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

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***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 regulated utilities requires models capable to account for these different regulatory objectives. Benchmarking analysis has been in use for a long time; however, whether these models should incorporate even quality as an additional regulated output is still a matter of debate.**

In this paper we study how benchmarking DEA models can be designed to correctly accommodate all regulated variables, including continuity of supply. To this end, we discuss different models to measure technical efficiency, using a comprehensive and balanced panel for 115 electricity distribution Zones, that belong to the largest Italian utility. Our results show that, for our data set, quality significantly affects efficiency scores . We thus claim that the effect of additional regulated outputs should always be tested in benchmarking models.

***Index Terms*—DEA, electricity distribution, incentive regulation, quality of supply.**

I. Introduction

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

Benchmarking analysis has been in use for a long time and largely applied to electricity distribution [6]. 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 [7]. 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) [9], [10]; on the contrary, the introduction of quality does not seem to produce any noticeable effect on the average technical efficiency scores estimated in [11], [12].

In this paper we study how Data Envelopment Analysis (DEA) models can be designed to correctly represent the electricity distribution activity and, using continuity of supply as an example, if and how they can accommodate additional regulated outputs, while still delivering meaningful and useful results. More specifically, on the basis of our knowledge of the distribution sector, we discuss the best choice of input-output variables to measure technical efficiency in a cost-only model and 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, the Italian Regulatory Authority for Electricity and Gas (*Autorità per l'energia elettrica e il gas* - AEEG) has provided several detailed measures of quality of supply.

Our results show that quality has a significant effect upon zonal efficiency scores (we also observe that specific structural variables, namely, territorial density and energy consumption per customer, characterise the most efficient Zones). We thus claim that the effect of additional regulated outputs should always be tested in benchmarking models. This is relevant when assessing incentive mechanisms that are designed to drive benefits for consumers and, at the same time, to provide companies with incentives to invest in quality and, more generally, in network innovation or sustainability.

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 discuss our choice for the input and output variables. In Section V we report the main results of the study. Section VI concludes.

II. Electricity distribution in Italy

In Italy in 2009 there were over 150 Distribution System Operators (DSO), that delivered a total volume of 279 TWh.

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[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 [8].

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 over the entire national territory and it was organized in four Macro Areas, eleven Territorial Units and 115 Zones (each Territorial Unit has its local managers and coordination is ensured at the level of Macro Areas).

DSOs are regulated by 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) a hybrid mechanisms applies where capital expenditures are subject to a fixed Rate of Return (RoR), while operational expenditures are required to decrease with an X efficiency factor (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 (in the third tariff period, a 2% extra WACC in addition to the ordinary return).

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 number of minutes lost per customer for long (longer than 3 minutes), unplanned interruptions - SAIDI indicator.[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 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 (in 2004), 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 under-performing 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 residential and non-residential customers. Since the third period (2008-11), the regulator included in the scheme a further quality dimension: the frequency of interruption for both short and long interruptions - again, with an objective to reach convergence in performance over a 12-year period [14].

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" (a fixed RoR on capital, an efficiency factor for operational expenditures, input-based incentives for specific investments and output-based regulation for quality of supply). 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 [13], [15]. Hence, within both the present and future regulatory frameworks (the fourth tariff period began in January 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.

III. Dataset and descriptive statistics

Our dataset was built with the support of the Italian regulatory authority, by means of a dedicated data collection. As mentioned, 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.

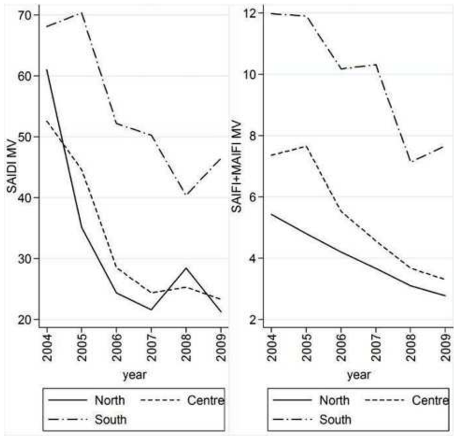
More specifically, as for technical variables, the dataset includes the number of Low Voltage (LV) customers, the energy consumed by LV residential and non-residential users and by Medium Voltage (MV) consumers, the area served (in km^2), the transformer capacity for primary and secondary substations (in MVA) and the network length (in km, for MV and LV, cable and overhead lines). Accounting data are given in terms of annual revenues, asset values (detailed for primary and secondary substations, MV and LV feeders and for points

[2]According to the Italian regulatory framework, investment decisions on electricity distribution networks are taken by DSOs. 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 [13].

