Output-based incentive regulation: benchmarking with quality of supply in electricity distribution

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DRAFT, January 26, 2012

Abstract

Incentive regulation is moving towards new schemes where standard efficiency mechanisms are combined with output-based incentives (related to quality of supply, sustainability and innovation). Assessing performance of distribution utilities requires models capable to account for these different (in part conflicting) regulatory objectives. Benchmarking analysis has been in use for a long time; however, whether these models should incorporate even quality as an additional output is still a matter of debate.

Using continuity of supply as an example, we study how benchmarking DEA models can be adjusted to correctly accommodate all regulated variables. To this end, we estimate different models to measure technical efficiency, using a comprehensive and balanced panel for 115 electricity distribution Zones, that belong to the largest Italian distribution utility. Together with other structural variables, quality significantly contributes to explain differences in efficiency scores. We thus claim that benchmarking models should include (monetary) measures of regulated outputs.

Keywords: DEA, electricity distribution, incentive regulation, quality of supply.

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[§]Financial support from the Italian Regulatory Authority for Electricity and Gas is kindly acknowledged.

1 Introduction

Incentive regulation is moving towards new schemes where standard efficiency mechanisms are combined with additional output measures that focus, for instance, on quality of supply but also on sustainability and innovation [1, 2, 3]. Both Italy and the UK (through the so called RIIO model) are moving in this direction [4, 5]. In this context, assessing performance of regulated utilities requires models capable to account for these different (in part, also conflicting) regulatory objectives[6].

Benchmarking analysis has been in use for a long time and it has been largely applied to electricity distribution [7]. From a survey of the literature two aspects emerge, that are relevant for this work. First, a consensus does not exists on the choice of input and output variables to be included in the benchmarking models [8]. This can be attributed to the different availability of data but also to the different objectives of the studies.[1] Second, whether it is appropriate to include quality measures in benchmarking models is still a matter of investigation. A couple of recent studies find a clear trade-off between quality and technical efficiency (companies with higher cost structures present higher levels of quality and vice versa) [10, 11]; on the contrary, the introduction of quality does not seem to produce any noticeable effect on the technical efficiency scores estimated in [12, 13].

In this paper, using continuity of supply as an example, we study how benchmarking Data Envelopment Analysis (DEA) models can be adjusted to correctly accommodate additional regulated outputs and still deliver meaningful and useful results. More specifically, we discuss the best choice of input-output variables to measure technical efficiency, in a cost-only model and then in a cost-and-quality model. Our dataset is a comprehensive and balanced panel for 115 different distribution zones, that belong to the largest Italian distribution utility, and spans a period of six years (from 2004 to 2009). In addition to these data, the Italian regulator has provided also detailed measures of quality of supply as well as information regarding of monetary incentives paid in quality-related penalties or received in rewards.

Our results show that, in addition to other structural variables (territorial density and energy consumption per customer), quality significantly contributes to explain differences in efficiency scores. We thus claim that benchmarking models should include (monetary) measures of additional outputs. This is relevant to design incentive mechanisms that both drive benefits for consumers and provide companies with incentives to invest in quality and, more generally, in network innovation.

The paper is structured as follows. In Section II we describe the electricity distribution sector in Italy and in Section III we present our dataset. In Section IV we describe the methodology for the analysis and define our choice for the input and output variables. In Section V we report the main results of the

[1] Benchmarking has been (and still is) largely employed for regulatory purposes, either directly to set parameters in tariff schemes or, indirectly, to evaluate company performances at tariff reviews [9].

study. Section VI concludes.

2 Electricity distribution in Italy

In Italy, in 2009, there were 135 Distribution Network Operators (DNO), that delivered a total volume of 279 TWh. The largest company, *Enel Distribuzione*, was responsible for 86.2% of the distributed energy, followed by *A2A Reti Elettriche* (4.1%) and *Acea Distribuzione* (3.6%). The other operators held marginal quotas (equal to or less than 1% in volumes). Enel was present in Italian territory and it was organized in four Macro Areas, eleven Territorial Units and 115 Zones.

DNOs are regulated by the Italian regulatory authority for electricity and gas (*Autorità per l'energia elettrica e il gas* - AEEG). Since the year 2000, an incentive-based mechanism applies (with a four-year regulatory period), with the objective to stimulate productive efficiency. As better explained below, the price-cap formula is modified by an additional parameter (Q), linked to quality of supply. Starting from the second regulatory period (in 2004) capital expenditures are subject to a Rate of Return regulation while operational expenditures remain incentivised with a price-cap approach (this decision was taken by the government and not by AEEG - Law n. 290/2003).[2] More recently, AEEG added an input-based element to the regulatory framework. Specific investments (for instance, certain new substations, but also selected smart grid demonstration projects) benefit from an increase in Weighted Average Capital Cost (WACC) for period of 8 to 12 years (a 2% extra WACC in addition to the ordinary return). Note that, as for smart grids, after this initial phase, the Italian regulator is eager to move from an input-based approach to an output-based regulation [14, 15].

