passes bordering Switzerland, Austria, and Slovenia. Hence, the 'border' effect should in fact be taken as a 'mountain' effect, and its sign would indeed turn out to be the expected one. The industrial areas dummy gave the expected result, again showing that distributors located in industrial districts are more favoured than rural, mountain, and coastline ones, and should then be regulated more tightly. Quite interestingly, the municipal dummy had a negative impact on efficiency. This is partly due to the presence of mountain and rural distributors among MUNIs (especially those from the North-East and South Tyrol) and, more generally, to the fact that both econometric and DEA models had ENEL's zones outperforming their MUNI counterparts on average, with almost 65% of favourable cases. Nevertheless, this is not sufficient to generalise ENEL's superiority and, of course, does not hinder the prospective expansion of those MUNIs which indeed proved to be superior to ENEL's zones within industrialised - and especially Lombard - districts.

The one-output DEA model confirmed the above outcomes for all INDY, BORDUM, INDUSDUM, and MUNIDUM coefficients. However, things get different when examining model DEA1Y2, which is the one featuring electricity delivered as the only output - hence showing most similarity to the original, stochastic frontier production translog specification. First of all, consumer density finally pops up again as a positive effect on technical efficiency (the expected result), even though its coefficient is particularly small, standing at a modest (–0.00059). INDY finally recovered a well-behaved sign because the number of customers had been excluded from the optimisation problem in DEA1Y2, and thus could not bias the direction of INDY's effect upon electricity distribution's efficiency. Industrial output as a percentage of the total turned out to positively affect technical efficiency in the end. The industrial-district dummy also showed the expected sign, thus confirming regulatory concern

about more favoured Northern units, which are today setting marginal prices that roughly approximate distributing cost averages throughout the country, thus transferring considerable surplus from their (especially industrial) customers. Finally, the 'municipal' dummy showed that, on average, ENEL zones outperformed MUNIs again, which - however - does not jeopardise the view according to which some prominent urban MUNIs were still faring better than their surrounding/neighbouring ENEL counterparts.

The next Subsection deals with a supplementary analysis of MUNIs as compared to ENEL zones, which was not carried out in the econometric Chapters of this thesis.

4.4 DEA Outcomes from Two MUNI-ENEL Sub-samples (1994-1996, 31 obs. each) with Statistical Comparisons and Second-Stage Tobit Analysis of Reported Efficiency Scores

Chapter 4 performed stochastic frontier translog regressions and estimated technical efficiency scores[82] with respect to MUNIs only. Then, it extended the efficiency analysis to a pooled sample of 76 MUNIs and their - somewhat imperfect - ENEL counterparts (there named 'peers', but not in the technical, DEA sense) being singled out of the overall sample of 147 ENEL/1996 units according to both geographical and economic proximity criteria. However, econometric analysis was not extended to two separate subsamples of MUNIs and ENEL counterparts because the resulting sample sizes would have been too small to accommodate a large number of variables. We then skipped that kind of investigation in Chapter 4 and introduce it here, within a DEA environment which better suits small samples.

From a methodological point of view, we took the 76-observation pooled sample and selected one-to-one (not more than one) MUNI/ENEL pairs. Therefore, we dropped multiple

counterparts - which are not compatible with "one-to-one" matched-pairs statistical testing - and reduced the pooled sample to 62 observations, corresponding to 31 matched MUNI/ENEL pairs. The new pooled sample was chosen because statistical testing had to be performed by matching one ENEL unit with one MUNI only[83]. For instance, for the tiny Piedmontese MUNI of Gattinara (in the North-Western Pre-Alps, not far from the Simplon Pass with Switzerland) we dropped two former ENEL counterparts (Vercelli, its provincial administrative centre, and Biella, now a provincial main town as well) to create the match Gattinara-Verbania, where Verbania (on Lake Maggiore) is the most similar ENEL unit to Gattinara in 'environmental' terms. By the same token, we coupled every MUNI to its *closest* ENEL counterpart, thus creating two related samples (MUNIs against ENEL) featuring 31 observations each. There obviously were no problems with urban units (e.g., Milan, Turin, Brescia, Parma, and so on), but matched pairs for rural and mountain units were much less easy to generate. As a choosing rule, we selected those ENEL units which most resembled non-urban municipalities according to both geographical location and economic characteristics (amount of inputs and outputs used, percentage of industrial customers, nature of distribution lines, and so on). For example, selection went on like this: Riva del Garda's MUNI (on Lake Garda) was matched to ENEL at Salo' (fifty kilometres to the south, on the same lake). Tirano's MUNI (located in Valtellina, near the Grigioni/Graubünden district in South-Eastern Switzerland) was matched with Lecco's ENEL zone (on Lake Como, to the West of Valtellina, again not far from the Swiss border). Even though Sondrio - Tirano's provincial capital - is closer to Tirano than Lecco is, we preferred to use Lecco's ENEL zone

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[82] Recall that the TEE model postulates full allocative efficiency *ex ante*.

[83] We reckon that non-parametric statistical tests are feasible even in the presence of differently sized samples. However, when sample sizes are equal some non-parametric statistics tend to distribute more nicely (for instance, the Wilcoxon-SR statistic will asymptotically distribute as a standard normal) and the outcomes of tests are straightforward in that they relate to one-to-one (paired) matches. On the criteria for matching different plants and firms, see Daly *et al.* (1985), and Steedman and Wagner (1987).

as a counterpart to Tirano's MUNI because the economic figures for these two units were much more similar to each other, with Sondrio's ENEL zone - on the other hand - being much larger than Lecco's. The whole selection process went on according to the above considerations.

What stemmed from the above work is a couple of related samples (31 MUNIs for 1994, 31 ENEL units for 1996), which were ready for DEA computations. Again, recall that DEA does not suffer from the same small sample problems affecting econometric techniques. The alternative DEA models which were run on the two sub-samples are exactly the same as those previously originated for MUNIs only and the ENEL-MUNI (76-obs.) pooled sample. Therefore, MDEA22 and PDEA22 are output-orientated, VRS DEA models for MUNIs (M) and ENEL's 'peers' (P), respectively, whereas MDEA1C and PDEA1C are their counterparts featuring total customers as a single output. Finally, MDEA1Y and PDEA1Y develop the same model for the MUNI/ENEL pairs, with delivered energy being taken as the (only) output. Output-orientated DEA scores are reported below. They are now expressed in the (0,100] scale, as no comparisons will be made with SFE outcomes - whose efficiency scores are generally reported as fractions of unity. Hence, we decided to retain the usual percentage format of scores which traditionally characterises DEA results.

Table 5.9: Sub-samples (1994-1996): DEA Efficiency Scores (DEA22OUT, DEA1C2, DEA1Y2) for Two 31-observation Sub-samples [Scores are expressed in the 0-100 scale]

MUNI/ENEL Peer	MDEA22	PDEA22	MDEA1C	PDEA1C	MDEA1Y	PDEA1Y
BOLZANO(M)/BOLZANO	57.59	43.28	48.74	38.75	57.47	43.28
BRESCIA(M)/BRESCIA	100	100	79.29	79.26	97.23	100
BRUNICO(M)/BASSANO	77.67	77.25	62.61	74.47	74.77	75.2
CREMONA(M)/CREMONA	100	73.75	100	65.35	100	73.75
GATTINARA(M)/VERBANIA	100	100	100	100	100	57.76
IMOLA(M)/BOLOGNA	100	100	71.21	100	100	99.39
MILANO(M)/MILANO	100	100	100	100	100	100

MODENA(M)/MODENA	100	99.06	79.95	84.87	98.87	98.21
OSIMO(M)/PESARO	60.56	73.95	60.04	73.95	53.88	45.1
PARMA(M)/PARMA	100	75.56	100	75.29	87.67	74.28
PRIMIERO(M)/BRENO	41.55	89.68	41.55	78.97	34.09	82.92
REP. S. MARINO(M)/RIMINI	74.74	76.84	44.13	76.84	74.74	53.67
RIVA d. GARDA(M)/SALO'	73.16	78.35	72.33	78.35	64.25	73.61
ROMA(M)/ROMA	100	100	100	100	100	100
ROVERETO(M)/TRENTO	97.99	70.28	45.42	70.28	97.99	59.9
SANREMO(M)/IMPERIA	69.35	100	69.35	100	39.24	51.46
SELVINO(M)/BERGAMO EXT.	100	91.51	100	91.51	44.82	83.75
SEREGNO(M)/LODI	93.81	100	83.19	100	92.54	100
SONDRIO(M)/SONDRIO	88.82	85.13	75.54	84.73	85.78	56.03
SORESINA(M)/MELZO	100	100	100	100	68.67	100
TERNI(M)/TERNI	100	48.09	100	48.09	100	35.72
TIRANO(M)/LECCO	75.39	100	73.81	96	57.05	100
TOLENTINO(M)/MACERATA	94.55	69.55	65.9	69.55	93.97	42.51
TORINO(M)/TORINO	88.36	98.62	88.36	98.62	70.6	92.86
TRANI(M)/MONOPOLI	93.23	73.72	93.23	73.72	53.79	37.46
TRIESTE(M)/TRIESTE	100	100	100	100	91.54	100
VERCELLI(M)/VERCELLI	100	50.08	100	49.03	84.39	50.08
VERONA(M)/VERONA NORD	100	77.15	56.82	77.15	100	60.44
VICENZA(M)/VICENZA	84.23	100	84.23	76.61	66.07	100
VIGO d. CADORE(M)/BELLUNO	100	59.8	100	59.8	100	36.39
VOGHERA(M)/VIGEVANO	83.52	91.46	83.52	91.46	47.54	82.01

The Table above should be interpreted as follows: the first column reports the pairs (MUNI/ENEL) to be compared; the following columns report VRS DEA scores for MUNIs (the ones with an 'M' prefix, e.g. MDEA22 for the two output/two input model) and ENEL counterparts (the ones with a 'P' prefix), stemming from *separate* DEA runs on separate (albeit related) sub-samples. Inputs (lines, employees) and outputs (customers, energy) are exactly the same as those utilised so far. For the sake of effective discrimination, and also in the light of the small sub-sample sizes, we once again excluded environmental effects and confined them to the usual, second-stage Tobit analysis of efficiency scores. To sum up, M-prefixed columns result from MUNI-DEA runs with different input-output specifications (two outputs, single output), whereas P-prefixed ones come from ENEL-DEA runs with the usual, alternative specifications. One should notice that, for a small sample size, two inputs and two outputs are enough in congesting the model to a limited extent, thus providing the investigator

with 'smooth' efficiency series featuring no full discrimination between frontier-efficient DMUs and inefficient ones[84]. Therefore, one should prefer one-output models, as they better discriminate among differently efficient DMUs.

To test the claim according to which local MUNIs are *in all respects* less efficient than their surrounding ENEL's *zone di distribuzione*, we now report a battery of paired-samples tests looking at statistical agreement among MUNI/ENEL separate efficiency series. Such tests can only show whether, from a statistical point of view, matched efficiency series basically provide the investigator with the same information (i.e., they are taken from populations sharing the same distribution function). Should the null hypothesis of no statistical disagreement between matched series fail to be rejected, we could not categorically claim that efficiency for all MUNIs and ENEL counterparts is exactly the same. Nonetheless, we might infer that no generalisation on efficiency differences must be made, because efficiency spreads between MUNIs and surrounding ENEL units are actually to be regarded as a case-by-case problem. This is the conclusion being reached throughout both Chapter 4 and this Chapter, in contradiction with ENEL's categorical assertions on MUNIs. In policy-making terms, acceptance of the null hypothesis of no statistical disagreement between matched ENEL/MUNI series would point to the regulatory issue of which MUNIs should be actually allowed to expand beyond municipal dimension - possibly at the expense of surrounding ENEL districts - and which ones, on the other hand, should be absorbed by ENEL itself for the sake of technical efficiency. We previously stated that generalisation is not possible here, and that a case-by-case approach ought to be adopted by the energy regulator instead. Statistical tests below might either add or subtract strength to such an assertion.

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[84] Look at columns for MDEA22 and PDEA22, showing a considerable amount of 100% efficient units.

Table 5.10: Sub-samples: Non-Parametric and Parametric Tests

Descriptive Statistics

Models	N	Mean	Std. Deviation	Minimum	Maximum
MDEA1C	31	79.9748	19.4667	41.55	100
MDEA1Y	31	78.6116	21.5187	34.09	100
MDEA22	31	88.8555	15.5146	41.55	100
PDEA1C	31	81.0532	17.0746	38.75	100
PDEA1Y	31	73.0897	23.5639	35.72	100
PDEA22	31	83.9713	17.3605	43.28	100

One-Sample Kolmogorov-Smirnov Test

	MDEA1C	MDEA1Y	MDEA22	PDEA1C	PDEA1Y	PDEA22
K-S Z (Normal)	1.13	0.989	1.379	0.771	0.999	1.225
Z Prob (2-tailed)	0.155	0.282	0.045	0.591	0.271	0.1
K-S Z (Uniform)	1.976	1.8	2.768	1.922	1.641	2.199
Z Prob (2-tailed)	0.001	0.003	0.000	0.001	0.009	0.000

Parametric Paired-Samples *t*-tests

Pairs/Values	MDEA22-PDEA22	MDEA1C-PDEA1C	MDEA1Y-PDEA1Y
t-value	1.238	-0.26	0.997
Deg. Freed.	30	30	30
t-prob	0.225	0.797	0.327

Additional Cross-Checking: Non-Parametric Tests

Tests		MDEA22-PDEA22	MDEA1C-PDEA1C	MDEA1Y-PDEA1Y
Wilcoxon (SR)	Z-value	-1.143	-0.648	-0.919
	Z-prob	0.253	0.517	0.358
Sign	Z-value	-0.981	-0.371	(*)
	Z-prob	0.327	0.71	0.541(*)
McNemar	n/a	n/a	n/a	n/a

(*): Exact Significance (2-tailed). Binomial Distribution used.

K Related-Samples Tests

Tests		Friedman	Kendall's W	Cochrane
Chi-Sq. Value		25.637	25.637	n/a
Deg. Freed.		5	5	n/a
Chi-Sq. Prob		0.000	0.000	n/a

First of all, one-sample Kolmogorov-Smirnov tests failed to reject the null hypothesis of normality for five out of the six models which we constructed, and showed just a weak rejection (at a 5% level) for the remaining model. This made paired-samples (mean-comparing) parametric *t*-tests feasible, so as to examine matched pairs for MUNIs and ENEL counterparts according to the three different VRS-DEA specifications. Surprisingly enough, all parametric tests for the three paired samples did not reject the null hypothesis of identical distribution functions for the populations from which the paired samples were extracted. Even non-parametric supplementary tests (Wilcoxon's Signed-Rank, Sign Test) confirmed that MUNI and ENEL efficiency series did not show any significant statistical disagreement. Of course, such findings are partly due to the fact that we were comparing scores resulting from the same measurement technique (DEA), so this did not amount to methodological cross-checking. However, it is interesting to notice that acceptance of H_0 was strong for all tests (both parametric and non-parametric) and that, after all, even though DEA was used in all cases, it had been applied to completely separate samples of - albeit geographically and economically related - ENEL/MUNI units.

The conclusion to be drawn is that, once again, there is no statistical evidence of significant differences in technical efficiency between municipal authorities and corresponding ENEL local units. Of course, on a case-by-case basis it will be easy to spot several ENEL zones which actually outperform corresponding territorial MUNIs to a large extent; however, it is also easy to find a great deal of (especially urban and Lombard) MUNIs behaving better than their ENEL counterparts on technical efficiency grounds. Therefore, the analysis carried out in this Chapter corroborates Chapter 4's econometric findings according to which no generalisation is feasible with respect to ENEL/MUNI efficiency comparisons.

A final remark before shifting to Tobit analysis of DEA efficiency scores is that the above examination of MUNIs and ENEL units was not able to reach any significant conclusion on the future of electricity distribution in the South of Italy. This is because, as previously noticed, only one municipality in the South is running the electricity business (Trani), with the remainder of Southern towns and villages being served by ENEL's distributing arm. Therefore, one can believe that a considerable subset of Northern towns might have a larger and stronger MUNI in the future, perhaps serving surrounding villages/provinces and replacing ENEL in some districts. On the contrary, nothing can be said of possible developments in municipal electricity distribution with reference to the South (*Mezzogiorno*), simply because statistical inference is still hindered by the fact that just one municipality is operating distribution in the whole macro-region (whose size is actually comparable to that of England). Of course, this fact *per se* is self-explanatory as regards the real prospects for alternative electricity distribution structures to be possibly devised in the Italian provinces lying to the south of Rome (including Sicily, maybe excluding Sardinia).