[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 (or customer minutes lost) 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).

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

Figure 1. Continuity indicators (MV)



of connection) and operating costs (including labour, services, materials and other costs).

AEEG provided data on customer minutes lost for 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 (indicators and incentives) are given per territorial district: these are smaller geographical areas than the Zones and are homogeneous in customer density - a parameter that is strictly correlated with continuity of supply (higher continuity is to be expected in more dense areas). However, to ensure coherence with the other variables in the dataset, zonal data were computed by aggregating district data. This means that, inevitably, the correlation between density and continuity became less precise.

A key aspect of Enel's (and therefore Italian) continuity data is illustrated in Figure 1. Even if the SAIDI and SAIFI+MAIFI values steadily improved over the observed period, it is clear that the average number of interruptions (both long and short) as well as the average number of customer minutes lost are, on average, more than double in the South of Italy, compared to the North and Center.[5]

This geographical classification (North, Center and South) is adopted also in the rest of the paper. As a matter of fact, it has been in use for regulatory purposes since the year 2000.[6]

IV. Methodology and choice of variables

In this paper we estimate a multi-input, multi-output distance function, using the 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.

More specifically, assuming an input-oriented approach and Constant Returns to Scale (CRS), the efficiency of a given unit i, which uses m inputs to produce s outputs is calculated as:

$$
\begin{aligned}
&min\, \theta_i \\
&s.t. \\
&y_{ri} \leq \textstyle\sum_{i=1}^{n} \lambda_i y_{ri} \qquad r = 1, 2, ...s \\
&\theta x_{pi} \geq \textstyle\sum_{i=1}^{n} \lambda_i x_{pi} \qquad p = 1, 2, ...m \\
&\lambda_i \geq 0 \qquad i = 1, 2, ...n
\end{aligned}
$$

where x_{pi} is the pth input and y_{ri} is the rth output for unit i and λ_i is an nx1 vector of constants.[7] The technical efficiency of unit i is θ_i and determines the amount by which observed inputs can be proportionally reduced, while still producing the given output level [16].

A few remarks on the methodology are in order. First, in electricity distribution it is fair to assume that demand is mostly beyond the control of the firm, hence the choice, in line with the literature, to use an input-oriented model. Second, our results show an average scale efficiency always above 93%, this motivating the choice of a CRS assumption. Third, DEA methods do not make a distinction between unobserved factors and inefficiency: to partially compensate for this shortcoming, we resorted to a bootstrap approach.[8]

Finally, *"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 work. Nonetheless, an exhaustive discussion over more or less appropriate choices of variables for the electricity distribution activity is rarely found in the literature. In this Section, we explain the reasons behind our choice of variables, also 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 extended use of output-based regulation, as in the regulator's intentions.

For further details on the DEA methodology, see [18].

A. Cost-only models

Drawing on previous work as well as on our knowledge of the distribution activity, we built a first model ($Econ$) with energy consumption ($energy_{it}$) and number of LV consumers ($LVcons_{it}$) as the outputs for Zone i in year t.[9] As mentioned, the energy requested by final users is not under the control of a DSO, however the network is built to have an adequate capacity to transport it; similarly, all requests for connection

[5] Data refer to average zonal values of SAIDI, SAIFI and MAIFI for MV interruptions (that provide the main contribution to the indicators) and exclude events of Force Majeure as well as events on the High Voltage network.

[6] AEEG refers to these three areas of Italy with the term *Circoscrizioni*.

[7] The Variable Returns to Scale (VRS) model differs from the CRS model for an additional constraint: $\sum_{i=1}^{n} = 1$. This convexity constraint ensures that the firm is compared against other firms with similar size. The ratio between CRS efficiency results (E_{CRS}) and VRS results (E_{VRS}) provide information about Scale Efficiency (SE), that is: $SE = E_{CRS}/E_{VRS}$.