As far as quality is concerned, in the year 2000 AEEG introduced a reward and penalty scheme that linked the distribution tariff to an output measure of continuity of supply: the average duration of interruptions per consumer - SAIDI indicator - for long (longer than 3 minutes), unplanned interruptions.[3] This indicator is measured separately in more than 300 territorial districts, covering the entire national territory: each district includes municipalities that are homogeneous in population density, that are located in the same administrative province and whose network is managed by the same distribution company. Economic incentives are calculated per district on an annual basis, as a function

[2] According to the Italian regulatory framework, investment decisions on electricity distribution networks are taken by DNOs. The regulator intervenes only *ex-post* checking the actual deployment of the investments and the correspondence between investments and reported costs. Each year the regulator updates the distribution tariff to take into account the actual changes in invested capital [14].

[3] Continuity of supply is described by the number and duration of supply interruptions. For a given distribution area and time period, the average duration of long interruptions per consumer is measured by SAIDI (System Average Interruption Duration Index), the average number of long interruptions per customer by SAIFI (System Average Interruption Frequency Index), and the average number of short (shorter than 3 minutes and longer than 1 second) interruptions per customer by MAIFI (Momentary Average Interruption Frequency Index).

of the difference between a target-SAIDI and the actual-SAIDI (performance standards are defined separately for each territorial district). The distribution tariff is unique across the entire national territory and the price p_t (in year t) changes according to the formula:

$p_t = p_{t-1}(1 + RPI - X + Q)$

where RPI is the retail price index, X is the efficiency factor and Q is the quality adjustment. Yearly values of the parameter Q are calculated, *ex post*, on the basis of companies' performances and can assume a negative or a positive sign. When Q is positive (negative), it means that, at a national level, quality has improved more (less) than required and consumers are called to contribute (consumers pay a reduced tariff).

Beginning with the second regulatory period, target-SAIDI are calculated using a formula that assumes a convergence in performance of all districts with equal population density to the same quality level, in the medium term (12 years).[4] This approach enables the regulator to expect greater improvements from district that are underperforming with respect to the national standards and vice versa. Moreover, the results of a customer survey are used to define penalties and rewards: two different valuations of quality are considered, to reflect the different Willingness To Pay (WTP) of domestic and non-domestic customers. Since the third period, the regulator included in the scheme a further quality dimension: the frequency of interruption for both short and long interruptions - short interruptions are more damaging for business customers than they are for households [16].

In summary, the constraint imposed by the law and the vast number and heterogeneity of distribution companies have resulted in a regulatory framework composed by several "building blocks" (price-cap on operational expenditures, input-based incentives for investments and output-based regulation for supply quality). Concerned about cost inefficiencies that might result from this approach (for instance, infrastructural interventions may help improving the reliability and the quality of the services provided), the Italian Regulator is keen on considering a more unified approach, based to a greater extent on an output-based regulation [14, 15]. Hence, within both the present and future regulatory frameworks (the third tariff period begins in 2012), it would be desirable to perform quantitive analyses to verify the overall efficiency of the regulatory scheme. This clearly motivates the study described in this paper.

3 Dataset and descriptive statistics

Our dataset was built with the support of the Italian regulatory authority, by means of a dedicated data collection. It is a comprehensive and balanced panel for 115 Zones, that belongs to Enel Distribuzione, tracked from 2004 to 2009 (one and a half regulatory period). For each Zone the dataset comprises a wide set of information, ranging from technical variables and accounting data to quality related variables.

[4]This is strictly related to the existence of a unique, national distribution tariff.

More specifically, as for technical variables, the data set includes the number of Low Voltage (LV) customers, the energy consumed by LV domestic and non-domestic users as well as by Medium Voltage (MV) ones, the area served (in km^2), the transformer capacity for primary and secondary substations (in MVA) and the network length (in km, for MV and LV, cable and overhead lines). Acconting data are given in terms of annual revenues, asset values (detailed for primary and secondary substations, MV and LV feeders and for points of connection) and operating costs (including labour, services, materials and other costs).