The next Tables report second-stage Tobit outcomes on environmental effects in standard estimation format.

Table 5.11: Sub-samples: Second-Stage Tobit Analysis of DEA Efficiency Scores (Two Runs)

Run 1

Available on request.

Run 2

DEPENDENTVARIABLE: PDEA22A

LOG-LIKELIHOOD FUNCTION	-14.9293
NUMBER OF OBSERVATIONS	31
NUMBER OF POSITIVE OBSERVATIONS	20
PERCENT OF POSITIVE OBSERVATIONS	0.645161

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	0.475946	0.148292	3.20952
DENS	-2.70E-03	1.09E-03	-2.46985
METRDUM	1.67402	0.826569	2.02526
INDUSDUM	-0.22902	0.156355	-1.46472
GENERDUM	0.183572	0.144782	1.26792
SIGMA	0.362804	0.060124	6.03423

DEPENDENTVARIABLE: PDEA1CA

LOG-LIKELIHOOD FUNCTION	-14.7373
NUMBER OF OBSERVATIONS	31
NUMBER OF POSITIVE OBSERVATIONS	23
PERCENT OF POSITIVE OBSERVATIONS	0.741935

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	0.470494	0.140826	3.34096
DENS	-2.47E-03	9.90E-04	-2.49732
METRDUM	1.31958	0.748098	1.76391
INDUSDUM	-0.06936	0.14903	-0.46539
GENERDUM	0.211341	0.140246	1.50693
SIGMA	0.360502	0.055053	6.54824

DEPENDENTVARIABLE: PDEA1YA

LOG-LIKELIHOOD FUNCTION	-17.3041
NUMBER OF OBSERVATIONS	31
NUMBER OF POSITIVE OBSERVATIONS	23
PERCENT OF POSITIVE OBSERVATIONS	0.741935

Parameter	Estimate	Std. Error	*t*-statistic
CONSTANT	0.881024	0.172388	5.11069
DENS	-2.83E-03	1.22E-03	-2.32532
METRDUM	1.70458	0.922049	1.84869
INDUSDUM	-0.65406	0.181411	-3.60538
GENERDUM	0.353967	0.170243	2.07918
SOUD	1.12355	0.450795	2.49237
SIGMA	0.421206	0.063509	6.63225

Standard Errors computed from analytic second derivatives (Newton)

The first run of the above Tobit estimation showed that all models based upon municipal authorities (M-prefixed) either had no relationship with environmental variables, or

highlighted just one significant coefficient for each regression. In particular, the percentage of industrial customers on the total again reported a 'wrong' sign where customer maximisation was a priority in the model, and reverted to its usual, positive impact on technical efficiency when energy delivered was assumed as the only maximisable output. In the end, a second Tobit run featured ENEL peers only (models PDEA22, PDEA1C2, and PDEA1Y2), as shown by the Tables above.

Consumer density (DENS) was found to enhance efficiency in all models. The METRDUM dummy pointed in the direction of lower efficiency for those metropolitan ENEL units whose city centres are very often served by municipalities (Milan, Turin, Rome, Verona, Trieste), thus jeopardising - in some cases - the efficiency level of metropolitan ENEL distributors as compared not to municipalities, but to other ENEL zones[85]. INDUSDUM's coefficient is significant in one case only (PDEA1Y2, where the only output is electricity delivered), but carries the 'right' sign in all three models - even where it is not statistically relevant at 5%. This confirms that industrial areas do matter in making the management of electricity distribution easier, other things being equal. GENERDUM's coefficient entails a negative effect of generating plants on distribution efficiency, and is statistically significant in the electricity-output model. As explained earlier, this might be either due to ENEL's internal transfer prices across different production subsets, or simply to the fact that power stations in the area require higher capital investment in substations and transformers - to be, at least partially, incurred by distributing units. This stems from the need for direct interconnection between local power stations and the distribution network, thus by-passing the trans-regional transmission grid. Finally, the territorial dummy (SOUD) confirmed that Southern location for ENEL units - nothing can actually be said of municipalities on this - is still a handicap in

[85] Recall that the P-prefixed models deal with ENEL 'peers' only, not with MUNIs.

terms of efficiency maximisation. From a regulatory point of view, this translates into the need for more generous regulation to be imposed on Southern units, with the noticeable exception represented by metropolitan distributors such as those located in Naples, Palermo, Bari, and Catania.

The next Sections conclude the Chapter and summarise our findings. Tentative policy-making suggestions for the Italian energy regulator are finally provided in Chapter 6.

5. The 'Cost' of ENEL's Technical Inefficiency

Chapter 5 reported a DEA study of both ENEL and municipal utilities. One of the most interesting aspects of DEA from the policy-maker's point of view is the availability of tables showing actual and optimal values for each (minimisable) input and (maximisable) output.

Thanks to its linear programming nature, DEA is capable of reporting 'theoretical' input-output values being computed by projecting actual observations upon the 'best-practice' unit isoquant, where the most similar efficient DMUs are linearly combined so as to give rise to a 'virtual' producer showing 'target' I/O values for non-100% efficient units. The diagrams below report actual and 'target' values for distribution lines (LINES), employees (LAB), energy delivered (YTOT), and total customers (TOTCUST). We took model DEA22IN, which minimises inputs. Even though an output-maximising linear program would have been a better option given ENEL's actual control upon energy delivered, the availability of input (but not output) prices pushed us to compute input (rather than output) slacks[86], which could

[86] However, the switch from output to input orientation - needed because of the unavailability of output prices to quantify inefficiency in monetary terms - comes at the expense of interpretation problems relating to the 'slacks' thus obtained. Typically, input orientation implies that distribution lines might be 'saved', even though there are reasons to believe that lines should be substantially exogenous to local DMUs. Moreover, the slacks being reported in the following Tables incorporate non-radial contractions, since slack-corrected DEA scores were computed here.

be 'priced' so as to generate monetary values for ENEL's technical inefficiency in energy distribution.

Notice the presence of lower and less jagged trends for 'target' input values, indicating the theoretical chance of minimising input usage for several technically inefficient ENEL zones.

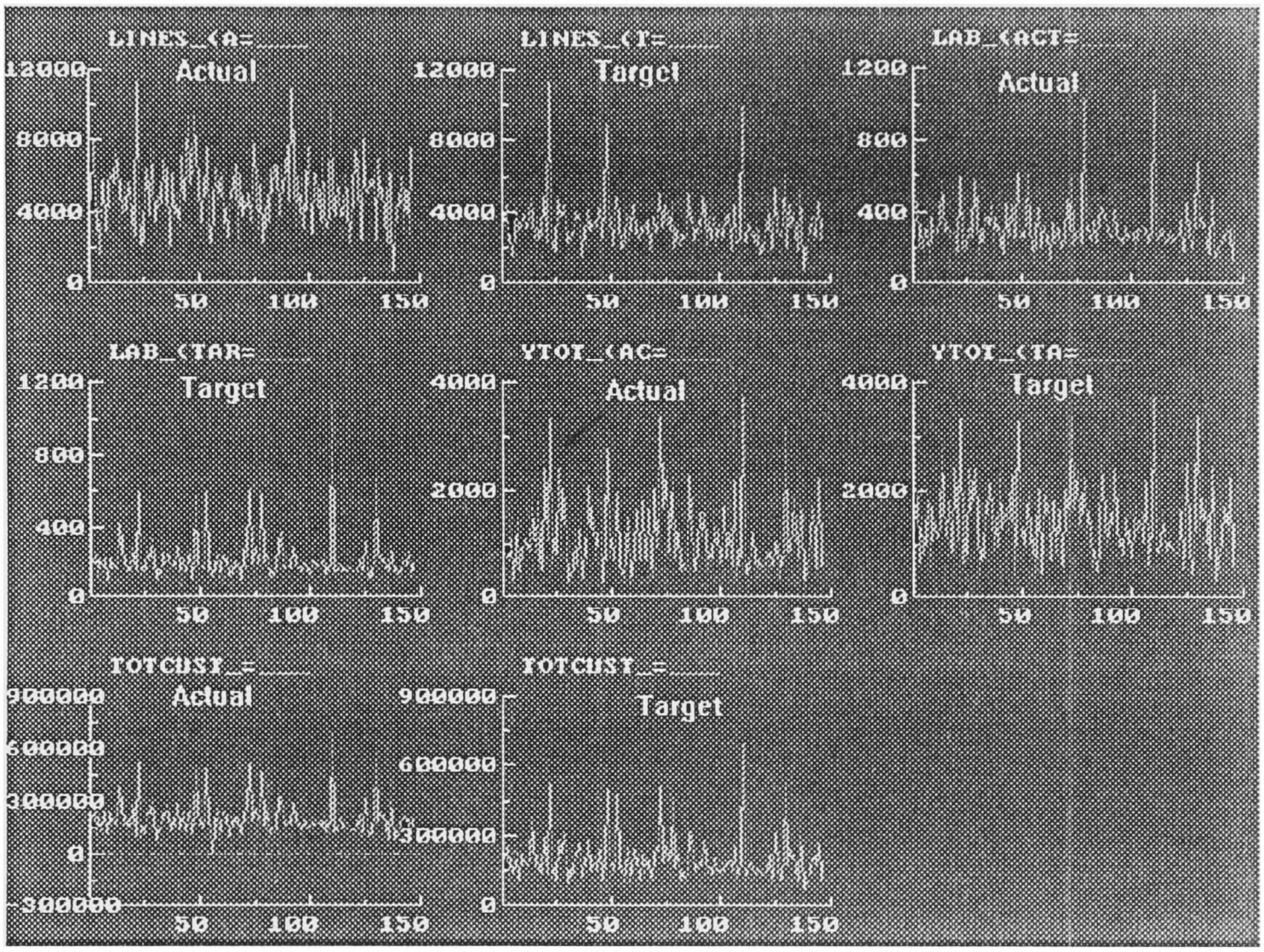


Figure 5.8. 'Actual' and 'Target' I/O Values for ENEL's Local Branches (DEA).

The Table below shows differences (Δs) between actual and target values. By multiplying efficiency differences (or 'slacks', to use the DEA terminology) by input prices (p_k, p_l), we obtained monetary slack values, i.e. the amounts of money which ENEL's distributing arm

would save should *all* of its local zones operate at technically (I/O) efficient levels. The sum of capital (lines) and labour (employees) savings totals more than 2,150 billion ITL (almost equally split between the two inputs), i.e. around GB£730 million at April 1998 exchange rates[87].

Unit	ΔLIN (km)	ΔLAB (#)	ΔYTOT (GWh)	ΔCUST (#)	SAVLIN (million ITL)	SAVLAB (million ITL)
ACIREALE	1098.8	62	681.6	0	5295.831	4477.962
AGRIGENTO	3577.6	206.5	1207.9	0	15145.32	15772.8
ALBA	1464.8	74.2	0	10170.5	5893.142	5820.203
ALBANO	1446	112.8	435.5	0	8209.987	9222.445
ALBENGA	129.5	15.9	459.9	0	997.6225	1266.596
ALESSANDRIA	2471.5	139.4	304.4	0	12281.17	10831.96
ANCONA	1577.3	88.2	340	0	6884.296	6489.795
AOSTA*	**0**	**0**	**0**	**0**	**0**	**0**
AQUILA	2178.6	143.3	753.3	0	10562.86	9140.886
AREZZO	2480.9	108.8	307.3	0	9715.338	8569.645
ASCOLI	2174.7	88.2	286.3	0	9105.338	6420.319
ASTI	2438.9	129.3	217.1	0	10072.33	11063.07
AVELLINO	3574.3	168.5	544.7	0	16538.95	11875.51
BARI	1710.1	151.9	1033.6	0	6538.757	11886.31
BARLETTA	1520.4	104.9	276.5	0	6585.553	7705.999
BASSANO	1761.3	102.7	0	0	8585.427	7375.991
BELLUNO	1650.1	109.2	203.4	0	8627.257	8173.418
BENEVENTO	2732.1	138.1	366.4	0	11796.73	10217.92
BERGAMO*	**0**	**0**	**0**	**0**	**0**	**0**
BERGAMO EXT.	501.4	33.4	0	0	2740.504	2675.622
BIELLA	419.5	27.9	0	26650.3	2701.188	2180.621
BOLOGNA*	**0**	**0**	**0**	**0**	**0**	**0**
BOLZANO	1836.4	84	0	45639	8458.886	6507.118
BOVISIO*	**0**	**0**	**0**	**0**	**0**	**0**
BRENO	715.5	62.4	0	0	4249.32	4482.352
BRESCIA	938.7	28.3	0	55435.9	5291.149	2053.434
BRINDISI	2275.8	91.8	830.9	0	8218.822	6971.717
BUSTO A.	165.1	10.8	0	11175.1	662.227	822.96
CAGLIARI	3336.9	253.2	744	0	23341.11	18933.44
CALTAGIRONE	1193.2	55.3	149.5	24337.4	4874.786	3969.535
CALTANISS.	2283.5	143.5	496.7	0	9996.211	10904.09
CAMPOBASSO	2234.4	106.2	267.6	0	8766.499	7253.903
CASERTA	1613.6	137.5	409.9	0	9177.058	9842.918
CASTROVILL.	2863.2	145.6	1003.2	0	10835.89	10029.49
CATANIA	812.8	56.9	849.4	0	3605.885	4658.903
CATANZARO	3293.2	224.8	924.6	0	15730.27	14359.04
CHIAVARI	558.6	61.3	497.6	0	3876.515	4781.66
CHIETI	2860.1	176.9	393.5	0	13109.88	11473.36
CIVITAV.	1588.9	128.5	320.8	0	9892.695	10017.81
COMO	270.2	19.6	150.2	0	1651.797	1504.006

[87] Considering PPP exchange rates (say, 1 GBP = 2,000 ITL), this works out at 1.075 billion GBP.

CONEGLIANO	1053.1	57.2	0	14129.8	4958.301	4274.23
CORSICO*	**0**	**0**	**0**	**0**	**0**	**0**
COSENZA	3585.7	224.8	1007.1	0	14308.78	15497.56
CREMONA	1502.9	67.2	0	24310.5	5840.107	5233.638
CUNEO	4536.6	164.5	1040.4	0	18943.12	12820.48
ENNA	2931.9	117.4	143.3	212.8	11057.94	8445.925
FERRARA	2308.1	86.6	479	0	8098.654	6379.338
FIRENZE	559.5	36.5	497.1	0	1315.95	3005.763
FOGGIA	3392.2	124.6	628.9	0	10495.82	9714.069
FORLI'	2072.6	85.9	138.8	0	8722.193	6662.206
FORMIA	1241.8	95.5	298.2	0	8472.183	7625.475
FROSINONE	2347	140.3	317.2	0	13446.98	10323.34
GENOVA*	**0**	**0**	**0**	**0**	**0**	**0**
GROSSETO	4059.8	128.2	488.4	0	14125.94	9583.742
IMPERIA	449.2	44.2	649.7	0	3503.534	3461.614
ISERNIA	143.3	8	124	105436.5	570.0487	507.5484
IVREA	1726.5	115.2	149.5	0	8986.477	8974.724
LATINA	2566.4	167.3	538.9	0	12143.3	13217.1
LAURIA	2206.9	95.6	194.1	26372.6	9004.953	6376.473
LECCE	1805.9	75.6	1061.7	0	7982.159	5910.48
LECCO	320.5	22.9	0	0	1507.221	1761.468
LIVORNO	1104.9	76.8	673	0	4969.048	5882.719
LODI	131.2	6.6	0	17127.8	456.7685	553.2587
LUCCA	1533.3	113.1	0	0	7969.722	8591.024
MACERATA	1960.6	90.1	84.1	0	7969.566	6535.806
MAGLIE	2109.7	126.6	782.1	0	12074.06	9169.789
MANTOVA	3179.4	103	0	0	12133.56	7457.056
MASSA	611.1	49.1	92.3	0	3349.292	3702.432
MATERA	3358.6	126.3	95.6	0	11718.53	8830.017
MELZO*	**0**	**0**	**0**	**0**	**0**	**0**
MESSINA	1518.9	165.9	758.4	0	10668.81	11301.98
MESTRE	791.7	54.2	336.5	0	4375.847	4231.338
MILANO*	**0**	**0**	**0**	**0**	**0**	**0**
MILANO EXT.	253.9	15.8	0	0	1048.079	1176.231
MODENA	3036.4	43	0	30002.3	11651.05	3309.29
MONOPOLI	1731.1	95.5	555.4	0	6950.721	7422.621
MONZA*	**0**	**0**	**0**	**0**	**0**	**0**
NAPOLI	847.4	447.4	0	0	3042.873	34230.24
NOCERA INF.	455.9	46.2	347.5	0	2473.512	3537.034
NOLA	915.1	83.1	507.8	0	5143.912	6250.717
NOVARA	1625	89.4	0	0	8269.318	6612.361
NOVI LIG.	1370.1	81.3	39.2	0	7604.162	6601.326
NUORO	3705.9	201.5	246.3	0	17739.21	13323.97
OLBIA	2582.9	121.7	6.7	0	8486.482	8565.021
ORISTANO	3879	215.7	313.5	0	19286.98	14371.23
PADOVA	1458.6	96.7	284.6	0	7190.622	7607.591
PALERMO CTR.	425.5	47	695.6	0	2666.668	3782.052
PALERMO EXT.	2831.9	157.7	816.1	0	13569.72	12254.17
PALMI	2536.2	170.6	514.8	0	11926.91	11645.1
PARMA	4307.7	79.4	0	0	15754.96	6515.667
PAVIA	1630.7	95.1	23.5	0	6030.917	7928.013
PERUGIA	6083.4	126.9	792.2	0	23184.09	8896.894
PESARO	2362.8	95	355	0	9526.453	6443.434
PESCARA	1070.7	85.8	349.4	0	5384.334	6065.009
PIACENZA	2300.1	91.7	260.5	0	8884.145	7406.483
PINEROLO	1465.1	83.4	88.8	0	6329.513	6637.311
PISA	2239.8	121.1	204.9	0	9452.187	9318.327
PISTOIA	869.3	70.8	87.5	0	5673.037	5498.414
PORDENONE	2223.2	115.4	0	1701.3	10668.95	8954.011
POTENZA	4286.8	148.4	119.3	0	18913.37	9553.116
POZZUOLI	980.9	79.2	548.4	0	7158.318	5887.484