[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 'analyzing the sensitivity of measured efficiency scores to the sampling variation' [17].

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

Table I
OUTPUT VARIABLES BY GEOGRAPHICAL AREA

Geo. area	res_energy_{it} (GWh)	$nonres\_energy_{it}$ (GWh)	$energy_{it}$ (GWh)
North	477.4	1794.4	2271.7
Center	384.8	1066.8	1451.6
South	487.3	880.9	1368.2
Total	*461.8*	*1301.0*	*1762.7*
	$perc\_res_{it}$ %	$LVcons_{it}$ (n°)	$area_{it}$ (km^2)
North	21.8	276945	2215.4
Center	27.5	223791	2340.9
South	35.7	272102	2853.6
Total	*28.2*	*264041*	*2480.2*

Table II
INPUT VARIABLES BY GEOGRAPHICAL AREA

Geo. area	$capital_{it}$ (mln €)	op_cost_{it} (mln €)	$empl_{it}$ (n°)
North	251.1	17.1	185.9
Center	227.5	14.9	176.4
South	297.5	18.6	210.7
Total	*263.5*	*17.2*	*193.2*
	$nlength_{it}$ (km)	$t\_cap\_p_{it}$ (MVA)	$t\_cap\_s_{it}$ (MVA)
North	8599.1	1014.4	706.8
Center	8803.6	701.0	517.9
South	10547.0	781.5	577.9
Total	*9370.1*	*862.0*	*619.2*

must be fulfilled by the distributor (within certain technical limits).

Our choice of inputs included capital and non-capital inputs (operating costs). As for the capital input, we preferred the total gross value of the assets (substations, feeders and points of connection) over capital expenditures, to avoid penalizing a Zone for making recent investments ($capital_{it}$) [18]. 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}).

Considering outputs first, we report in Table I the average zonal values by geographical area. Zones in the Center of Italy have, on average, a lower, annual residential consumption (res_energy_{it}) relative to Zones in the North and South (384 GWh against 477 and 487 GWh, respectively); non-residential LV consumption plus MV consumption (in brief, non-residential consumption, $nonres\_energy_{it}$) is almost twice as high in the North (1794 GWh) with respect to the Center (1067 GWh) and the South (881 GWh).[10] As a result, total consumption ($energy_{it}$) is, on average, 2271 GWh in the North, 1452 GWh in the Center and 1368 GWh in the South; clearly, the percentage of residential consumption with respect to total consumption is higher in the South ($perc\_res_{it}$). The average number of LV consumers per Zone ($LVcons_{it}$) is around 277,000 in the North, 272,000 in the South, while it amounts to a lower value (around 224,000 on average) in the Center.

Average zonal values of input variables are reported in Table II: both capital and non-capital inputs are higher in the South relative to the North and Center: the zonal average of $capital_{it}$ is around 297 million € in the South, 251 million € in the North and 227 million € in the Center; average values of op_costs_{it} are around 19 million € in the South, 17 million € in the North and 15 million € in the Center.[11]

In addition to these descriptive statistics, we found it extremely informative to look at output-input ratios. This preliminary analysis produced also two hypotheses on the expected results from the benchmarking excercise.

Table III
INPUT-OUTPUT RATIOS IN $Econ$ MODEL

Geo. area	$capital_{it}$/ $LVcons_{it}$ (€)	$capital_{it}$/ $energy_{it}$ (€/MWh)
North	980.5	128.8
Center	1072.5	176.7
South	1172.3	242.6
Total	*1071.4*	*181.3*
	op_cost_{it} $LVcons_{it}$ (€)	op_cost_{it} $energy_{it}$ (€/MWh)
North	63.6	8.5
Center	67.7	11.2
South	70.3	14.7
Total	*67.0*	*11.4*

As illustrated in Table III, the ratios of capital and non-capital inputs to the number of LV consumers show similar values in the South and in the Center, and they are only a 10% higher than the amount registered in the North. In turn, the differences between the ratios of capital and non-capital inputs over energy consumption are much larger. The South of Italy presents average values of capital/MWh and of operating costs/MWh that are around 1.8 times greater than in the North and around 1.3 times greater than in the Center.