AEEG provided also data on the duration of long interruptions (SAIDI) as well as on the frequency of long and short interruptions (SAIFI and MAIFI, respectively); moreover, a key novelty of our dataset is the detailed information on the amounts annually received in rewards (paid in penalties) for out-performing (under-performing) with respect to the regulatory standards. Note that continuity of supply data (both indicators and monetary incentives) are given per territorial districts: these are smaller geographical areas than the Zones and are homogenuous in customer density - a parameter that is strictly correlated with continuity of supply (higher continuity is to be expected in more dense areas). For the purpose of this work, zonal data were derived (aggregating district data), to make this information coherent with the other variables in the dataset. This also means that, inevitably, the correlation between density and continuity became less precise.

A simple descriptive statistic of continuity indicators shows large geographical difference between three areas of Italy: North, Center and South.[5] Consider the average zonal values of SAIDI, and SAIFI+MAIFI, as depicted in Figure 1.[6] Even if SAIDI and SAIFI+MAIFI values steadly improved over the observed period, it is clear that the average number of interruptions (both long and short) as well as the duration of long interruptions are more than double in the South of Italy, compared to the North and Center. These differences are relevant also for the benchmarking analysis described in this work.

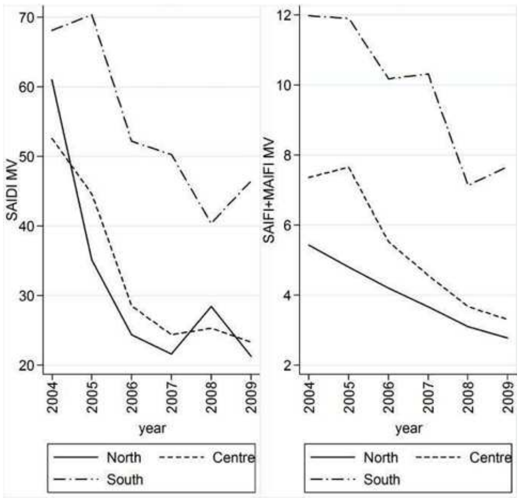
4 Methodology and choice of variables

In this paper we estimate a multi-input, multi-output distance function, using the Data Envolpment Analysis (DEA) methodology. DEA involves the use of linear programming methods to construct, non-parametrically, a frontier surface over the data. Efficiency measures are computed relative to this surface: the units for which the efficiency score is equal to 1 are considered efficient, while the remaining units have a score smaller than 1, that represents their distance from the efficiency frontier. A few remarks on our approach to this methodology are in order. First, in electricity distribution it is fair to assume that demand

[5]Here we refer to the AEEG classification in “Circoscrizioni”, that has been in use since 2000 for aggregating data on continuity of supply.

[6]Data refer to MV interruptions (these represent the main contribution to the continuity indicators) and exclude events of Force Majeure.

Figure 1: Continuity indicators (MV)



is mostly beyond the control of the firm, hence, we deemed it appropriate to use an input-oriented model. In this formulation, technical efficiency indicates the amount by which observed inputs can be proportionally reduced, while still producing the given output level. Second, DEA models can assume Variable or Constant Returns to Scale (CRS): the assumption of CRS was preferred in this study to avoid misleading results for the largest and smallest units in the sample - they would have been considered efficient, regardless of their input level [17].[7] Finally, DEA methods do not make a distinction between unobserved factors and inefficiency: to partially compensate for this shortcoming, we resort to a bootstrap DEA approach [18].[8] For further details on the DEA methodology, see [19].

Choosing the input–output variables is an important step in DEA" (Giannakis et al., 2005, p. 2263). Similar statements are found in almost every benchmarking analysis with DEA. Nonetheless, an exaustive discussion over more or less appropriate choices of variables for the eletricity distribution activity seems lacking. In this Section we provide strong arguments in favour of a choice of variables over another, in particular, in cases where benchmarking is extended to additional regulated outputs (such as quality in the Italian example). A discussion of this sort appears extremely relevant, in view of a more

[7] Moreover, our results show an average scale efficiency above 93%, this indicating an homogeneity in our sample and providing an additional motivation for computing a CRS DEA frontier.

[8] The process involves using the original sample values to construct an empirical distribution of the variable of interest by repeated sampling of the original data series, application of the estimation process to the sampled data and then calculating relevant statistics, e.g. means and standard deviations from these results. The bootstrap has been advocated as a way of 'analysing the sensitivity of measured efficiency scores to the sampling variation' [18].

extended use of output-based regulation, as in the regulator's intentions.

4.1 Cost-only models

As for output variables, drawing on previuos work as well as on our knowledge of the distribution activity, we built a first model (*Econ*) with energy consumption in MWh per year ($energy_{it}$) and number of LV consumers ($LVcons_{it}$) as outputs for the Zone i in year t.[9] The energy requested by final users is not under the control of a DNO, however the network is built to have an adequate capacity to transport it; similarly, all requests for connection must be fulfilled by the distributor (within certain technical limits).