PRATO*	**0**	**0**	**0**	**0**	**0**	**0**
RAGUSA	2561.7	123.6	512.1	0	11737.18	9026.933
RAVENNA	2249.3	101.3	182.5	0	8342.08	7150.812
REGGIO CAL.	1502.2	141.3	456.1	0	10099.05	10114.54
REGGIO EMIL.	2812.9	53.3	0	7724.8	10247.57	4309.936
RIETI	1768.8	106.1	243.2	0	7288.885	8084.553
RIMINI	967	78.8	275.6	0	5188.869	5618.26
RIVOLI	1517.1	102.5	369	0	7854.333	8263.276
ROMA*	**0**	**0**	**0**	**0**	**0**	**0**
ROVIGO	1859.2	122	0	0	7140.654	8755.106
S. AGATA MIL.	1506.4	96.3	445.8	0	8478.568	7220.551
SALA CONS.	2841.5	131.9	603.4	0	10813.23	9108.402
SALERNO	1735.3	111.9	295.2	0	8320.298	8314.689
SALO'	1039.8	56.3	0	0	5262.52	4399.711
SAN DONA'	1461.9	92.6	215.7	0	6767.382	6794.95
SAN SEVERO	2530.4	98.8	486	0	7159.137	7656.216
SASSARI	2067.6	140.5	313.1	0	16440.95	10046.9
SAVONA	599.5	60	301.5	0	4106.909	4837.143
SESSA A.	2295.7	132.3	231.7	0	11596.05	9381.795
SIENA	4045.8	135.5	99.1	0	15328.59	10411.88
SIRACUSA	2641.3	143.3	769	0	11019.07	10914.21
SONDRIO	666.5	49.4	0	0	3440.337	3863.134
SPEZIA	368.5	29.4	420.3	0	2380.566	2741.439
TARANTO	2784	127.3	1461.8	0	10746.39	10104.33
TERAMO	2153.6	119	60.3	0	9167.628	8214.895
TERMINI IMER.	2427.9	101	87.8	5617.3	9976.312	7839.454
TERNI	3022	140	0	3305.8	12691.14	9928.905
TIVOLI	2053.1	133.2	942.1	0	10990.01	10317.93
TORINO	181.9	19.4	225.9	0	1081.664	1566.043
TORRE ANN.	521.8	64.7	316	0	3948.17	4527.115
TRAPANI	2737.9	129.5	951.8	0	11767.81	10046.77
TRENTO	1852.8	114.1	57	0	10567.44	7675.419
TREVISO	1418.7	75.1	0	0	6209.864	5813.049
TRIESTE	299.8	22.4	0	29077.5	1676.525	1765.799
UDINE	3523.4	176.9	750.9	0	15955.37	12301.72
VARESE	348.2	22.2	59.5	0	1586.098	1772.236
VENEZIA*	**0**	**0**	**0**	**0**	**0**	**0**
VERBANIA	554.7	46.8	225.5	0	3878.88	3508.128
VERCELLI	1712.2	87.5	0	26302.9	7975.345	6386.318
VERONA NORD	1318.2	70.1	0	0	7320.037	5772.797
VERONA SUD	2205.3	74.9	0	0	9405.843	5982.123
VESUVIANA	395.6	40.5	548.8	0	2249.077	3055.408
VIBO VAL.	2353.5	144.3	707	0	9426.911	10105.02
VICENZA	467.9	12.3	0	65366.7	2226.976	956.5719
VIGEVANO	332.8	15.6	0	19682.1	1052.048	1344.415
VITERBO	3766.6	141.7	688.6	0	16723.92	10842.41
ENEL	**251,802.9**	**13,651.4**	**45,493.4**	**549,778.9**	**1,138,832**	**1,012,398**

Table 5.12. Input/Output Improvement Margins for ENEL's Zones. [(*) indicates 100% technically efficient, or 'reference', DMUs.]

POTENTIAL SAVINGS (million ITL)	**LABOUR**	**LINES**	**TOTAL**
North	305,675.2 (30.2%)	366,713.7 (32.2%)	672,388.9 (31.2%)
Centre	224,331.9 (22.2%)	275,989.2 (24.2%)	500,321.1 (23.3%)
South	482,390.9 (47.6%)	496,129.1 (43.6%)	978,520 (45.5%)
ENEL (Model DEA22IN, 1996)	**1,012,398**	**1,138,832**	**2,151,230**
POTENTIAL OUTPUT INCREASES	**ENERGY (GWh)**	**CUSTOMERS (#)**	**(-)**
North	8,406.5 (18.5%)	384,496.5 (69.9%)	-
Centre	10,039.8 (22.1%)	108,742.3* (19.8%*)	-
South	27,047.1 (59.4%)	56,540.1 (10.3%)	-
ENEL (Model DEA22IN, 1996)	**45,493.4**	**549,778.9**	-

Table 5.13. Input/Output Improvement Margins (ENEL): North, Centre, and South of Italy.

* The customer improvement figure for Italy's Central regions is influenced by a large outlier (Isernia). Since Isernia is on the border between Central and Southern Italy, it is not clear whether to include it in Central Italy or not. It would perhaps be more sensible to view the customers' improvement breakdown 'dichotomously', i.e. in Northern vs. non-Northern terms (that is, 70% for the North, against 30% for the Centre-South).

It is worthwhile noticing that both DEA input slacks exceed 30%, according to model DEA22IN (see Tables below). However, estimates of technical inefficiency in DEA tend to be upward-biased, as a result of the deterministic nature of the Data Envelopment technique. As noticed elsewhere, DEA's incapability of separating inefficiency from random noise leads to measurement interference with respect to inefficiency computations. Also notice from the 'Actual/Target' Tables below that, although DEA22IN is an input-oriented model, a considerable improvement was spotted for energy delivered (+27.8%), whereas 'optimal' customers stood at around 29.2 million units (just 1.92% more than actual customers at 31.XII.1996). This confirms that customers are the real 'exogenous' output to ENEL - since they are entitled to electricity supply irrespective of location, quantity requirements, income,

etc., out of universal service obligations - whereas ample room for manoeuvre in maximising electricity delivered exists. In fact, given the absence of quantity regulation upon ENEL (1996), the national monopolist used to occasionally ration customers - especially at industrial levels - on the grounds of energy shortages resulting from Italy's heavy dependence upon electricity imports[88]. Then, apart from around 30% slacks in lines and labour, ENEL's distributing arm also showed an overall improvement margin for Y(GWh) of almost 28%.

ENEL (Distribution, 1996)	
LINES (Actual)	736,275.4 km
LINES (Target)	484,472.5 km
Labour (Actual)	45,111
Labour (Target)	31,459.6
Y (Actual)	163,701 GWh
Y (Target)	209,194.4 GWh
CUST (Actual)	28,660,811
CUST (Target)	29,210,590
Model: DEA22IN	
Lines Slack (ENEL)	**251,802.9 km (34.2%)**
Labour Slack (ENEL)	**13,651.4 units (30.3%)**
Lines Savings (billion ITL)	**1,138.832 (~386 million GBP at 1 GBP = 2,950 ITL)**
Labour Savings (billion ITL)	**1,012.398 (~343 million GBP at 1 GBP = 2,950 ITL)**
Total Inefficiency (billion ITL)	**2,151.23 (~729 million GBP at 1 GBP = 2,950 ITL)**
Customer Improvement (%) (ENEL)	**1.92%**
Energy Improvement (%) (ENEL)	**27.79%**
No. of 100% Efficient Units (ENEL)	**12 out of 147 (8.163%)**
Technical Inefficiency as % of TDC/1996	**16.629%**

Table 5.14. Summary of DEA 'Inefficiency Costs' (ENEL's Local Distribution, 1996).

Finally, if one considers that ENEL's total distribution cost (TDC) at end-1996 totalled 12,936.787 billion ITL[89] - that is, around GB£4.385 billion, April 1998 - the impact of technical inefficiency on TDC, in percentage terms, amounts to 16.63%. This appears to be in

[88] See Chapter 1.
[89] Source: ENEL (1997).

line with the latest regulatory estimates[90]. As regards the labour slack (13,651 units), this points towards heavy labour shedding in the future. Over the last four years, ENEL has laid off almost 6,000 people, which is a stunning result given Italy's sticky and over-guaranteed labour market. As privatisation approaches (end of 1998?), personnel restructuring will probably go on at faster rates.

With only 12 out of 147 local zones (8.16%) being fully efficient in technical (I/O) terms according to VRS-DEA model DEA22IN, ENEL's distributing arm now faces the need for increasing delivered energy (+27.8%) - while reducing both labour and capital usage (-30%) - so as to save at least ITL2,000 billion. If capital is assumed to be stickier than labour in the short run, labour shedding will pop up as the only viable option for ENEL's management on the way to cost rationalisation.

As regards output 'slacks', Southern zones are responsible for about 59% of total theoretical energy improvement, whereas the Northern share amounts to just 18.5% - notwithstanding the fact that Northern areas show a much stronger electricity demand (ENEL, 1997) than Southern ones. The picture changes when looking at customer improvement. Model DEA22IN reports nearly 70% of possible improvement for Northern zones, with Central and Southern areas being responsible for the remainder of 'customer slack'. By also considering that the South of Italy reported high shares in input slacks, the energy outcome is not surprising, whereas the customers one is. However, it should be recalled from previous discussions that there are strong reasons to believe that energy delivered is not a really exogenous variable to ENEL. If one treats Y(GWh) as a controllable variable, the large Southern share in Y's slack can be explained by exactly the same reasoning used for input

[90] Private correspondence with one of the regulator's consultants highlighted 16.3% as the technical inefficiency estimate for ENEL's distributing arm as a whole, on 1996 cross-sectional data. Nonetheless, ENEL's gains from becoming more efficient might even be higher than we suggested here because frontier-efficient DMUs may be inefficient in the first place: this seems to be, for instance, the experience of English and Welsh RECs.

slacks - that is, a combination of (negative) exogenous cost drivers with endogenous X-inefficiency. On the other hand, the exogenous nature of total customers is such that the "potential improvement" figure for CUST will be much less of interest to both ENEL's managers and third-party evaluators. The fact that Northern zones as a whole were responsible for a substantial fraction of 'customer slack' is probably due to the simple reason that the largest Italian metropolitan areas (apart from Rome and Naples) are located in the North of the country. Starting from high customer values, the linear program then reacted by assigning larger percentage slacks to Northern zones, which - again - are of limited relevance given both CUST's exogenous nature to ENEL and the negligible amount of CUST slacks in absolute terms.

Another possible explanation to the outcome according to which Southern zones showed large energy slacks coupled with negligible customer ones could be given by considering that ENEL's distributing units in the *Mezzogiorno* more often ration customers as opposed to their Northern counterparts. Because of universal service obligations, Southern units are not allowed to reject demand for new connections - even under uneconomic circumstances - but they still retained the implicit 'right' - at least, prior to the regulatory agency's set-up at the end of 1996 - of rationing customers to some extent. This has much less frequently happened in the North, due to the presence of important industrial customers to which energy supply was traditionally 100% guaranteed, not to mention the average quality and availability of excess electricity utilised by Northern zones in order to meet peak demand[91].

[91] Recall that Italy imports electricity at its Northern borders, and that the most powerful generating units have traditionally been located in the more industrialised and densely populated Northern districts. The South of the country mainly 'imports' electricity from the Centre and North via the national transmission grid (ENEL-owned). To have a rough idea of geographical distances, notice that Northern regions are max. 200 kilometres far from national borders with Central European countries, whereas the distance between Milan and Reggio di Calabria is almost 1,300 km. Furthermore, energy availability in the North is boosted by the simultaneous presence of municipal operators.

The diagrams below show input and output slacks from model DEA22IN by ordering them smallest to largest. Differences (slacks) for LIN, LAB, YTOT, and CUST are expressed in input/output units (kilometres, employees, GWh, and units of customers, respectively), whereas saving potentials (SAVLIN, SAVLAB) are given in million ITL[92]. To get a rough idea of the spread of theoretical (DEA) savings - in both terms of capital and labour - across ENEL's distribution zones throughout Italy, recall that

- in the SAVLIN[93] diagram, the 50 smallest DEA saving potentials (lines) featured 35 Northern units (70%), 5 zones from the Centre of Italy (10%), and 10 zones from the South (20%);
- in the SAVLAB diagram, the 50 smallest DEA saving potentials (employees) came from 38 Northern units (76%), 5 Central zones (10%), and 7 Southern ones (14%).

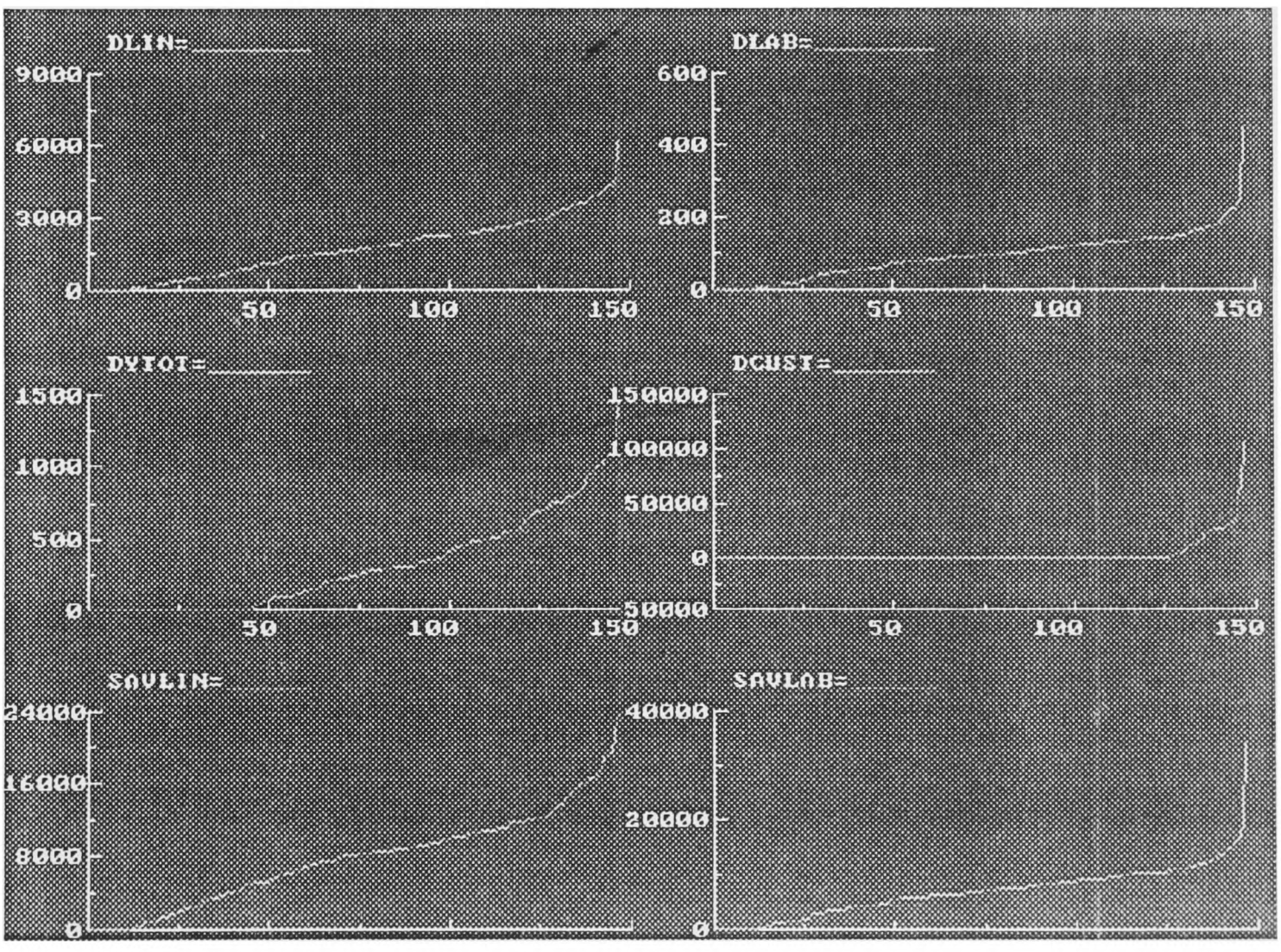


Figure 5.9. DEA Slacks and Savings for ENEL (1996).