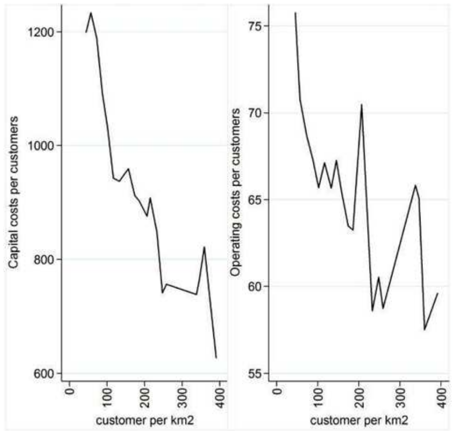
Assuming a rational conduct on the part of Enel Distribuzione, we deduct that the costs of distribution are strongly related to the number of customers served. We thus expect that Zones where the single customer consumes relatively more energy will make a "better" use of their inputs and, thus, will be more efficient. In other words, these statistics suggest that in the North of the country, where the percentage of residential consumption is lower, Zones will present a higher efficiency relative to other parts of Italy.

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

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

[11] In line with the regulatory framework, operating costs have steadily decreased over the observed period ranging from (a company average of) 19.56 million € per Zone in 2004 to 16 million € in 2008; in 2009, operating costs increased to 18.55 million €.

Figure 2. Costs and territorial density



vs. the number of customers per km^2. To be precise, those represented in Figure 2 are average zonal values over the observed period; moreover, as density presents a large standard deviation and several outliers, we limited the graph to the 95% percentiles of the observed data.[12] The effect of territorial density is as expected: both capital and non-capital costs decrease with the number of ubt/km^2. We thus anticipate a second result from the benchmarking analysis, i.e. to find higher technical efficiency in more densely populated Zones.

Given the amplitude of our dataset, we considered also building an alternative benchmarking model ($Tech$), where input and output variables were expressed in terms of physical units. In analogy with the $Econ$ model, capital input was measured by transformer capacity in MVA (t_cap_{it}) and network length in km ($nlengh_{it}$) while operating costs were approximated by the number of employees ($empl_{it}$). As for the outputs, we considered adding to the energy consumption and the number of customers also the area served - another variable that can be considered exogenous for a DSO ($area_{it}$).

Two of the outputs ($energy_{it}$ and $LVcons_{it}$) were already commented upon. As reported in Table I, the extension of the area served, constant over time is, on average, equal to 2853 km^2 in the South, 2340 km^2 in the Center and 2215 km^2 in the North.

As for the inputs, Table II shows that 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).[13] The average network length ($nlengh_{it}$) per Zone is around 10,500 km in the South, and only around 8600 km in the North and 8800 km Center.[14] The average 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. The average 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.[15]

As we did for the $Econ$ model, we looked also at input-output ratios: a DEA model finds the units of observation that are efficient with respect to a combination of these ratios. As for the number of employees, we encountered no particular problems: it seemed reasonable to define "efficient" a distribution Zone that minimizes the number of workers per consumer, or per energy delivered, or even per km^2 of area served. Similarly, as for network length, it sounded reasonable to label as more efficient a Zone with less km of feeders per customer, or per km^2 of area served; however, it was more difficult to argue that a distribution Zone is more efficient than another because it is characterized by less km of feeders per MWh delivered. The interpretation became even more difficult when dealing with transformer capacities. While a Zone with an adequate installed transformation capacity per MWh delivered is indeed efficient, there is no practical meaning in labeling as efficient a Zone that minimizes its transformer capacity per km^2 or per customer (remember that we are including in the model only the number of LV customers).

In summary, when using technical input variables it seemed inevitable to incur in input-output combinations that had no practical significance (for instance network length/MWh or transformer capacity per LV customer). We thus concluded that a "technical" DEA model would have always led to a combination of meaningful and unreasonable results when considered in the light of the activity of a DSO.[16] This is why the so-called $Tech$ model will not be commented further in this paper.

B. Cost-and-quality models

As for the inclusion of quality of service as an input variable of the DEA model, we considered three main options:

- to use the total number of interruptions (or the total duration) expressed, as in [11], 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 receive rewards (present higher levels of quality than requested by the regulator) become more efficient in terms of non-capital inputs;
- 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 higher levels of quality are, again, relatively more cost efficient.