Our choice of inputs included capital and non-capital inputs (operating costs). As for capital input, we preferred total gross value of the assets (substations, feeders and points of connection) over capital expenditures, to avoid penalising a Zone for making recent investments ($capital_{it}$); as for non-capital input, we included labour (the main voice), services, materials and other operating costs - and excluded depreciation and taxes (op_costs_{it}).

Another possibility for the input variables was to express capital and non-capital inputs in terms of physical units. We thus built an alternative model (*Tech*) where capital input was measured by transformer capacity in MVA (t_cap_{it}) and network length in km ($nlengh_{it}$) and operating costs were approximated by the number of employees ($empl_{it}$). As for outputs, in we considered adding to the energy consumption and the number of customers also the area served in km^2 - another variable that can be considered exogenous for a DNO ($area_{it}$).

In order to choose between the two models we looked at several descriptive statistics and, more importantly, at ratios obtained combining output and inputs. This preliminary analysis produced also some hypotheses on the expected results.

Considering outputs first, we report in Table 1 the average values of output variables by geographical area (North, Center and South of Italy). We note that Zones in the Center of Italy have, on average, a lower domestic consumption (dom_energy_{it}) relative to Zones in the North and South (384 GWh/y against 477 and 487 GWh/y, respectively); non-domestic LV consumption plus MV consumption (in brief, non-domestic consumption, $nondom\_energy_{it}$) is almost twice as high in the North (1794 GWh/y) with respect to the Center and the South (1067 GWh/y in the Center and 881 GWh/y in the South); total consumption is on average 2271 GWh/y in the North, and it is around 1452 GWh/y in the Center and 1368 GWh/y in the South.[10]

The average number of LV consumers per Zone is around 277,000 in the North, 272,000 in the South, while it amounts to a lower value (around 224,000

[9] The option to separate domestic and non-domestic consumption was considered but it did not alter the results in any significant way.

[10] Consumption grows over the observed period, except non-domestic consumption in 2009 as a consequence of the economic crisis.

Table 1: Output variables by geographical area

Geog. areas	dom_energy_{it}	$nondom\_energy_{it}$	$energy_{it}$	$LVcons_{it}$	$area_{it}$	$perc\_dom_{it}$
	GWh/y	GWh/y	GWh/y	n°/y	Km^2	%
North	477.4	1794.4	2271.7	276945.0	2215.4	21.8
Center	384.8	1066.8	1451.6	223791.0	2340.9	27.5
South	487.3	880.9	1368.2	272102.0	2853.6	35.7
Total	*461.8*	*1301.0*	*1762.7*	*264041.0*	*2480.2*	*28.2*

on average) in the Center.[11] Note that the percentage of domestic consumption is higher in the South ($perc\_dom_{it}$).

The extension of the area served, constant over time is, on average, equals to 2853 km^2 in the South, 2340 km^2 in the Center and 2215 km^2 in the North.

As for input variables average values are reported in Table 2. In the *Econ* model, we observe that average capital and non-capital inputs per Zone are higher in the South relative to the North and Center: $capital_{it}$ is around 297 million € (on average per Zone) in the South, 251 million € in the North and 227 million € in the Center; average zonal values of op_costs_{it} are around 19 million € in the South, 17.5 million € in the North and 15 million € in the Center. In line with the regulatory framework, operating costs have steadly decreased over the observed period ranging from average 19.56 million € in 2004 to 16 million € in 2008. In 2009 operating costs increased to 18.55 million €.

Turning to inputs of the *Tech* model, the average zonal number of employees ($empl_{it}$) is higher in the South (210 workers on average) relative to the North and the Center (around 180 workers). The number of employees decreased sensibly between 2004 and 2009 (by more than 60 workers per Zone, on average) from 231 in 2004 yp 167 in 2009 (by more than 60 workers per Zone, on average). The average zonal network length ($nlengh_{it}$) is around 10,500 km in the South, and only around 8600 km in the North and 8800 km Center.[12] The average zonal capacity of primary substations ($t\_cap\_p_{it}$) is around 1014 MVA in the North, 701 MVA in the Center and 781 MVA in the South. Over the observed period it grows more significantly in the North (around 2%) relative to the Center (1.2%) and the South (around 0.9%). The average zonal capacity of secondary substations ($t\_cap\_s_{it}$) is equal to 707 MVA, 518 MVA and 578 MVA, respectively for the North, Center and South (and it grows with similar proportions, around 2%, in all the geographic areas).

As mentioned, before calculating relative zonal efficiencies, we found extremely informative to look at output-input ratios.