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[92] 1 million ITL = 338.983 GBP at 1 GBP = 2,950 ITL, with no PPP adjustments.

[93] If one believes that lines are not really under the firms' control, the SAVLIN outcomes should be discarded altogether. Moreover, environmentally-corrected DEA of the Banker and Morey (1986) type could have avoided the lines outcome by effectively capturing exogenous influences.

In order to interpret the outcomes above, note that the 147 ENEL zones are subdivided as follows:

ENEL	North	Centre	South
No. Of Zones (Total: 147)	67	30*	50*
%	46%	20%*	34%*
Lines-Efficient Zones (Top 50)	35	5	10
%	70%	10%	20%
Labour-Efficient Zones (Top 50)	38	5	7
%	76%	10%	14%
Efficiency 'Surplus' ('Deficit'): LIN	24%	(10%)	(14%)
Efficiency 'Surplus' ('Deficit'): LAB	30%	(10%)	(20%)

*** Including the island of Sardinia within the Centre of Italy (as Italian geographers sometimes do) would result in 35 Central zones (24%) and 45 Southern ones (30%).**

Table 5.15 DEA Efficiency Breakdown for ENEL: North, Centre, and South of Italy.

Therefore, 70-76% of Northern zones within the best group (first 50 units) are an overwhelming majority, even after considering that the North of Italy alone features 46% of all ENEL's local distribution zones. If Sardinia is regarded as part of Southern Italy, the above results will spot higher inefficiency levels for Southern zones ('missing' share = 34% - 20% = 14% for distribution fines, 34% - 14% = 20% for employees) than for Central ones ('missing' share = 20% - 10% = 10% for both input slacks). Then, the North of Italy has 24 to 30% 'efficiency surplus' (depending on which input is considered) among the 'Top 50' units, whereas the Centre has 10% 'efficiency deficit' (for both inputs), with the South showing 14 to 20% 'excess inefficiency' (again, depending on inputs). It is worth noticing that the overmanning problem is bigger for Southern units, whose share among the best 50 zones in terms of labour slack stood at only 7/50 = 14% (against 34% Southern share on total ENEL zones). The excessive use of labour has actually been one of the most traditional ENEL problems with special reference to Southern departments, this fact being mainly due to

political and socio-economic reasons[94].

As regards the two outputs (customers, energy delivered), it must be noticed that DEA22IN was an input-orientated model. Therefore, it pointed to input minimisation by leaving output maximisation as a 'low optimisation priority'. As a result, output slacks are not particularly large in DEA22IN when compared to input excesses. However, as diagrams referring to DYTOT and DCUST above show, the potential for maximising electricity delivered (YTOT) is much larger than that regarding maximisation of customers (CUST). As noticed before, this corroborates the idea according to which the 'real' exogenous output for ENEL is given by customers, whereas electricity delivered seems to be a *decision* variable to some extent, especially during 'rationing times' for some kinds of customers (e.g., industrial users). Finally, notice that the input-oriented nature of model DEA22IN gave rise to a much larger number of 'zero-slack' units in output terms than those being found in the 'zero-slack' input set (that is, the frontier made up of 100% technically efficient, or 'best-practice', DMUs).

To conclude, recall that MUNIs could not be analysed here because of the lack of input prices for municipal electricity distribution. Hence, we were not capable of quantifying municipal slacks and inefficiencies in monetary terms. This obviously stems from the fact that MUNIs did not provide price/cost figures within their yearly accounts. Therefore, the analysis of monetary slacks for municipal electric utilities is left to further research, conditional upon the future availability of monetary - not only physical - figures from MUNIs via regulatory accounts (whose development is now under way, following the energy regulator's most recent prescriptions).

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[94] Together with other public utility sectors (telecommunications, post offices, municipalities, publicly-owned credit institutions, railways), the Italian electricity supply industry has long been viewed by the Government as a (distortionary) solution to Southern employment issues. Consequently, intentional overmanning was encouraged at ENEL, too - although the electricity monopolist managed to limit governmental interference into its hiring policies to some extent - and this also generated perverse electoral effects of 'political exchange' consisting of favours (employment promises) being swapped with votes.

The analysis above suffers from DEA22IN's main caveat, i.e. the lack of environmental effects (demand characteristics, geographical and demographic constraints, and the like). Should they have been inserted - together with controllable inputs - in the DEA optimisation run, some more Southern units would have probably popped up as technically efficient within the 'Top 50' group[95]. However, as Chapter 5 explains, the insertion of external efficiency drivers in the DEA models would have jeopardised methodological cross-checking with SFM outcomes[96].

Therefore, given that methodological cross-checking was a high priority of the present thesis, external effects were separately analysed in Chapter 5 thanks to second-stage Tobit econometric analysis. We reckon that this is only a second-best option when compared with environmentally-augmented DEA[97], but environmental analysis was not as highly prioritised in Chapter 5 as it was in Chapter 3.

6. The 'Peer Count'

The 'peer count'[98] is the number of times a reference unit ('peer') appears in the 'reference set' of a relatively inefficient DMU. The 'reference set' is the set of efficient units to which an inefficient unit has been most directly compared when calculating its efficiency rating. It contains the efficient units which have the most similar input/output orientation to the inefficient unit, and which should therefore provide examples of good operating practice for it to emulate *(ceteris paribus)*. By construction, the 'peer count' gives an idea of how much

[95] To get an idea of the rank differences resulting from 'environmental' and 'non-environmental' models, look at the efficiency score series stemming from models M0TE/1996 (featuring no external cost drivers) and M12TE/1996 (featuring twelve external cost drivers) in Chapter 3.
[96] See Chapters 3 and 4.
[97] Banker and Morey (1986).

every peer is really 'representative' as a benchmark for non-frontier units.

We took models DEA22IN and DEA22OUT from Chapter 5, and calculated the 'peer count' for those units which were classified as '100% technically efficient' (ENEL). The Table below reports our results.

PEER COUNT			**DEA22IN**	**DEA22OUT**		**TOTAL**		**RANK**		**ORDER**
AOSTA			105	42		147		2		**1.BERGAMO**
BERGAMO			64	109		173		1		**2. AOSTA**
BOLOGNA			5	39		44		8		**3. MONZA**
BOVISIO			43	6		49		6		4. MILANO
CORSICO			30	16		46		7		5. VENEZIA
GENOVA			1	0		1		12		6. BOVISIO
MELZO			3	4		7		9		7. CORSICO
MILANO			19	59		78		4		8. BOLOGNA
MONZA			69	50		119		3		9. MELZO
PRATO			3	4		7		9		9. PRATO
ROMA			1	3		4		11		11. ROMA
VENEZIA			45	17		62		5		12. GENOVA

Table 5.16. The DEA 'Peer Count' for ENEL (1996).

The peer-count exercise is useful in separating default-efficient units from 'really' efficient ones. A really efficient unit will often feature as a 'reference' to inefficient units, whereas a default-efficient one will much less frequently act as a peer. The diagram above shows that - considering both input-oriented and output-oriented DEA models - Bergamo (Eastern Lombardy), Aosta (Vallée d'Aoste), and Monza (Central Lombardy) were by far the most relevant and significant 'peers' for inefficient units. This is because such DMUs were not statistical outliers (as Rome and Genoa were). On the contrary, they either were the typical medium-sized, Northern city zones (Monza, Bergamo) which the stochastic-frontier analysis

[98] Although 'peer' means 'equal in rank', the way this word is used by DEA authors is somewhat misleading. In DEA, 'peer' stands for "one of the closest best-practice DMUs - in input/output terms - to the inefficient unit

(Ch. 3) had already spotted as efficient, or were less favoured areas (Aosta) which had come off with flying colours after taking exogenous cost drivers into account (Model M12TE/96). Also notice that, apart from Milan, larger towns lagged behind in the peer count for ENEL (Bologna, Rome, Genoa), whereas smaller units from the Milanese area fared better, as usual (Bovisio, Corsico). Milan's performance should be stressed, since a big unit would not be expected to show up so frequently as an efficient peer for other DMUs in the sample. Furthermore, note the rank difference between Rome and Milan in the peer count, indicating that Rome was just efficient 'by default' - thus corroborating Chapter 3's outcomes on ENEL/Rome - whereas Milan stood the peer-count test successfully.

DEA is capable of imposing 'weight restrictions' upon peer combinations. In DEA, reference units (or 'peers') for inefficient DMUs take part in constructing an 'ideal' reference input/output mix[99] by contributing their own input/output mixes according to 'weights', which may vary between zero and one. If the investigator wants a particular input/output to be stressed over the other ones as the 'efficiency driver' for DMUs in the sample, then she can force that input/output's weight in the DEA optimal point calculations to lie within constrained intervals (e.g., between 0.75 and 1). The computer will allow for this additional constraint before performing the DEA linear optimisation run(s). Several computer packages allow the researcher to pre-specify weight intervals for both inputs and outputs in DEA. However, we preferred not to impose any *ex ante* weight restrictions in the current study, because the previous, econometric analysis showed that both labour and capital were equally significant in explaining ENEL's distributing cost (and production). Therefore, we let the computer package run DEA optimisation problems freely, i.e. with no specific restrictions being imposed upon input/output weights.

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under examination".

[99] The 'ideal' I/O mix is also referred to, in geometric terms, as 'projected point': see Ali and Seiford (1993).

As regards both ENEL and municipal electric utilities (pooled sample), the peer count for the DEA22OUT (1994) model is reported in the following Table.

PEER COUNT	DEA22OUT	RANK		ORDER
BRESCIA	7	9		**1. MILANO**
CORSICO	17	5		**2. VIGO DI C. (M)**
GATTINARA (M)	10	7		**3. MELZO**
MELZO	25	3		4. MONZA
MILANO	35	1		5. CORSICO
MILANO (M)	5	10		6. VICENZA
MONZA	20	4		7. GATTINARA (M)
ROMA	1	11		7. TERNI (M)
TERNI (M)	10	7		9. BRESCIA
VICENZA	11	6		10. MILANO (M)
VIGO DI C. (M)	30	2		11. ROMA

Table 5.17. The DEA 'Peer Count' for the MUNI/ENEL Sample (1994-1996).

Among the most output-efficient DMUs within the 1994-1996 pooled sample (Chapters 4 and 5), those which most often appeared as actual 'peers' for less efficient units were Milan (ENEL), Vigo di Cadore (MUNI), and Melzo (ENEL). Milan confirmed its good 'ENEL-only' performance, thus showing its nature of 'really efficient' (not default-efficient) metropolitan unit. Melzo (ENEL) was again included in the reference set, but behaved much better in the pooled sample than in the ENEL-only one. This might be explained by considering that the average size of units in the pooled sample was much more compatible with Melzo's input-output mix[100], thus making it a more frequent 'peer' for other DMUs.

Finally, the North-Eastern mountain village of Vigo di Cadore in the Dolomites (a MUNI) surprisingly featured as a frequent peer in the pooled sample. This becomes much less surprising if one considers that the sample included a number of (less efficient) mountain

villages whose input/output mixes were in fact very similar to Vigo di Cadore's one. In the end, whereas Melzo and Milan (ENEL[101]) can be regarded as standard efficient units under normal circumstances (urban areas, no mountains, high industrial development, etc.), Vigo should be viewed as an *ad hoc* benchmark to all those mountain distributors which cannot be fruitfully compared to 'standard' peers because of their peculiar exogenous settings. Finally, notice that Vigo di Cadore's distribution system is a municipally-run one (similarly to many others being located in Italy's Alpine districts).

The peer count for municipalities is somewhat less interesting, due to the strong presence of small Alpine units in the 1994 cross-section. However, as the following Table shows, the two leading MUNIs which by far outscored the remaining 100% technically efficient units in model DEA22OUT/MUNI[102] were Cremona (Southern Lombardy) and, again, Vigo di Cadore (North-Eastern Alps). Whereas the previous pooled-sample discussion on Vigo is still applicable here, the fact that Cremona (M) turned out to be the leader is just a nice confirmation of our previous econometric results about the technical efficiency of this medium-sized Lombard municipality, which won against its ENEL counterpart - together with other MUNIs from the same region[103]. Vigo di Cadore itself managed to outscore its most similar ENEL zones (Belluno, Bassano in the Venetian region) - and was then set as a benchmark for Northern Italy's mountain distributing units[104]. All remaining MUNIs in the DEA peer count (1994) featured low frequencies (see below), and should therefore be considered as not particularly relevant to (yardstick) regulation. Furthermore, some of them (Brescia, Milano, Modena, Verona) were too big relative to remaining MUNIs in the sample,

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[100] Melzo is a small industrial town at Milan's eastern metropolitan borders.
[101] Milan (ENEL) fared much better than Milan (MUNI) in the peer count. This strengthens the view according to which ENEL does better within metropolitan contexts (although metropolitan comparability between ENEL and MUNIs is indeed questionable).
[102] See Chapter 5.
[103] See Chapter 4.

and - given their very low peer count - one would then be led to just classify them as 'efficient by default'.

MUNI	PEER COUNT	RANK		ORDER
BRESCIA (M)	1	14		**1. CREMONA (M)**
CREMONA (M)	19	**1**		**2. VIGO DI C. (M)**
GATTINARA (M)	1	14		3. IMOLA (M)
IMOLA (M)	6	3		3. MEZZOL. (M)
MEZZOL. (M)	6	3		3. SORESINA (M)
MILANO (M)	2	12		6. SELVINO (M)
MODENA (M)	1	14		7. PARMA (M)
PARMA (M)	4	7		7. TERNI (M)
ROMA (M)	3	10		7. TRIESTE (M)
SELVINO (M)	5	6		10. ROMA (M)
SORESINA (M)	6	3		10. VERCELLI (M)
TERNI (M)	4	7		12. MILANO (M)
TRIESTE (M)	4	7		12. VERONA (M)
VERCELLI (M)	3	10		14. BRESCIA (M)
VERONA (M)	2	12		14. GATTINARA (M)
VIGO DI C. (M)	12	**2**		14. MODENA (M)

Table 5.18. The DEA 'Peer Count' for MUNIs (1994).

7. Conclusions

This Chapter presented a comprehensive theoretical introduction to Data Envelopment Analysis (DEA) in its first Sections (Section 1 to Section 3). DEA was examined according to its different model options (constant returns to scale, variable returns to scale) and orientations (input minimisation, output maximisation).

After introducing DEA theoretically, we replicated the ENEL and MUNI analysis which had already been proposed - by means of Stochastic Frontier Estimation (SFE) techniques -

[104] Both Chapters 4 (SFE) and 5 (DEA) show this.

throughout Chapters 3 and 4. First of all, a 1996 cross-section for 147 ENEL local units was used as data set in a series of different DEA runs. VRS DEA was chosen, so as to cope with the assumption that electricity distribution does not generally show constant returns to scale. Secondly, both input and output-orientated DEA models were run. As regards the input-output mix, two different options were selected: the first one was a two-input, two-output model featuring kilometres of distribution line and total number of employees as inputs, plus total energy delivered and total number of customers as outputs. The second option was an augmented version of the former, with the number of transformers - primary and secondary - being added as a further input. For the sake of comparability with SFE scores, environmental variables were not inserted in the DEA runs, as they would have smoothed efficiency scores and biased them upwards, thus reporting an excessive number of 100% efficient DMUs. We also tried with a very limited number of environmental effects (consumer density and the percentage of industrial deliveries, in the limit), but the output files still reported a number of 100% efficient units which were hardly credible. Therefore, we decided to confine environmental effects to a second-stage, Tobit econometric estimation with transformed efficiency scores as dependent variables, thus imposing left censoring at zero.

By displaying efficiency scores for all 147 ENEL units and comparing them with SFE outcomes in a single table, we had the impression that at least a pair of series could actually provide the investigator with the same bottom-line suggestions about most and least efficient units, Southern distribution performance, and so on. Some statistical tools are available to compare paired samples even when one suspects that, given the nature of the series being matched (here, normalised efficiency scores), normality as an *ex ante* assumption might be questionable. In order to provide methodological cross-checking between SFE and DEA

results[105], we then tested for normality of each efficiency score series[106], and subsequently performed either parametric paired-samples *t*-tests or non-parametric procedures[107], according to the nature of the paired samples under examination[108]. Methodological cross-checking based upon paired-samples tests for ENEL's 1996 cross-section showed that models DEA23IN (input-orientated DEA, two outputs and three inputs) and M0TE (stochastic frontier estimation with zero environmental variables) were consistent with each other, and showed statistical agreement in terms of location parameters (medians). This confirms that - provided model specification is similar throughout the two methodologies - it is not always true that, due to their different computational assumptions, econometric methods and DEA linear programs must necessarily provide the investigator with inconsistent - and sometimes starkly contrasting - results. By examining Tobit estimates of DEA efficiency scores for ENEL, we saw that the energy regulator should be particularly concerned - when setting peculiar exceptions to (possibly yardstick) future economic regulation of electricity distribution - with efficiency effects stemming from

(*a*) industrial areas (positive effect);

(*b*) the presence of rural customers to be served as a consequence of universal service obligations (negative effect);

(*c*) the presence of overhead lines in crowded city centres (negative effect), and

(*d*) the persistence of internal transfer prices between ENEL's distributing arm and other production subsets (negative effect on distribution).

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[105] See Pollitt (1995).
[106] Kolmogorov-Smirnov one-sample Chi-square tests were used.
[107] Wilcoxon Signed-Rank, Sign, Friedman, and Kendall's W tests.
[108] As determined by normality-uniformity tests.

Municipal analysis followed on the same basic assumptions, and three alternative, output-oriented VRS DEA models were run with respect to a 1994 cross-section of 37 Italian municipal electricity distributors. Input orientation was skipped, as it would not have been consistent with the stochastic frontier analysis of Chapter 4, which relied upon translog production frontier estimation - hence regarding output as an endogenous variable (with exogenous inputs). Data constraints on MUNIs also hindered the development of a cost-minimising model. Once again, environmental effects were excluded from DEA and treated econometrically by Tobit estimation, for the sake of comparability with efficiency scores resulting from the stochastic-frontier MUNI10 model[109]. Once again, both paired-samples *t*-tests and non-parametric tests (Wilcoxon, etc.) were used, according to Kolmogorov-Smirnov's preliminary results on distribution functions, in order to test statistical consistency between SFE and DEA-originated efficiency score series for the 37 municipalities. It turned out that those VRS DEA models featuring a single output against two inputs (i.e., the most similar specifications to MUNI10, which also was a single-output model) showed high statistical consistency with MUNI10 - according to both parametric and non-parametric tests - whereas the two-output DEA model in consumers and energy failed the tests. As noticed earlier, DEA and SFE results can be compatible, conditional upon consistency of model specifications. Tobit analysis of MUNIs highlighted the following negative effects on technical efficiency in distribution: mountain areas, and coastline distribution[110]. On the other hand, positive effects came again from industrial districts and customers, and from metropolitan areas (Milan, Rome, Turin, Naples, etc.).

DEA models on a 1994-1996 pooled sample of 76 municipalities and their ENEL territorial/economic counterparts were instrumented in exactly the same way as those used for

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[109] See Chapter 4.

MUNIs. Given Kolmogorov-Smirnov results on normality, parametric paired-samples *t*-tests only were used in order to compare DEA models (two-output, one-output) with stochastic-frontier model SFM3 from Chapter 4[111]. The only matched pair which proved to show statistical agreement was, unsurprisingly, the one made up of DEA1Y2 (one output, electricity delivered) facing SFM3 (same model for SFE). This again confirms that SFE/DEA analogous models can actually lead to statistically similar efficiency series. Tobit analysis of efficiency scores against environmental variables confirmed for the pooled sample, too, that the positive efficiency drivers were industrial areas, industrial deliveries, and consumer density. On the other hand, the negative drivers were borderline/mountain conditions (North-East, Alpine regions), and the presence of MUNIs within city centres - for ENEL zones only, of course - skimming more dense and easy-to-serve areas[112].

Finally, Chapter 5 introduced a brand-new analysis of MUNIs and corresponding ENEL zones, aimed at testing the crucial ENEL claim according to which MUNIs are - with a few exceptions - far less technically efficient than ENEL's distributing local units themselves. The regulatory issue concerning the future of municipal electricity distribution in Italy is really interesting, especially in the light of those relatively successful European systems which are still based upon electric municipalities[113]. SFE model labelled SFM3 suggested that, even though ENEL is actually more efficient on a general basis, several municipalities based in the North of Italy - with special respect to the Milanese region of Lombardy - actually managed to systematically outperform their ENEL counterparts[114]. By statistically conforming to SFM3, DEA model DEA1Y2 (electricity delivered as output, plus two inputs) indirectly corroborated

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[110] Italy's coastlines are not always densely populated, and seaside weather is often harmful to distribution lines - as it is to coastline railways, thus increasing the need for new lines and maintenance staff.

[111] This model features three environmental effects only, given the pooled sample's own nature of 'homogeneous construct'.

[112] This is particularly true of metropolitan and Northern urban areas situated in the Po Valley.

[113] On Switzerland and Norway, see Filippini (1994), and Forsund and Kittelsen (1997), respectively.

econometric findings. We then decided to further cross-check such results by splitting the pooled sample into two 31-obs. sub-samples of one-to-one matched pairs - one MUNI against one ENEL unit only, with no multiple peers. Small sample problems would have hindered serious econometric estimation on those two sub-samples, so we chose DEA. We obtained separate DEA efficiency scores for MUNIs only and for ENEL counterparts only, which naturally lent themselves to paired-sample statistical testing. Once again, our previous findings on the impossibility of systematically superior efficiency claimed by ENEL over MUNIs were confirmed. In fact, statistical testing failed to reject the null hypothesis according to which MUNI-ENEL matched efficiency series came from populations sharing the same mean. Of course, this simply leads the investigator to infer that the ENEL/MUNI efficiency dispute must not be solved in general terms. Indeed, case-by-case analyses are needed so as to spot efficient MUNIs (e.g., Lombard ones) and keep them separated from inefficient ones, which could be shut down in favour of ENEL (or simply be absorbed by it). Several Po Valley MUNIs would deserve to survive and expand, instead of simply being merged into ENEL's surrounding distribution districts. Statistical agreement was confirmed by both parametric and non-parametric tests[115], thus conferring robustness upon our previous findings[116]. This might be of interest for future restructuring and regulation of local electricity distribution in Italy, with special reference to Northern and - albeit to a lesser extent - Central regions. Finally, Tobit analysis of efficiency scores stemming from the two 31-observation sub-samples confirmed that consumer density and industrial areas are positive efficiency drivers. On the other hand, internal transfer prices within ENEL, metropolitan presence of MUNIs (for ENEL zones), links to local generating plants (for ENEL again), and Southern

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[114] Around 46% of MUNIs did better than ENEL 'peers' once that mountain-based, 'social' operators were excluded. The figure jumped to 55.6% in Lombardy.
[115] See Subsection 4.4.
[116] See Chapter 4 and Subsection 4.3 in this Chapter.

locations turned out to be handicaps to technical efficiency maximisation. Again, this might be of prospective interest on regulatory grounds.

Chapter 6 follows, providing some tentative policy-making suggestions.

[5A.1] ENEL Units (1996): DEA Efficiency Scores (Output, Input) as Compared to SFE Results (Models M0TE and M12TE)

Unit	DEA22OUT	DEA23OUT	M0TE	M12TE	DEA22IN	DEA23IN
ACIREALE	0.7763	0.9112	0.685736	0.906635	0.7632	0.9215
AGRIGENTO	0.6127	0.6297	0.54975	0.71826	0.5471	0.6319
ALBA	0.5066	0.5157	0.781979	0.805857	0.6254	0.6431
ALBANO	0.6664	0.6787	0.816783	0.881991	0.6518	0.6915
ALBENGA	0.903	1	0.76849	0.929418	0.9215	1
ALESSANDRIA	0.583	0.6072	0.693769	0.752869	0.5519	0.6054
ANCONA	0.7517	0.7685	0.844204	0.811814	0.7217	0.7368
AOSTA	1	1	0.760045	0.955663	1	1
AREZZO	0.6434	0.6434	0.560295	0.794051	0.6127	0.6127
ASCOLI	0.7053	0.7053	0.733064	0.779246	0.6794	0.6796
ASTI	0.5882	0.6021	0.785954	0.815719	0.5602	0.5718
AVELLINO	0.5832	0.6013	0.625791	0.692452	0.532	0.5923
BARI	0.772	0.7786	0.781657	0.878294	0.7335	0.7818
BARLETTA	0.6035	0.6198	0.638827	0.839627	0.6226	0.6439
BASSANO	0.7172	0.7585	0.752965	0.757705	0.6771	0.7504
BELLUNO	0.5657	0.632	0.738505	0.769822	0.5955	0.6795
BENEVENTO	0.5235	0.5562	0.541108	0.589447	0.5068	0.5879
BERGAMO	1	1	0.937863	0.906844	1	1
BERGAMO EXT.	0.8693	0.8961	0.983148	0.940518	0.866	0.9012
BIELLA	0.7163	0.8388	0.945289	0.907329	0.8477	0.8999
BOLOGNA	1	1	0.807455	0.833498	1	1
BOLZANO	0.373	0.4539	0.736906	0.590102	0.5884	0.6595
BOVISIO	1	1	1	0.967221	1	1
BRENO	0.575	0.8968	0.890405	0.840179	0.7099	0.9261
BRESCIA	0.9555	0.9753	0.852427	0.676636	0.9089	0.963
BRINDISI	0.7309	0.7386	0.560926	0.754374	0.7011	0.7111
BUSTO A.	0.9655	0.9655	1	0.97713	0.9577	0.9577
CAGLIARI	0.6235	0.6554	0.713845	0.668324	0.565	0.6729
CALTAGIRONE	0.4447	0.533	0.517086	0.64351	0.6651	0.7338
CALTANISSETTA	0.5056	0.6197	0.535134	0.644406	0.5216	0.6701
CAMPOBASSO	0.5751	0.6102	0.649025	0.711469	0.5575	0.6438
CASERTA	0.6545	0.7044	0.88524	0.876101	0.641	0.7286
CASTROVILLARI	0.6358	0.6642	0.505906	0.580096	0.5875	0.6702
CATANIA	0.8478	0.8842	0.804701	0.954755	0.8276	0.8871
CATANZARO	0.5438	0.5869	0.573976	0.641549	0.488	0.6137
CHIAVARI	0.6926	0.7817	0.748158	0.899195	0.7404	0.8215
CHIETI	0.5822	0.597	0.75635	0.723125	0.5345	0.5913
CIVITAVECCHIA	0.5172	0.5657	0.727846	0.760583	0.5672	0.6189
COMO	0.9458	0.9503	1	0.9729	0.9383	0.9435
CONEGLIANO	0.6943	0.7335	0.724404	0.774092	0.7328	0.7994
CORSICO	1	1	1	0.975878	1	1
COSENZA	0.5537	0.5822	0.538831	0.624546	0.4948	0.6011
CREMONA	0.6511	0.6745	0.693393	0.718258	0.6814	0.7611
CUNEO	0.6889	0.6935	0.768534	0.861659	0.6244	0.6481

ENNA	0.4689	0.5199	0.503553	0.513275	0.4713	0.5982
FERRARA	0.7316	0.7474	0.73123	0.867674	0.7066	0.7195
FIRENZE	0.9571	0.9571	0.735866	0.912396	0.9404	0.9404
FOGGIA	0.6439	0.6545	0.587105	0.657764	0.6055	0.6187
FORLI'	0.6976	0.6976	0.743747	0.829038	0.6695	0.6712
FORMIA	0.5811	0.6617	0.760268	0.834865	0.6368	0.7116
FROSINONE	0.6372	0.6554	0.80938	0.684523	0.5969	0.6402
GENOVA	1	1	0.830339	0.956307	1	1
GROSSETO	0.5827	0.5908	0.543069	0.657273	0.547	0.5559
IMPERIA	0.7911	0.8927	0.750935	0.835388	0.8205	0.9103
ISERNIA	0.5185	0.7164	0.68285	0.793298	0.9353	0.9916
IVREA	0.5841	0.6156	0.828427	0.815442	0.597	0.6502
L'AQUILA	0.6492	0.7049	0.688913	0.742198	0.6065	0.7217
LA SPEZIA	0.7967	0.9511	0.783523	0.9631	0.8523	0.9613
LATINA	0.6592	0.6734	0.841032	0.841214	0.6016	0.666
LAURIA	0.3702	0.44	0.515988	0.47732	0.5291	0.6153
LECCE	0.7893	0.8235	0.669929	0.828826	0.7599	0.8099
LECCO	0.8822	0.893	1	0.976957	0.898	0.9165
LIVORNO	0.7554	0.781	0.737382	0.923882	0.7316	0.7888
LODI	0.8331	0.8986	0.784641	0.962174	0.9502	0.9589
LUCCA	0.7183	0.7232	0.866884	0.837876	0.6731	0.6882
MACERATA	0.6363	0.6385	0.68103	0.65566	0.6047	0.6047
MAGLIE	0.6459	0.6933	0.636704	0.751656	0.6129	0.7074
MANTOVA	0.6902	0.7174	0.740274	0.688751	0.6399	0.7071
MASSA	0.6555	0.7249	0.901032	0.931791	0.7569	0.7835
MATERA	0.4749	0.4957	0.55378	0.509944	0.4508	0.5522
MELZO	1	1	1	0.96718	1	1
MESSINA	0.618	0.6856	0.762863	0.793885	0.6477	0.7126
MESTRE	0.8337	0.8897	0.908845	0.930706	0.8131	0.8996
MILANO	1	1	1	0.974775	1	1
MILANO EXT.	0.9219	0.9524	1	0.96336	0.9245	0.9643
MODENA	0.9415	0.9415	0.804341	0.722621	0.8686	0.8686
MONOPOLI	0.6859	0.7043	0.605485	0.791966	0.6661	0.6733
MONZA	1	1	1	0.97545	1	1
NAPOLI	0.8849	1	1	0.977581	0.8446	1
NOCERA	0.7799	0.8425	0.918724	0.955729	0.8115	0.8681
NOLA	0.732	0.812	0.884807	0.942106	0.7504	0.8317
NOVARA	0.6954	0.7303	0.93563	0.899084	0.6762	0.7495
NOVI LIG.	0.5139	0.5738	0.671807	0.824377	0.6092	0.6564
NUORO	0.4398	0.5246	0.593211	0.57577	0.4193	0.5844
OLBIA	0.4634	0.5594	0.578158	0.651076	0.4888	0.6456
ORISTANO	0.4462	0.5259	0.626816	0.558457	0.4154	0.5811
PADOVA	0.8202	0.8236	0.834883	0.837607	0.7752	0.798
PALERMO CTR.	0.8781	1	0.963096	0.974525	0.8887	1
PALERMO EXT.	0.6078	0.6471	0.605416	0.704753	0.5618	0.6632
PALMI	0.482	0.5698	0.603068	0.602734	0.4907	0.6195
PARMA	0.718	0.718	0.67215	0.675752	0.6956	0.6956
PAVIA	0.6491	0.6731	0.69317	0.848275	0.6384	0.6852
PERUGIA	0.7508	0.7508	0.734911	0.632049	0.6912	0.6912
PESARO	0.6888	0.6958	0.722512	0.747938	0.662	0.6697
PESCARA	0.5884	0.6597	0.796992	0.777777	0.6607	0.7087
PIACENZA	0.6714	0.6786	0.694422	0.803791	0.6403	0.6509