Beginning from the *Econ* model, we observe that the ratios of capital and non-capital inputs to the number of LV consumers (Table 3) report average zonal costs in the South similar to the ones in the Center and a 10% higher than the amount registered in the North. This difference is not as striking

[11] A lower number of consumers is observed in 2008, due to a re-calculation made by Enel itself.

[12] Values for MV and LV only reflect this same differences.

Table 2: Input variables by geographical area

Geog. areas	$capital_{it}$	op_cost_{it}	$empl_{it}$	$nlength_{it}$	$t\_cap\_p_{it}$	$t\_cap\_s_{it}$
	mln €	mln €	n°	Km	MVA	MVA
North	251.1	17.5	185.9	8599.1	1014.4	706.8
Center	227.5	15.3	176.4	8803.6	701.0	517.9
South	297.5	19.0	210.7	10547.0	781.5	577.9
Total	*263.5*	*17.6*	*193.2*	*9370.1*	*862.0*	*619.2*

Table 3: Input-Output ratios in *Econ* model

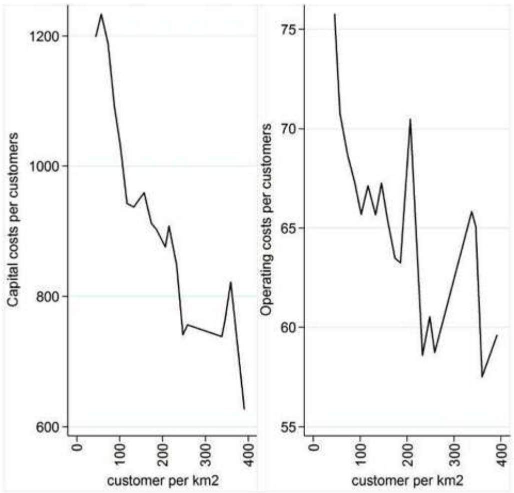
Geog. areas	$capital_{it}/LVcons_{it}$	$capital_{it}/energy_{it}$	$op\_cost_{it}/LVcons_{it}$	$op\_cost_{it}/energy_{it}$
North	980.5	128.8	65.3	8.7
Center	1072.5	176.7	69.5	11.5
South	1172.3	242.6	72.0	15.0
Total	*1071.4*	*181.3*	*68.7*	*11.6*

as the one between the ratios of capital and non-capital inputs over energy consumption. The South of Italy presents average zonal values of capital/MWh and of operating costs/MWh that are around 1.8 times those in the North and around 1.3 times the values for the Center. Assuming a rational conduct on the part of Enel Distribuzione, we deduct that the costs of distribution are strongly related to the number of customers served. We thus expect that in Zones where the single customer consumes relatively more energy will make a better use of their inputs and, thus, will be more efficient. Descriptives suggest that, in the North of the country, where the percentage of domestic comsumption is lower, Zones should present higher efficiency than those operating in the other parts of Italy (see $perc\_dom_{it}$ in Table 1).

Another aspect that is usually associated to distribution costs is territorial density. This is true also for Enel Distribuzione. Figure 2 shows capital and non capital inputs per customers vs. the number of customers per km^2; to be precise, those represented in Figure 2, are average values over the observed period. Moreover, as density data present a large standard deviation and several outliers we limit the graph to the 95% percentiles of the observed data: the dataset average density is 186 ubt/km^2, but a few (5%) Zones present densities of over 400 ubt/km^2 while others of less than 37 ubt/km^2 (5%). The effect of territorial density is as expected: both capital and non-capital costs decrease with the number of ubt/km^2. We thus expect higher technical efficiency in more densely popolated Zones.

Turning now to the $Tech$ model, we considered that DEA finds those units of observation that are efficient with respect to a combination of input-output ratios. As for the number of employees, we encountered no particular problems: it is reasonable to define "efficient" a distribution Zone that minimises the number of workers per consumer or energy delivered or even per km^2 of area served. As for network length, it is reasonable to label as more efficient a Zone with less km of feeders per customer or per km^2 of area served; however, it is more difficult to argue that a distribution Zone is more efficient than another because

Figure 2: Costs and territorial density



it is characterized by less km of feeders per MWh delivered. The interpretation becomes even more difficult when dealing with transformer capacities. While a Zone with an adequate installed tranformation capacity per MWh delivered is indeed efficient, there is no practical meaning in labelling as efficient a Zone that minimises its transformer capacity per km^2 or per customer (remember that we are including the in the model only the number of LV customers).