PINEROLO	0.601	0.6368	0.872299	0.895482	0.6312	0.6799
PISA	0.6611	0.6611	0.775142	0.828811	0.6252	0.6252
PISTOIA	0.6509	0.6509	0.7307	0.911291	0.711	0.711
PORDENONE	0.5648	0.5742	0.742133	0.715379	0.5711	0.6143
POTENZA	0.5088	0.5158	0.565249	0.558604	0.4661	0.4892
POZZUOLI	0.698	0.8083	0.886065	0.941084	0.716	0.8357
PRATO	1	1	1	0.937946	1	1
RAGUSA	0.6203	0.6488	0.620989	0.788886	0.5865	0.6448
RAVENNA	0.6824	0.6824	0.777532	0.834443	0.6543	0.6553
REGGIO CAL.	0.5107	0.6246	0.682147	0.67781	0.5624	0.6824
REGGIO EMIL.	0.8701	0.8701	0.814421	0.79716	0.8247	0.8247
RIETI	0.4841	0.543	0.587266	0.594684	0.5544	0.6112
RIMINI	0.6528	0.6641	0.762092	0.894144	0.6993	0.7028
RIVOLI	0.6162	0.6949	0.913813	0.849005	0.6298	0.7324
ROMA	1	1	1	0.787766	1	1
ROVIGO	0.4556	0.5935	0.710679	0.691927	0.5414	0.6751
S. AGATA MIL.	0.5648	0.6644	0.537331	0.670591	0.6101	0.7135
SALA CONS.	0.5769	0.604	0.525119	0.594921	0.5438	0.6025
SALERNO	0.6526	0.6814	0.773796	0.834898	0.6296	0.6912
SALO'	0.7013	0.7208	0.74842	0.841807	0.7319	0.797
SAN DONA'	0.5825	0.6396	0.689974	0.809105	0.6219	0.6865
SAN SEVERO	0.6424	0.6847	0.551729	0.663343	0.608	0.7045
SASSARI	0.5208	0.6074	0.63125	0.615738	0.5393	0.659
SAVONA	0.6931	0.7931	0.838756	0.929302	0.7404	0.8409
SESSA AUR.	0.4999	0.5768	0.649445	0.697699	0.5205	0.6334
SIENA	0.5576	0.5576	0.555827	0.666981	0.5196	0.5196
SIRACUSA	0.6426	0.6623	0.551853	0.745147	0.5964	0.6481
SONDRIO	0.5929	0.7322	0.863296	0.951146	0.7318	0.8112
TARANTO	0.7662	0.7716	0.580362	0.745774	0.7114	0.7326
TERAMO	0.5782	0.5912	0.827411	0.698809	0.5672	0.572
TERMINI IMER.	0.4679	0.4963	0.52257	0.589905	0.512	0.575
TERNI	0.4496	0.4682	0.604597	0.558958	0.4719	0.5452
TIVOLI	0.665	0.702	0.68181	0.806449	0.6247	0.7112
TORINO	0.9862	0.9863	1	0.981058	0.9711	0.9718
TORRE ANN.	0.7604	0.8325	1	0.925767	0.7906	0.8594
TRAPANI	0.6921	0.7184	0.5927	0.779927	0.6431	0.7135
TRENTO	0.6604	0.6893	0.748963	0.689454	0.6342	0.6965
TREVISO	0.7628	0.7993	0.816739	0.79287	0.7429	0.7694
TRIESTE	0.6604	0.9754	0.985518	0.934177	0.8645	0.987
UDINE	0.6978	0.7019	0.889011	0.838482	0.6323	0.654
VARESE	0.9094	0.9145	1	0.98157	0.9037	0.9062
VENEZIA	1	1	1	0.986897	1	1
VERBANIA	0.6682	0.7512	0.803241	0.889253	0.7662	0.8048
VERCELLI	0.4576	0.6661	0.866972	0.701933	0.6059	0.7504
VERONA NORD	0.7059	0.7586	0.736543	0.882687	0.6924	0.7909
VERONA SUD	0.7375	0.7646	0.711344	0.72654	0.7255	0.7568
VESUVIANA	0.8433	0.9829	0.982759	0.977959	0.8622	0.9857
VIBO VAL.	0.5813	0.6537	0.591236	0.607533	0.5532	0.6863
VICENZA	0.9618	1	0.77218	0.699422	0.9552	1
VIGEVANO	0.6703	0.8024	0.695608	0.903042	0.8828	0.924
VITERBO	0.6157	0.6167	0.593955	0.6119	0.5719	0.5778

[5A.1bis] UNIT	AVE/SCO*
VENEZIA	0.997816
CORSICO	0.99598
MONZA	0.995908
MILANO	0.995796
BOVISIO	0.994537
MELZO	0.99453
PRATO	0.989658
TORINO	0.982743
BERGAMO	0.974118
BUSTO A.	0.970588
ROMA	0.964628
GENOVA	0.964441
COMO	0.958467
MILANO EXT.	0.95441
AOSTA	0.952618
NAPOLI	**0.95118**
PALERMO CTR.	**0.950737**
BOLOGNA	0.940159
VESUVIANA	**0.939136**
VARESE	0.935895
LECCO	0.927776
ALBENGA	0.920401
BERGAMO EXT.	0.909378
FIRENZE	0.90721
TRIESTE	0.901166
VICENZA	0.8981
LODI	0.897936
BRESCIA	0.888627
LA SPEZIA	0.884671
MESTRE	0.879275
CATANIA	**0.867693**
NOCERA	**0.862742**
TORRE ANN.	**0.861445**
BIELLA	0.85922
MODENA	0.85786
REGGIO EMIL.	0.83353
IMPERIA	0.833487
ACIREALE	**0.827429**
NOLA	**0.825502**
PADOVA	0.814915
POZZUOLI	**0.814192**
VIGEVANO	0.813025
BRENO	0.806397
SAVONA	0.805926
MASSA	0.792271
BARI	**0.787642**
LIVORNO	0.786344
NOVARA	0.781019
TREVISO	0.780668
CHIAVARI	0.780592

VERBANIA	0.780482
SONDRIO	0.780424
LECCE	0.780226
ISERNIA	0.772991
ANCONA	0.772453
VERONA NORD	0.761172
SALO'	0.756871
LUCCA	0.75126
FERRARA	0.750667
CASERTA	0.748307
CONEGLIANO	0.743083
RIVOLI	0.739353
VERONA SUD	0.737047
BASSANO	0.735645
UDINE	0.735582
ALBANO	0.731196
RIMINI	0.729206
PISTOIA	0.727632
PINEROLO	0.719447
FORLI'	0.718114
TARANTO	0.717989
RAVENNA	0.714396
CUNEO	0.714182
LATINA	0.713741
ASCOLI PICENO	0.713652
SALERNO	0.710582
PERUGIA	0.708493
MESSINA	0.703441
BRINDISI	0.6995
PESCARA	0.698712
TIVOLI	0.698527
PAVIA	0.697874
PESARO	0.697792
FORMIA	0.697722
MANTOVA	0.697271
CREMONA	0.696625
PISA	0.696092
PARMA	0.69585
TRAPANI	0.689955
PIACENZA	0.689902
MONOPOLI	0.687842
TRENTO	0.68647
L'AQUILA	0.685569
IVREA	0.681795
VERCELLI	0.674818
MAGLIE	0.674643
SAN DONA'	0.671597
FROSINONE	0.670601
BELLUNO	0.663505
BARLETTA	0.661376
ASTI	0.653996
RAGUSA	0.651713

CAGLIARI	0.649828
ALBA	0.646439
AREZZO	0.644424
SAN SEVERO	0.642445
NOVI LIG.	0.641581
SIRACUSA	0.641067
TERAMO	0.639137
MACERATA	0.636815
ALESSANDRIA	0.632356
PALERMO EXT.	0.631678
CHIETI	0.630746
PORDENONE	0.630319
FOGGIA	0.627912
S. AGATA MIL.	0.626787
CIVITAVECCHIA	0.626238
CAMPOBASSO	0.624516
REGGIO CAL.	0.623343
AGRIGENTO	0.614902
VIBO VALENTIA	0.612212
ROVIGO	0.611368
CASTROVILLARI	0.607284
AVELLINO	0.604507
VITERBO	0.597993
SESSA AURUNCA	0.596291
SASSARI	0.595581
CALTAGIRONE	0.589533
CALTANISSETTA	0.582757
GROSSETO	0.579457
CATANZARO	0.574654
SALA CONSILINA	0.57454
BOLZANO	0.566968
COSENZA	0.565863
OLBIA	0.564406
SIENA	0.562868
RIETI	0.562442
PALMI	0.5613
BENEVENTO	0.550826
TERMINI IMERESE	0.527279
ORISTANO	0.525646
NUORO	0.522847
POTENZA	0.517292
TERNI	0.516409
ENNA	0.512521
MATERA	0.506221
LAURIA	0.491318
** Average Score from all of the above 6 models (SFM, DEA).*	

N.B.: Units printed in bold are those Southern distributors which were found, according to all models, among the top 50 performers.

[5A.2] MUNIs (1994): DEA Efficiency Scores (DEA22OUT, DEA1C2, DEA1Y2) as Compared to SFE Results (Model MUNI10TE)

MUNIs	MUNI10	DEA22	DEA1C2	DEA1Y2
Bolzano	0.569	0.5759	0.4874	0.5747
Brescia	0.969	1	0.7929	0.9723
Bressanone (BZ)	0.492	0.5624	0.4501	0.545
Brunico (BZ)	0.601	0.7767	0.6261	0.7477
Cremona	0.983	1	1	1
Gattinara (VC)	0.431	1	1	1
Imola (BO)	0.946	1	0.7121	1
Laces (BZ)	0.294	0.5122	0.2659	0.5122
Levico Terme (TN)	0.39	0.399	0.3835	0.3455
Mezzolombardo (TN)	0.46	1	0.4405	1
Milano	0.981	1	1	1
Modena	0.968	1	0.7995	0.9887
Osimo (AN)	0.606	0.6056	0.6004	0.5388
Parma	0.984	1	1	0.8767
Primiero (TN)	0.467	0.4155	0.4155	0.3245
Rep. S. Marino	0.563	0.7474	0.4413	0.7474
Riva del Garda (TN)	0.719	0.7316	0.7233	0.6425
Roma	0.987	1	1	1
Rovereto (TN)	0.573	0.9758	0.4542	0.9758
Sanremo (IM)	0.876	0.6935	0.6935	0.3924
Selvino (BG)	0.809	1	1	0.4482
Seregno (MI)	0.973	0.9365	0.8319	0.8968
Silandro (BZ)	0.323	0.704	0.3643	0.704
Sondrio	0.772	0.8882	0.7554	0.8076
Soresina (CR)	0.984	1	1	0.5832
Terni	0.981	1	1	1
Tione (TN)	0.427	0.7077	0.4815	0.6466
Tirano (SO)	0.697	0.7539	0.7381	0.5705
Tolentino	0.709	0.9455	0.659	0.9397
Torino	0.986	0.8836	0.8836	0.706
Trani (BA)	0.973	0.9323	0.9323	0.5267
Trieste	0.966	1	1	0.9154
Vercelli	0.987	1	1	0.8168
Verona	0.966	1	0.5682	1
Vicenza	0.976	0.8423	0.8423	0.6578
Vigo di Cadore (BL)	0.529	1	1	1
Voghera (PV)	0.978	0.8352	0.8352	0.4754

[5A.2bis] MUNIs	SUM*
Roma	3.987
Cremona	3.983
Milano	3.981
Terni	3.981
Trieste	3.8814
Parma	3.8607
Vercelli	3.8038
Modena	3.7562
Brescia	3.7342
Imola (BO)	3.6581
Seregno (MI)	3.6382
Soresina (CR)	3.5672
Verona	3.5342
Vigo di Cadore (BL)	3.529
Torino	3.4592
Gattinara (VC)	3.431
Trani (BA)	3.3643
Vicenza	3.3184
Selvino (BG)	3.2572
Tolentino	3.2532
Sondrio	3.2232
Voghera (PV)	3.1238
Rovereto (TN)	2.9788
Mezzolombardo (TN)	2.9005
Riva del Garda (TN)	2.8164
Tirano (SO)	2.7595
Brunico (BZ)	2.7515
Sanremo (IM)	2.6554
Rep. S. Marino	2.4991
Osimo (AN)	2.3508
Tione (TN)	2.2628
Bolzano	2.207
Silandro (BZ)	2.0953
Bressanone (BZ)	2.0495
Primiero (TN)	1.6225
Laces (BZ)	1.5843
Levico Terme (TN)	1.518

** All Models.*

[5A.3] Pooled Sample (1994-1996): DEA Efficiency Scores (DEA22OUT, DEA1C2, DEA1Y2) as Compared to SFE Results (Model POOL3TE)

Unit	SFM3	DEA22	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

[5A.3bis] UNIT	**SUM***
MONZA	3.99
MILANO	3.977
Terni (M)	3.976
CORSICO	3.975
Vigo di Cadore (M)	3.937
MELZO	3.9075
BOLOGNA	3.8439
Parma (M)	3.8227
TORINO	3.787
ROMA	3.744
BUSTO A.	3.7006
Gattinara (M)	3.662
BOVISIO	3.6434
MILANO EXT.	3.5879
MODENA	3.5507
Milano (M)	3.4965
Roma (M)	3.495
BRESCIA	3.4834
Soresina (M)	3.4833
BERGAMO EXT.	3.4803

VICENZA	3.4406
LECCO	3.3947
Selvino (M)	3.2262
VERONA SUD	3.0287
Vercelli (M)	2.9865
BASSANO	2.9215
PARMA	2.9147
ANCONA	2.8922
Torino (M)	2.8667
LODI	2.7881
Mezzolombardo (M)	2.7765
SALO'	2.7732
VERONA NORD	2.7141
Cremona (M)	2.6255
TRENTO	2.61
Sondrio (M)	2.5691
PESARO	2.556
IMPERIA	2.5486
BIELLA	2.5446
VIGEVANO	2.4922
CREMONA	2.491
MONOPOLI	2.479
Seregno (M)	2.4349
Verona (M)	2.4278
RIMINI	2.42
Trani (M)	2.3775
MACERATA	2.3279
Vicenza (M)	2.3266
VERBANIA	2.2521
BRENO	2.1744
Trieste (M)	2.1361
TRIESTE	2.117
BELLUNO	2.0809
Brescia (M)	2.0696
Tirano (M)	2.0635
SONDRIO	2.0619
Tione (M)	1.991
Rovereto (M)	1.8934
Voghera (M)	1.8638
Riva del Garda (M)	1.8367
VERCELLI	1.8272
Imola (M)	1.8049
Tolentino (M)	1.7933
Modena (M)	1.7649
TERNI	1.7276
Brunico (M)	1.6478
Sanremo (M)	1.6444
Silandro (M)	1.462
Osimo (M)	1.4518
BOLZANO	1.441
Rep. S. Marino (M)	1.3006
Primiero (M)	1.2612

Bressanone (M)	1.1184
Levico Terme (M)	1.0402
Laces (M)	1.0378
Bolzano (M)	0.9954

** All Models.*

CHAPTER 6

CONCLUSIONS

1. Introduction

This thesis analysed technical efficiency of electricity distribution in Italy, by applying both econometric and linear programming techniques to two samples of electricity distributing units. The first sample was made up of 147 local distributing zones (1996) from ENEL, Italy's integrated electricity monopolist which is now going to be restructured and (slowly) transferred to the private sector. The second sample contained input-output data for 37 municipally-owned electric utilities (MUNIs, 1994) which are often found in Italy's Northern - and, albeit to a lesser extent, Central - districts. A pooled sample resulting from two subsets of the above observations was also constructed, so as to analyse comparative efficiency of ENEL units and their nearest municipal utilities. Methodological cross-checking was employed, in order to compare econometric (Stochastic Frontier Estimation) outcomes with non-parametric (Data Envelopment Analysis) ones. Checking was implemented thanks to distribution-free statistical tests of the Wilcoxon and Sign type.

Chapters 1 to 5 covered the following topics:

(*i*) Chapter 1 is an introduction to the electricity industry in Italy, with some attention being paid to other European and North American experiences;

(*ii*) Chapter 2 deals with deterministic frontier analysis (translog total cost function) of

ENEL distributing zones; it also estimates some basic statistics of interest (returns to scale, input elasticities of substitution, returns to density);

(*iii*) Chapter 3 analyses the 147-observation cross-sectional sample by a different methodology, that is the 'Technical Efficiency Effects', or TEE, model[1]. Apart from standard estimation outcomes and statistics of interest (Minimum Efficient Scales, elasticities, etc.), this Chapter also provides technical efficiency rankings for all units in the sample;

(*iv*) Chapter 4 proposes Stochastic Frontier Analysis outcomes, again based upon the TEE model, from a translog stochastic production frontier encompassing the municipal cross-sectional figures (1994). Moreover, it extends the investigation to a pooled sample of ENEL units and municipal distributors, making a direct comparison between 'twin' operators and paving the way to regulatory decisions about the future structure of local electricity distribution in Italy, with special reference to those Central and Northern towns currently featuring 'double' distribution systems;

(*v*) Chapter 5 re-runs the whole investigation (ENEL, MUNIs, pooled sample) utilising a different quantitative technique known as Data Envelopment Analysis (DEA), which does not parameterise technology. DEA minimises Farrell-type distance functions, thus calculating technical (and even allocative) efficiency levels for each unit in the sample. No functional forms are then required: this improves the 'envelopment' of real data at the expense of failing to separate actual inefficiency from measurement error or random noise. Finally, Chapter 5 performs non-parametric statistical tests in order to compare efficiency score series stemming from Chapters 3 and 4 (econometric methods) with those computed via linear programming (DEA). Methodological cross-checking is useful in highlighting possible convergence between different techniques, at least with regard to location parameters (medians) of

[1] Battese and Coelli (1995).

efficiency series. Chapter 5 shows that this is sometimes the case (for 'consistent' model comparisons only).

2. 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 (Chapter 5) failed to spot any statistically significant superiority of ENEL's units[2].

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 a trans-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[3]. 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[4], 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

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[2] The fact that 'internal' DEA tests were performed should not subtract power to those tests: Chapter 3 showed that paired-samples tests are well able to strongly reject concordance even when paired efficiency series come from the same computational methodology and from identical data sets.

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

[4] See Chapter 1.

(1994) notices, DEA techniques in particular might be viewed within a principal-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[5].

As regards point (*b*), neither the econometric nor the linear programming analyses of Chapters 4 and 5 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[6]. Paired-samples statistical tests and DEA runs in Chapter 5 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

[5] Yardstick regulation typically applies to electricity, water, and gas distribution.
[6] See Chapter 4.

limits), case-by-case analysis is called for, as no generalisation was suggested by the work carried out in this thesis. We immediately put this into practice by sketching a tentative, crude table reporting those MUNIs which could be granted expansion[7]. We think that the case-by-case approach with MUNIs should by far be preferred by the Italian energy regulator. Finally, notice that the MUNIs which systematically outscored their ENEL counterparts - according to all methodologies - are mainly from the Northern plains (Po Valley) and, more precisely, from the Milanese region of Lombardy.

MUNIs which might be granted expansion (provincial distribution)	MUNIs which were outscored by surrounding ENEL units	Indecisive cases
	All other units in the 37-obs. sample (featuring several mountain and rural MUNIs)	Metropolitan areas (Rome, Milan, Turin), where direct comparison was not feasible
Brunico (South Tyrol)		
Cremona (Lombardy)		
Gattinara (Piedmont)		
Parma (Emilia)		
Selvino (Lombardy)		
Sondrio (Lombardy)		
Soresina (Lombardy)		
Terni (Umbria)		
Tirano (Lombardy)		
Trieste (Venezia Giulia)		
Vercelli (Piedmont)		
Vigo di Cadore (Veneto)		

Table 6.1. Relatively Efficient MUNIs (Candidate for Expansion).

As the Table above indicates, 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

[7] See the enclosed map for geographical reference.

(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[8].

To conclude, regulatory perspectives stemming from this thesis 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 Chapters unambiguously rejected the feasibility of any generalisation with respect to the ongoing, comparative efficiency dispute between ENEL's distribution zones and local municipal

[8] 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.

administrations.

A number of caveats must be pointed out as a conclusion. They are discussed in the following paragraphs.

Deterministic Frontier Analysis. Traditional estimation of dual cost functions does not allow for the distinction of measurement error and/or random noise from inefficiency effects. This - as Greene (1993b) notices - generally leads to stark differences between deterministic frontier and stochastic frontier estimates. We also encountered this problem in Chapter 2, whose estimates did not appear to be as reliable as those obtained in Chapter 3 from stochastic frontier analysis.

Stochastic Frontier Analysis. The decomposition of disturbances into random and inefficiency elements leads to a better understanding of technical - if not allocative - efficiency performances of different firms (or branches). However, as Chapter 3 shows, the specification of both the total cost model and the 'external cost drivers' (Efficiency Effects) is crucial in determining estimated values (parameters, efficient scales, elasticities, etc.) and final efficiency rankings of firms. Therefore, alternative specifications might be devised and tested against each other. Furthermore, sensitivity analysis of stochastic frontier models might be performed.

Comparability Between SF and DEA Outcomes. A trade-off exists between the introduction of several 'external cost drivers' and the degree of comparability between stochastic-frontier and DEA efficiency rankings. Indeed, the insertion of too many - possibly irrelevant and/or collinear - environmental variables gives rise to unreliable efficiency score

series which are of limited validity, especially when set - and statistically tested - against the results stemming from alternative methodologies.

Deterministic Nature of DEA. Even though stochastic versions of DEA are now being developed, the main applied models still feature a traditional, deterministic linear programming framework in which stochastic elements are simply treated as deviations from the efficient, or 'best-practice', frontier. Therefore, a dilemma exists between the optimising nature of DEA - as opposed to the 'central tendency' analysis performed by statistical/econometric techniques - and its incapability of coping with those random deviations from the optimal frontier which should *not* be treated as inefficiency.

Second-Stage Tobit Analysis. In order to prevent excessive 'smoothing' of DEA efficiency scores as a result of environmental effects being inserted in the linear programs, we preferred not to perform 'environmental DEA' of the Banker and Morey (1986) kind. Smoothing of rankings may not necessarily be a nuisance - provided that sensible efficiency discrimination among different firms is preserved - but it certainly jeopardises methodological cross-checking between 'flat' environmental DEA series and 'jagged' stochastic-frontier ones. For the sake of paired-samples statistical testing, then, we decided to analyse external effects by regressing DEA efficiency scores against environmental variables according to a Tobit econometric approach[9]. We reckon that this is a second-best option as opposed to more advanced multi-stage DEA programs, but methodological cross-checking was prioritised in Chapter 5 - whereas 'environmental' analysis had been prioritised in Chapter 3.

[9] Tobit was used because it sorts out censoring problems.

Statistical Paired-Samples Tests. A general criticism of both paired-samples parametric *t*-tests and rank-order, non-parametric ones is that such testing procedures only inform the investigator about 'central' concordance (means, medians) among the different series being compared. Therefore, statistical 'agreement' between different couples of efficiency score series must be taken *cum grano salis.* Moreover, some non-parametric tests use less information than other ones, thus showing different degrees of power. For instance, the reader should recall that the Sign distribution-free test for matched pairs is less powerful than the Wilcoxon one, thus tending to accept the null hypothesis of statistical concordance more often.

Cross-Sectional Analysis. The reliability of cross-sectional data is obviously limited. With special reference to stochastic frontier analysis, the investigator would like to use panel data instead, so as to improve on estimation efficiency and on the effectiveness of separation between random noise and firm-specific inefficiency. DEA, too, needs panel data so as to analyse productivity change by means of Malmquist/Törnqvist indices which are also easily linked to traditional Total Factor Productivity (TFP) measures.

The Results Are Just as Good as the Data Are. We trusted the figures used in this thesis as they came from official sources. However, it must be recalled that ENEL is still vertically - if not horizontally - integrated, and that a limited degree of internal accounting separation has been imposed upon the Italian electricity monopolist over the last four years only. Municipal figures were probably more reliable - as they resulted from really separate economic entities - but only covered physical values, thus excluding cost data. Both internal restructuring - and maybe break-up - of ENEL, and the future availability of cost figures from municipal utilities

might boost the robustness of efficiency analyses and policy-making suggestions regarding the future structure of electricity distribution in Italy.

Finally, future research directions stemming from this thesis are tentatively listed below.

Availability of Panel Data. As emphasised earlier, multi-year data on both ENEL's distributing units and municipal electric utilities would be crucial in obtaining comprehensive and robust outcomes from both stochastic-frontier and DEA techniques.

Allocative Efficiency. The availability of more reliable price figures for ENEL - as well as the publication of cost values from MUNIs - would help extend the DEA investigation to the analysis of input-allocative - not only technical - efficiency.

Stochastic DEA. The development of Stochastic Data Envelopment Analysis (SDEA) would overcome the basic limitation of linear-programming efficiency measurement techniques - as opposed to econometric methods - by coupling the flexibility of DEA with the effective distinction between random effects and proper inefficiency components.

Specification Tests. Chapters 2 and 3 showed that deterministic and stochastic frontier analyses tend to draw somewhat different conclusions from identical data sets. Since parameter estimation differences between deterministic and stochastic frontiers are often substantial, a specification test for one against the other might be useful, even though no specification tests of deterministic vs. stochastic models have been accurately treated by the econometric literature so far.

International Comparisons. An interesting development of this thesis could be a comparative analysis of technical efficiency in electricity distribution - especially at local levels - within a European framework. EU Directives on public utilities substantially point towards liberalisation and competition. As compared to - say - telecommunications, the electricity supply industry is much stickier and reluctant to change because of heavy technological and statutory constraints. Electricity liberalisation in the EU is conditional upon substantial restructuring to be implemented by several countries (France, Italy, and Spain for instance) which still keep their ESIs under command-and-control regimes. In the light of previous studies on other European experiences[10], this thesis might pave the way to a comprehensive, European-level efficiency debate on future policy-making decisions to be taken with regard to the 'Euro-ESI'.

'Counterfactual' Analysis. Should ENEL's privatisation finally be put into practice, a future research path could also extend the present efficiency analysis to a 'counterfactual' scenario[11] (public vs. private ownership) in which social gains and losses from divestiture might be tentatively computed following a cost-benefit approach. Of course, 'counterfactual' analysis heavily relies upon strong *ex ante* assumptions which may or may not be crucial to quantitative outcomes. Then, a serious cost-benefit investigation would also be complemented by comprehensive sensitivity analysis of results (alternative specifications, different hypotheses, and the like).

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[10] Filippini (1994); Pollitt (1993, 1995); Kittelsen (1993, 1996); Forsund and Kittelsen (1997).

[11] See Galal et al. (1994) for an international study, and Newbery and Pollitt (1997) for an application to the defunct Central Electricity Generating Board of England and Wales.

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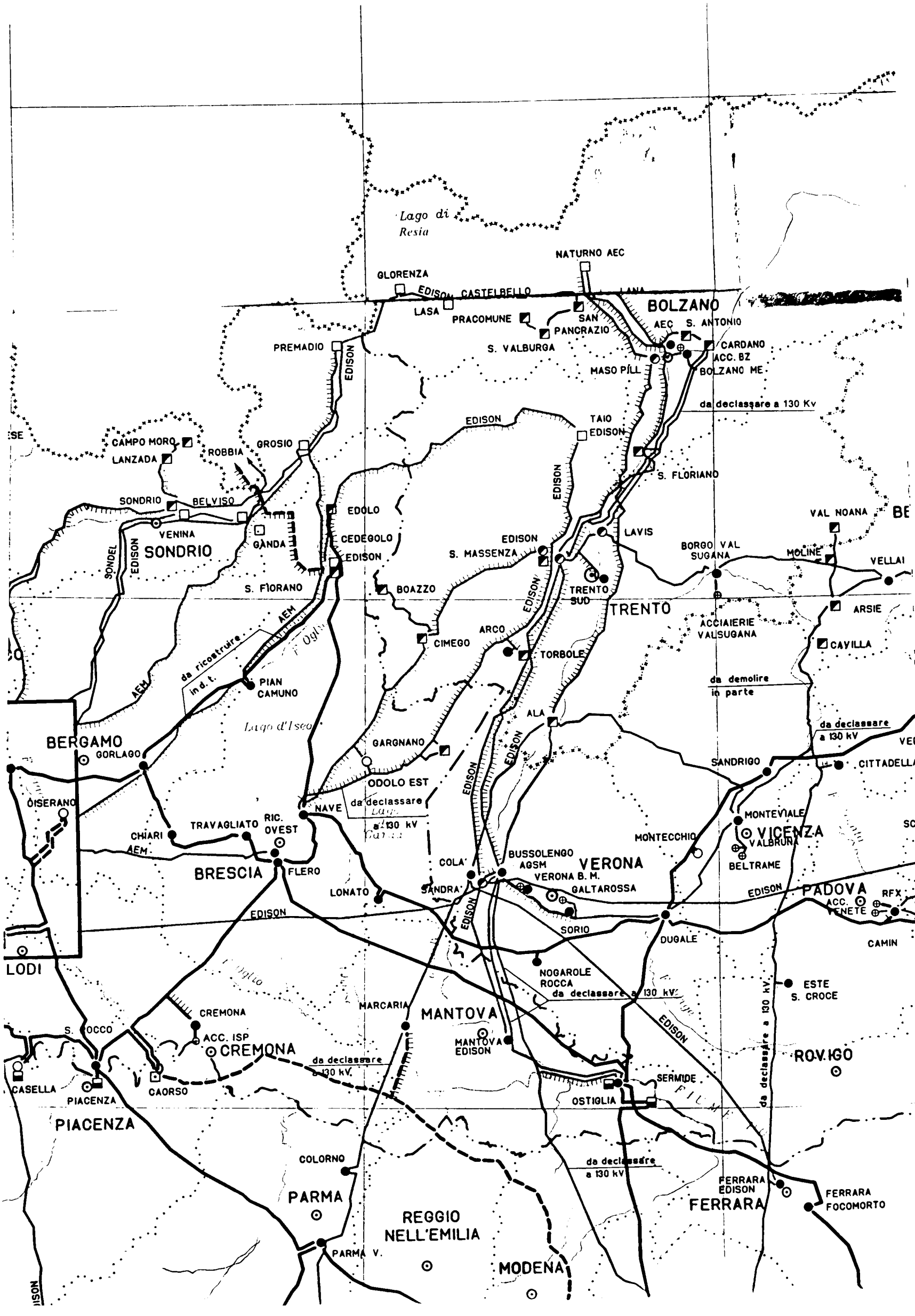
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Maps of Italy

PONTE
PIEDILAGO
VERAMPIO
GONDO
MOREL
da demolire o da declassare a 130 kV
RONCOVALGRANDE
PALLANZENO
SOAZZA
GORDUNO
LAVORGO
Lago Maggiore
Lago di Lugano
Lago di Como
VERBANIA
LEC
CAGNO
RIDDES
VALPELLINE
COGNE AS
CHATILLON
AVISE
QUART
MONTJOVET
AOSTA
VILLENEUVE
ALBERTVILLE
F. Dora Baltea
da declassare a 130 kV
BIELLA
BIELLA EST
CARISIO
ROSONE
VILLA
VARESE
COMO
MERCALLO
BULCIAGO
CISLAGO
VERDERIO
TURBIGO
BOVISIO
BRUGHERIO
OSPIATE
NOVARA
MAGENTA
BARACCO
MILANO
NOVARA SUD
VERCELLI
LACCHIARELLA
TAVAZZANO
GRAND'ILE
VILLARODIN
VENAUS
FERRERO
F. Dora Riparia
LEINI
RONDISS.
TRINO N.
TEKSID
TRINO
BALZOLA
PAVIA
TORINO
da demolire
PIOSSASCO
CASANOVA
ASTI
CASTELNUOVO S.
ALESSANDRIA
ILVA LP
NOVI L.
VIGNOLE B.
BISTAGNO
esercita a 220 kV
CUNEO
MAGLIANO ALPI
MORIGALLO
ILVA CORN.
ERZELLI
GENOVA
da decl
S. COLOMBA
SAVONA
VADO L.
SAVONA
PIASTRA
Golfo di Genova
CAMPOCHIESA
CAMPOROSSO
LE BROC-CARROS
IMPERIA
MAR
FRANCIA


Lago di Resia
NATURNO AEC
GLORENZA
EDISON CASTELBELLO
LANA
BOLZANO
LASA
PRACOMUNE
SAN PANCRAZIO
AEC
S. ANTONIO
CARDANO
ACC. BZ
BOLZANO ME
S. VALBURGA
MASO PILL
PREMADIO
EDISON
da declassare a 130 Kv
EDISON
TAIO
EDISON
CAMPO MORO
LANZADA
ROBBIA
GROSIO
S. FLORIANO
SONDRIO
BELVISO
EDOLO
VENINA
CEDEGOLO
GANDA
EDISON
SONDRIO
SONDEL
EDISON
EDISON
S. MASSENZA
LAVIS
VAL NOANA
BORGO VAL SUGANA
MOLINE
VELLAI
S. FIORANO
BOAZZO
TRENTO SUD
TRENTO
ARSIE
ACCIAIERIE VALSUGANA
CAVILLA
AEM
da ricostruire in d. t.
PIAN CAMUNO
CIMEGO
ARCO
TORBOLE
da demolire in parte
ALA
Lago d'Iseo
da declassare a 130 kV
BERGAMO
GORLAGO
GARGNANO
SANDRIGO
CITTADELLA
ODOLO EST
da declassare a 130 kV
NAVE
OISERANO
MONTEVIALE
VICENZA
VALBRUNA
MONTECCHIO
BELTRAME
CHIARI
TRAVAGLIATO
RIC. OVEST
AEM
BRESCIA
FLERO
COLA'
BUSSOLENGO
AGSM
VERONA
VERONA B. M.
SANDRA'
GALTAROSSA
LONATO
EDISON
PADOVA
ACC. VENETE
RFX
SORIO
DUGALE
CAMIN
LODI
NOGAROLE ROCCA
da declassare a 130 kV
ESTE
S. CROCE
CREMONA
MARCARIA
MANTOVA
S. ROCCO
ACC. ISP
CREMONA
MANTOVA EDISON
da declassare a 130 kV
ROVIGO
CASELLA
PIACENZA
CAORSO
SERMIDE
OSTIGLIA
PIACENZA
COLORNO
da declassare a 130 kV
PARMA
REGGIO NELL'EMILIA
FERRARA EDISON
FERRARA
FERRARA FOCOMORTO
PARMA V.
MODENA

RIA

SLO

LIENZ

da demolire

SOMPLAGO

BUIA

FERRIERE NORD

SOVERZENE

LUNO

Lago di S. Croce

FADALTO

ACC. BERTOLI

UDINE EST

UDINE

PORDENONE

UDINE OVEST

SAFAU

CORDIGNANO

GORIZIA

DIVACCIA

CONEGLIANO

PORDENONE

ODERZO

REDIPUGLIA

Z. I.

PLANAIS

MONFALCONE

DIVACCIA

SALGAREDA

TREVISO

PADRICIANO

TRIESTE

TREVISO S.