In summary, when using technical input variables it is inevitable to incur in input-output combinations that have no practical significance (for instace network length/MWh or transformer capacity per LV customer). We thus concluded that a "technical" DEA model would always lead to a combination of meaningful and unreasonable results when considered in the light of the practical activity of a DNO. Indeed, our results from this benchmarking model confirm this hypotesis.[13] Hence, the $Tech$ model will not be commented further in this paper.

4.2 Cost-and-quality models

For the inclusion of quality of service as an input variable in the $Econ$ model we considered three main options:

- to use the total number of interruptions (or the total duration) expressed, as in [12], by the product of the number of LV consumers times SAIFI (or SAIDI);
- to substitute op_costs_{it} with the sum of op_costs_{it} plus penalties paid and minus rewards received ($op\_costsRP_{it}$): as a consequence, Zones that

[13] They are available from the authors upon request.

receive rewards (present higher levels of quality than requested by the regulator) become more efficient in terms of non-capital inputs;[14]

- to add to op_costs_{it} the value of the Energy Not Supplied (ENS) obtaining a new variable ($op\_costsENS_{it}$); in this way Zones with lower levels of quality are relatively less efficient.

In particular, to derive a meaningful value of ENS we considered:

- the SAIDI values;
- the WTP parameters indicated by the Italian regulatory authority: C_1 for domestic users and C_2 for non-domestic ones (respectively 18 and 36 c€/min/kW) [20];
- the domestic and non-domestic energy consumption (in MWh);

and then calculated the product:

$SAIDI \cdot (C_1 \cdot \frac{domestic\ cons.}{8760} + C_2 \cdot \frac{non-domestic\ cons.}{8760})$.

Again, in order to choose among the different options to describe quality of service we look at descriptive statistics as well as at input-output ratios.

As for quality of supply, the variables $NINT = SAIFI \cdot ubt$ and $DINT = SAIDI \cdot ubt$ maintain the regional differences illustrated in Section 3.

The first two column of Table 4 report the average values, by geographical areas, of the two proxies used to correct operating costs by the quality of the service supplied. If we consider the average zonal values of $op\_costsRP_{it}$, we find that these are always lower than op_costs_{it}, indicating that, on average, more rewards were received than penalties paid; as expected, the difference between the two variables is larger in the North than in the Center or South.

On the contrary, $op\_costsENS_{it}$ are obviously always greater than op_costs_{it} and on average, over the observed period, the ENS added 3.26 million € in the North, 2.48 million € in the Center and 3.55 million € in the South.

When we consider the ratio between $op\_costsRP_{it}$ and the number of consumer, we find that regulatory incentives slighlty amplify the distances among geographical areas described above for op_costs_{it}. In particular, incentives cut operating costs, on average over the observed period, by 6 € per customer in the North, by 3.1 € per customer in the Center and only by 2 € per customer in the South. The ratios of $op\_costsRP_{it}$ over energy consumption do not alter the geographical distances found above: larger rewards obtained in the North are distributed over greater amounts of distributed energy.

As for the ratios of $op\_costsENS_{it}$ over the number of customers, we observe that, on average over the observed period, the ENS adds 13 € per customer in the North, 12.7 € per consumer in the South and 11 € per customer in the Center (it slighlty decreases the geographical distances, especially between North and South). On the contrary, ENS adds on average 1.6 €/MWh in the

[14] Similarly we considered altering the capital input with rewards and penalties; this however, is not so interesting because the regulatory scheme demands DNOs to minimise operating costs.

Table 4: Operating costs including quality and Input-Output ratios

Geog. Area	op_costRP_{it}	$op\_costENS_{it}$	op_costRP_{it}/	op_costRP_{it}/	$op\_costENS_{it}$/	$op\_consENS_{it}$/
	mln €	mln €	$LVcons_{it}$	$energy_{it}$	$Lvcons_{it}$	$energy_{it}$
North	16.0	20.8	59.3	8.0	78.3	10.3
Center	14.6	17.8	66.4	11.0	80.4	13.2
South	18.6	22.6	69.9	14.6	84.7	17.6
Total	*16.7*	*20.8*	*64.8*	*11.1*	*81.1*	*13.6*

North, 1.7 €/ MWh in the Center and 2.6 €/ MWh in the South (it amplifies the distances, especially between Center and South). However, these changes are relatively small compared to the ones observed in the case of $op\_costsRP_{it}$.

Then, we observed the following. In case we represent quality using the $NINT$ or $DINT$ we add an input variable to the model. For the properties of DEA, we expect to find equal or higher efficiency scores for all observed units; measuring the difference in efficiency scores we can thus isolate those Zones that exibit a trade-off between costs and quality (are less efficient in the cost-only model and more efficient in the cost-and-quality model). In doing this we observed, that the model while producing, in general, reliable results (Zones with low values of $DINT/ubt$ receive a high score), it attributes a high efficiency score also to Zones with low values of $DINT/MWh$. This are normally Zones with good levels of quality, but we cannot say that the results are totally robust. For this reason, we decided to drop this option.

By choosing the second option $op\_costsRP_{it}$ we maintain the same number of variables; since adding the regulatory incentives amplifies the geographical distances we expect to find numerous cases where efficiency scores in the cost-and-quality model are lower than in the costs-only model; in other words, with this representation we can find those Zones that are penalized by the inclusion of the quality variable, while we maintain the possibility to extract those Zones with a higher score in the cost-and-quality model (as before). In addition, this option does not present the approximations of the previuos case. Note that this derives from the fact that all inputs are expressed in monetary terms, in other words, we can always considere efficient a Zone that minimises costs.

Nevertheless, also this second option for representing quality was considered not completely satisfactory: in fact, efficiency scores in the cost-and-quality model do not provide additional information relative to quality regulation, that already attributed rewards and penalties on the basis of the regulatory targets. In order to get an "independent" view on cost-and-quality efficiency we preferred the third option, where zonal costs incurred by the DNO are increased by the customer costs for quality. In other words, we preferred a "social" cost representation of the non-capital inputs.[15]

Note that once we employ the variable $op\_costsENS_{it}$, we can hardly predict the changes in the efficiency scores (geographical distances are both decreased and amplified by adding the costs of the ENS). In any case, we are still in the position to measure the differences in efficiency scores between the cost-only and the cost-and-quality model and thus to identify the Zones that

[15]This is in line with the choice made in [13].

Table 5: Benchmarking models

	Input	**Output**
Model 1	$capital_{it}$ (mln €)	$energy_{it}$ (MWh)
Cost-only	op_costs_{it} (mln €)	$LVcons_{it}$
Model 2	$capital_{it}$ (mln €)	$energy_{it}$ (MWh)
Cost-and-quality	$op\_costENS_{it}$ (mln €)	$LVcons_{it}$

present a trade-off between the two (in both directions). In addition, it will be interesting to observe also the change (if any) in the efficiency ranking, between cost-only and the cost-and-quality models; this to verify if there are Zones that are efficient (inefficient) in both and costs and quality.

5 Results

According to the discussion in Section 4, we present here the results of two benchmarking models estimated using with the input and output variables described in Table 5. In particular, efficiency scores derive from an input-oriented, CRS DEA model, applied to 114 Zones belonging to Enel Distribuzione (one Zone had to be dropped because of a major asset divestiture in 2006); using the FEAR Software Package, we estimated bootstrapped efficiency scores for each Zone with respect to a different frontier for each of the six years of the observed period [21].

A first representation of the results is given in Table6, where we report average scores by year per geographical areas and for the two models. As expected, on average, efficiency in the North is always higher than in the rest of Italy (in both models) and the geographical differences are always statistically significant (at 1% confidence level). This evidence suggests an higher homogeneity among the Zones operating in the northern part of Italy than in the other geographical areas. Conversely, Zones in the South present the lowest values in efficiency scores (the differences with the efficiency scores in the Center are also negative and significant at 1% confidence level), this indicating a more heterogeous picture among zonal efficiencies in this part of the country.

We also report the difference (in percentage) between the efficiency scores obtained in the cost-only model (Model 1) and cost-and-quality model (Model 2).

The difference in efficiency scores between the two models (reported in the last column of Table 6) is significantly different from 0 (at 1% confidence level) and equals to -1.52% on average over time. In general a negative (positive) value of this difference indicates a larger variance in the results for Model 2 (Model 1). Results obtained in our sample, thus, indicate that including quality in bechmarking analysis, contributes to obtain a more detailed pictures of efficiency in Enel Distribuzione, as it entails higher differences among zonal efficiencies. Moreover, looking at differences in the two models, according to the three ge-

Table 6: Efficiency scores

	Model 1	Model 2	Diff. (2-1)
North			
2004	0.82	0.77	-0.07
2005	0.81	0.80	0.00
2006	0.83	0.83	0.00
2007	0.84	0.84	0.00
2008	0.84	0.84	0.00
2009	0.86	0.87	0.01
Average	*0.83*	*0.82*	*-0.01*
Center			
2004	0.76	0.71	-0.07
2005	0.74	0.71	-0.03
2006	0.77	0.77	0.00
2007	0.79	0.78	-0.01
2008	0.78	0.80	0.02
2009	0.77	0.80	0.03
Average	*0.77*	*0.76*	*-0.01*
South			
2004	0.72	0.69	-0.04
2005	0.70	0.68	-0.04
2006	0.75	0.73	-0.03
2007	0.76	0.72	-0.05
2008	0.76	0.76	0.00
2009	0.76	0.75	-0.01
Average	*0.74*	*0.72*	*-0.03*
ENEL			
2004	0.77	0.73	-0.06
2005	0.75	0.74	-0.02
2006	0.79	0.78	-0.01
2007	0.80	0.78	-0.02
2008	0.79	0.80	0.01
2009	0.80	0.81	0.01
Average	*0.78*	*0.77*	*-0.02*

ographical areas, it is clear that the South of Italy is the area in which the inclusion of quality engenders the highest contribution: the average difference over time is, in this case, equal to -2.66% and significant at 1% confidence level.