VENEZIA N.

MALCONTENTA MARGHERA

ALUMIX

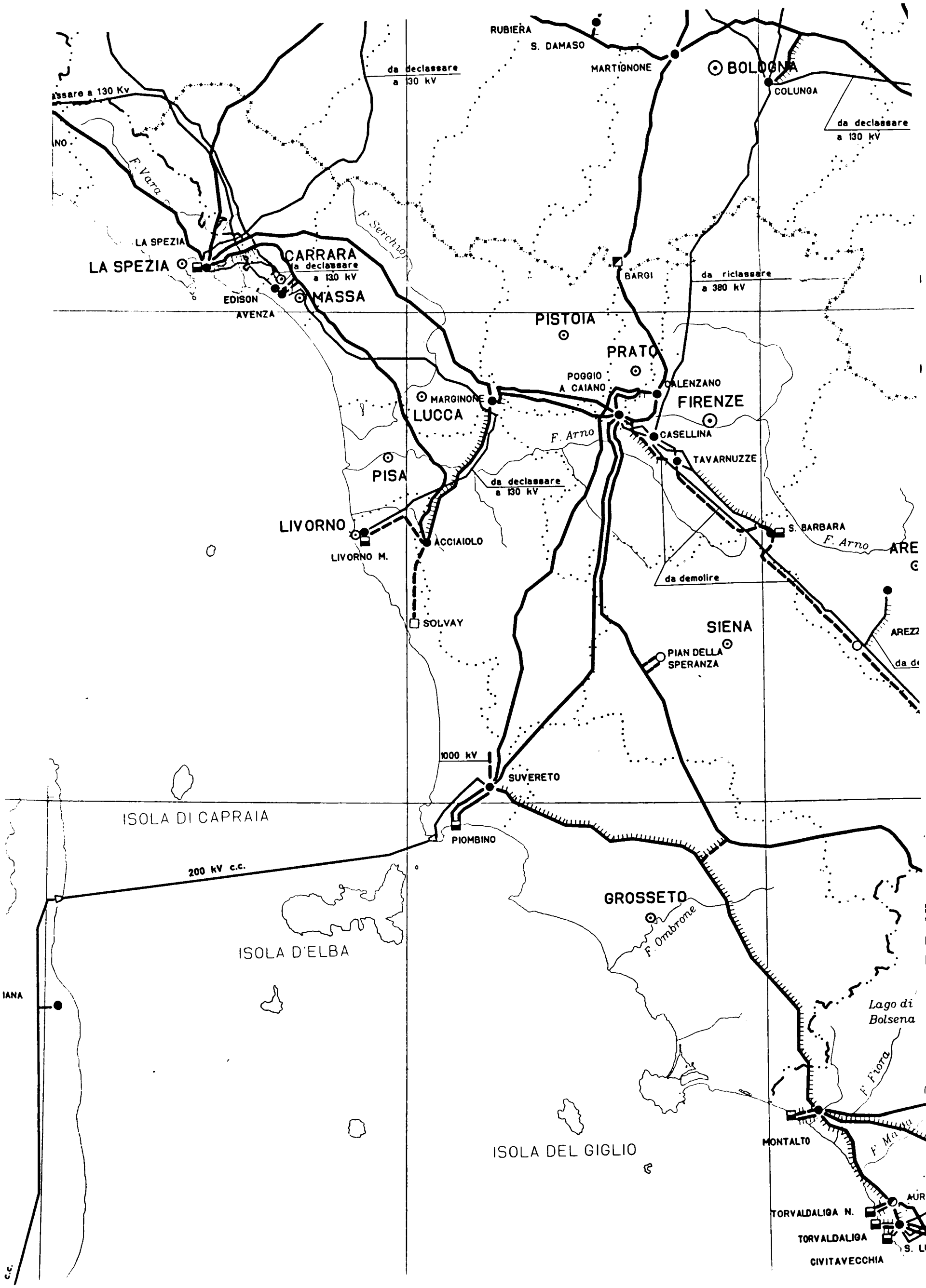
FUSINA

VENEZIA

Golfo di Venezia

ADRIA

PORTO TOLLE


RUBIERA
S. DAMASO
MARTIGNONE
BOLOGNA
COLUNGA
da declassare a 130 kV
da declassare a 130 kV
F. Vara
F. Serchio
LA SPEZIA
LA SPEZIA
CARRARA
da declassare a 130 kV
MASSA
EDISON AVENZA
BARGI
da riclassare a 380 kV
PISTOIA
PRATO
POGGIO A CAIANO
CALENZANO
MARGINONE
LUCCA
FIRENZE
F. Arno
CASELLINA
TAVARNUZZE
PISA
da declassare a 130 kV
LIVORNO
LIVORNO M.
ACCIAIOLO
S. BARBARA
F. Arno
da demolire
SOLVAY
SIENA
PIAN DELLA SPERANZA
1000 kV
SUVERETO
ISOLA DI CAPRAIA
PIOMBINO
200 kV c.c.
GROSSETO
F. Ombrone
ISOLA D'ELBA
Lago di Bolsena
F. Fiora
MONTALTO
ISOLA DEL GIGLIO
TORVALDALIGA N.
TORVALDALIGA
CIVITAVECCHIA

PORTO CORSINI
da demolire
RAVENNA C.
RAVENNA
FORLI'
FORLI'
da declassare
a 130 kV
RIMINI
S. MARTINO IN VENTI
PESARO
F. oglia
FANO
da declassare a 130 kV
URBINO
F. Tevere
ANCONA
CANDIA
MACERATA
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ZO
ssare a 130 Kv
PERUGIA
Lago Trasimeno
da demolire
PIETRAFITTA
F. Trec
da declassare
a 130 kV
ASCOLI PICENO
ROSARA
Tronto
TERAMO
F. Vomano
BASCIANO
tutte da demolire
Lago di Campotosto
TERNI
da declassare
a 150 kV
VILLAVALLE
da demolire
GALLETO
MONTORIO
S. GIACOMO
PROVVIDENZA
PESCARA
VILLANOVA
da declassare
a 130 kV
CHIETI
VITERBO
Lago di Vico
RIETI
Lago del Salto
Lago del Turano
L'AQUILA
Pescara
Lago di Bracciano
da declassare
a 150 kV
POPOLI
ROMA N.

FLAMINIA (ACEA)

da trasformare in trinata

ROMA O.

S. PAOLO

ROMA

FS

TIBURT

P. DANTE

CINECITTA'

ROMA E.

da declassare a 150 kV

ROMA S.

VALMONTONE

AVEZZANO

Amene

FROSINONE

F. Liri

F. Sacco

CEPRANO

da declassare a 150 kV

LATINA

LATINA

Lago di Fogliano

Lago di Fondi

CAPRIATI

Lago del Matese

PRESENZANO

ISERNIA

CAMPOBASSO

F. Trigno

F. Biferno

LARINO

PARIGLIANO

da declassare 150 Kv

BENEVENTO

BENEVENTO

CASERTA

S. MARIA C. V.

S. SOFIA

PATRIA

NAPOLI

AVELLINO

STRIANO

SALERNO

SALERNO

MONTECORVINO

TUSCIA

LE PONZIANE

SICILIA

ISOLE TREMITI

Lago di Lesina

Lago di Varano

FOGGIA

FOGGIA

Salina

T. Carapelle

CANDELA

ASCOLI S.

ANDRIA

BARI

BARI OVEST

F. Ofanto

F. Bradano

MATERA

MATERA

POTENZA

da declassare a 150 kV

F. Basento

ILVA

TARANTO

ANIC

PISTICCI

F. Agri

da declassare a 150 kV

CASTROCUCCO

da declassare a 150 kV

ROTONDA

MERCURE

da declassare a 150 kV
o da demolire

ROSSANO

MUCONE 1

MUCONE 2

Lago di Cecita

COSENZA

Lago Arvo

F. Neto

Lago Ampollino

da declassare
a 150 kV
o da demolire

SCANDALE

CROTONE

FEROLETO

CATANZARO

VIBO VALENTIA

F. Mesima

GIOIA
TAURO

RIZZICONI

REGGIO DI CALABRIA

BRINDISI
BRINDISI P.

BRINDISI N.

BRINDISI S.

NTO N.

LECCE

GALATINA

± 400 kV c. c.

GRECI

ISOLE EOLIE

ISOLE EGADI

BELLOLAMPO

PALERMO

PARTINICO

TERMINI I.

CARACOLI

TRAPANI

TRAPANI

esercita a 150 kV temporaneamente

F. Belice

PARTANNA

da demolire

CIMINNA

1 terna da esercire a 220 kV

CALTANISSETTA

ENNA

F. Platani

CALTANISSETTA

AGRIGENTO

FAVARA

F. Salso

S. FILIPPO DEL MELA

ACCIAIERIE TIRRENO

CORRIOLO

SORGENTE

da eliminare

esercita a 220 kV

F. Simeto

Lago di Pozzillo

PATERNO'

F. Dittaino

CATANIA

MISTERBIANCO

ANAPO

MELILLI

PRIOLO G.

ISAB

SIRACUSA

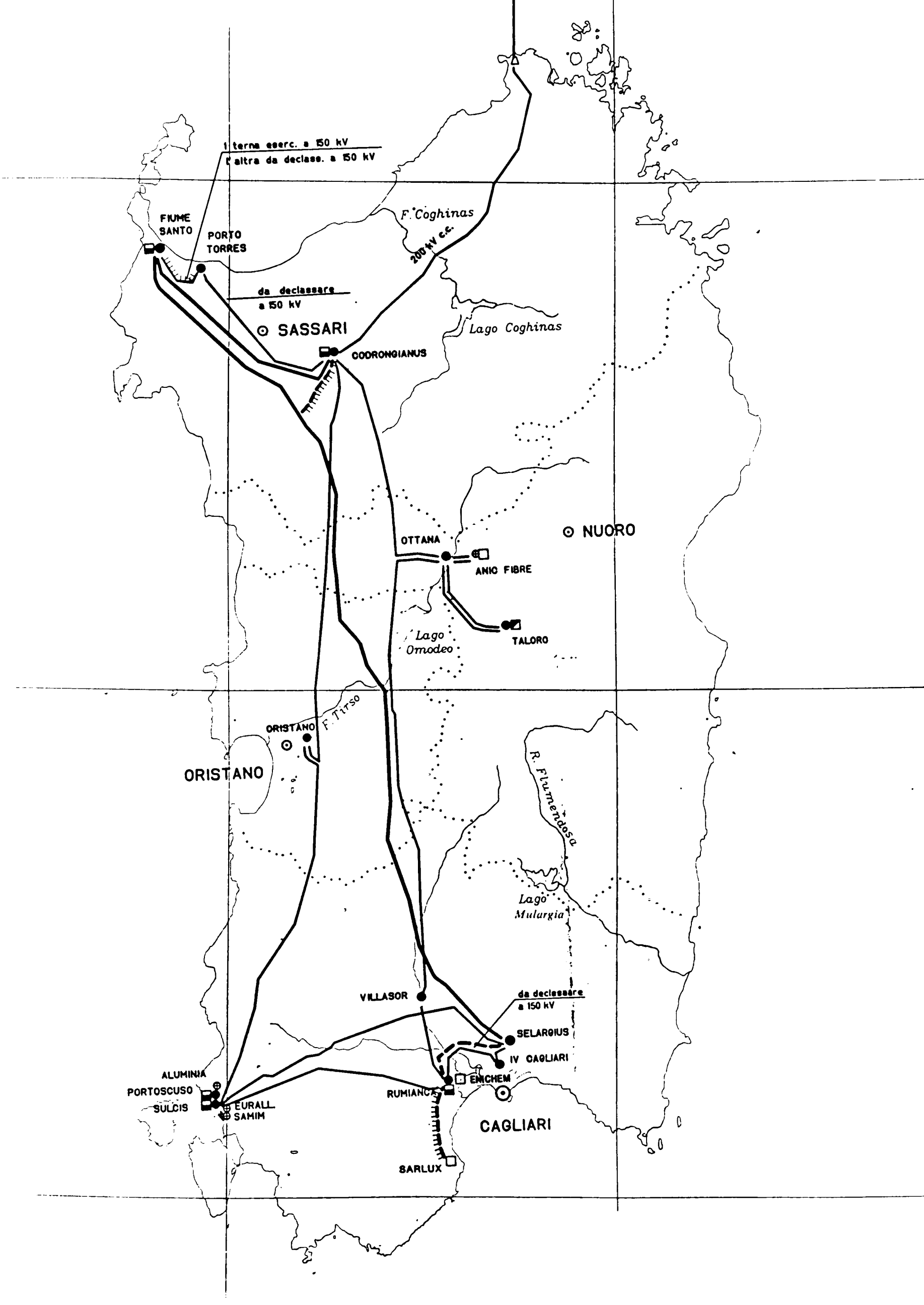
CHIARAMONTE G.

da declassare a 150 Kv

ENICHEM

RAGUSA

RAGUSA


1 terna eserc. a 150 kV
l'altra da declass. a 150 kV
FIUME SANTO
PORTO TORRES
F. Coghinas
200 kV c.c.
da declassare
a 150 kV
SASSARI
Lago Coghinas
CODRONGIANUS
NUORO
OTTANA
ANIC FIBRE
TALORO
Lago Omodeo
ORISTANO
F. Tirso
ORISTANO
R. Flumendosa
Lago Mulargia
VILLASOR
da declassare
a 150 kV
SELARGIUS
IV CAGLIARI
ENICHEM
ALUMINIA
PORTOSCUSO
SULCIS
EURALL.
SAMIM
RUMIANCA
CAGLIARI
SARLUX

ADDENDUM

Footnote 27 on page 33 should now read:

The Convention on Climate Change was initiated at the UN Headquarters, New York City, in May 1992; it was open for signature at Rio de Janeiro from 4 to 14 June 1992, and thereafter at the UN Headquarters themselves until 19 June 1993. By that date, the Convention had received 166 signatures. It entered into force on 21 March 1994. Ratification of the Convention went on until the Kyoto Conference on Climate Change (1997) and is still taking place. Italy ratified the Convention on 15 April 1994, after signing it on 5 June 1992. Following ratification, the agreement entered into force on 14 July 1994 on the Italian territory. Italy confirmed its emissions commitments (CO_2) for the year 2000 at the Kyoto Conference on Climate Change, and also promised to reduce its carbon dioxide emissions by 6.5% (as compared to 1990 levels) by 2010. This is not a tremendous commitment, since (e.g.) Germany committed to a 21% reduction from 1990 levels by the year 2010. Recall that Italy suffers from lack of indigenous energy resources and from stickiness in switching to less polluting energy sources because of its long-term dependence upon imports (France, Switzerland, Eastern Europe, Algeria, etc.).