Looking at the trend over time of efficiency scores, the increase in Enel's average scores in both models over time, from 2005 until 2009 (even if small) must be interpreted as a reduction of differences between the different Zones over time.

We now turn to consider, specifically, each Zone. First, it is interesting to analyse whether a Zone presents, on average over time, an higher rank in the efficiency in Model 2 (when efficiency is estimated relative to "social" costs) and thus is rewarded by the inclusion of quality control or is, instead, penalized. Out of the 114 Zones, for 46 Zones, on average, the inclusion of quality allows the Zones to reach an higher rank, this result suggesting that, in these Zones,

Table 7: Descriptives for efficient and non-efficient Zones

	$capital_{it}$/ $LVcons_{it}$	$capital_{it}$/ $energy_{it}$	op_cost_{it}/ $LVcons_{it}$	op_cost_{it}/ $energy_{it}$	$energy_{it}$/ $LVcons_{it}$	$LVcons_{it}$/ $area_{it}$
Non-efficient Zones	1216.25	225.31	74.16	13.89	5.68	157.28
Efficient Zones	927.41	139.02	63.25	9.50	7.41	216.32

the higher costs are justified by an higher quality of the service provided to the customers. Conversely,57 are penalized by the inclusion of quality (i.e. their rank in Model 1 is higher than that they obtained in Model 2), this indicating the existence of a negative trade-off between costs and quality. In 11 cases, DMO's ranks are not influenced by the inclusion of quality.[16]

In Table 7 we report the average value of the ratio between cost (capital and non-capital) and number of consumers and the ratio between cost (capital and non-capital) and energy consumption by distinguishing between "efficient" and "non efficient" Zones. A Zone is defined as "efficient" ("non-efficient") if the average value over time of efficiency (estimated trough Model 1) is higher (lower) than median value of the variable estimated on all sample Zones. Our results indicate a higher efficiency in Zones with a low ratio of capital (or non-capital) inputs over energy consumptions. On the efficient frontier we also find Zones with a low ratio of capital inputs over the number of consumers. In other words, and according to our expectations, we find higher efficiency in Zones where the average consumption is relatively large (or $perc\_dom_{it}$ relatively low) and in Zones where territorial density is more significant. Conversely, less efficient Zones are mainly characterized lower average consumption per consumer and lower territorial density. This evidence is illustrated by the ratios reported in the last two columns of Table 7 (differences are significant at 1% confidence level) .

6 Conclusions

Incentive regulation in electricity distribution is expected to enlarge its scope, from a cost efficiency instrument to one that includes objectives such as innovation and sustainability: regulators are keen to structure incentives in this direction as additional regulated outputs. As for assessing companies' performance, benchmarking analysis has been in use for years; however, it is still unclear if and how additional regulated output, such as quality (but then also sustainability and innovation), are to be included in the benchmarking models.

In this paper we studied how different choices of input and output variables in a DEA model influence the results of a benchmarking analysis and argue that not all representations of a DNO activity, implied by these choices, really capture the essence of an efficient DNO. In particular, when using energy delivered and

[16] A Table that reports average efficiency scores over time for these different classes of Zones (i.e. penalized by quality, rewarded by quality and not influenced by quality) is available from the authors upon request.

number of consumers as outputs, we have a strong preference for monetary variables and excluded the option to express inputs in technical units. Similarly, we deemed more correct to express quality in monetary terms, as the cost of the ENS.

The results of the analysis show that higher efficiency in electricity distribution is found in areas characterised by high territorial density (confirming a well known result) and by high energy consumption per consumer (a less explored evidence). Moreover, not only average efficiency scores are affected by the inclusion of quality, but also the individual rankings indicate, for several observations, a trade-off between cost efficiency and quality.

Having designed a robust DEA model for our data set, we believe that further work should focus on refining the analysis, to address some of the limitations of the DEA approach. On such a stronger quantitative basis, we deem it interesting to address the new regulatory challanges mentioned above and formulate policy indication for the future.

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