In particular, to derive the value of ENS we considered:

- the values of SAIDI per Zone and year;
- the WTP parameters indicated by the Italian regulatory authority: C_1 for residential users and C_2 for non-

[12] 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%).

[13] The number of employees sensibly decreased over the observed period, from 231 in 2004 to 167 in 2009 (on average, more than 60 workers per Zone).

[14] Separate values for MV feeder and LV feeders show the same geographical difference.

[15] Over the observed period, primary substation capacity grew more significantly in the North (around 2%) relative to the Center (1.2%) and the South (around 0.9%); as for secondary substations, capacity grew in similar proportions in all geographic areas - around 2%.

[16] Results from DEA confirm this hypothesis and are available from the authors upon request.

residential ones (respectively 18 and 36 c€/min/kW) [19];
- the residential and non-residential energy consumption per Zone and year (in MWh);

and then calculated the product:
$SAIDI \cdot (C_1 \cdot \frac{res\_energy}{8.76} + C_2 \cdot \frac{nonres\_energy}{8.76})$.

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

As for the statistics, the variables $NINT = SAIFI \cdot LVcons$ and $DINT = SAIDI \cdot LVcons$ maintain the regional differences illustrated in Figure 1. The average zonal values of $op\_costsRP_{it}$ (Table IV) are always lower than op_costs_{it}, indicating that, in general, 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, ENS added 3.3 million € in the North, 2.5 million € in the Center and 3.6 million € in the South.

When we considered the ratios between $op\_costsRP_{it}$ and the number of consumer, we observed that regulatory incentives slightly 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. Conversely, 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 found that, on average over the observed period, ENS adds 13 € per customer in the North, 12.7 € per consumer in the South and 11 € per customer in the Center (it slightly decreases the geographical distances, especially between North and South). On the contrary, ENS adds on average 1.6 €/MWh in the North, 1.7 €/MWh in the Center and 2.6 €/MWh in the South (it amplifies the distances, especially between Center and South).

Finally, we observed the following. When we represent quality using $NINT$ or $DINT$ we are adding an input variable to the cost-only 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 between the cost-only and the cost-and-quality model we can thus identify Zones that exhibit a trade-off between costs and quality (are less efficient in terms of costs but provide better levels of quality). Nonetheless, this model, while producing in general reliable results (Zones with low values of $DINT/LVcons$ receive a high score), attributes a high efficiency score also to Zones with low values of $DINT/MWh$. These are often Zones with good levels of SAIDI but, at the same time, we could not completely exclude to obtain some approximated results. For this reason, we decided to drop this option.

By choosing the second option, $op\_costsRP_{it}$, we maintain the same number of variables in both models. However, adding the regulatory incentives amplifies the geographical distances:

Table IV
OPERATING COSTS INCLUDING QUALITY AND INPUT-OUTPUT RATIOS

Geo. areas	op_costRP_{it} (mln €)	$op\_costENS_{it}$ (mln €)	$op\_costRP_{it}/LVcons_{it}$ (€)
North	15.5	20.3	57.6
Center	14.2	17.4	64.5
South	18.1	22.1	68.3
Total	*16.2*	*20.4*	*63.0*
	$op\_costRP_{it}/energy_{it}$ (€/MWh)	$op\_costENS_{it}/LVcons_{it}$ (€)	$op\_costENS_{it}/energy_{it}$ (€/MWh)
North	7.7	76.6	10.1
Center	10.7	78.6	12.9
South	14.3	83.0	17.2
Total	*10.8*	*79.4*	*13.3*

we thus anticipated that, in numerous cases, efficiency scores in the cost-and-quality model would be lower than in the costs-only model. Moreover, with this representation we would be able to find Zones that are penalized by the inclusion of quality, while maintaining, as before, the possibility to identify Zones with a higher score in the cost-and-quality model. Finally, this option did not present the approximations of the previous case; this derives from the fact that all inputs are expressed in monetary terms (and we can always consider efficient a Zone that minimizes its costs). Nevertheless, we do not present here the results of this option either: efficiency scores obtained with this cost-and-quality model do not provide additional information with respect to what we already know from continuity of supply regulation (rewards and penalties are assigned on the basis of the regulatory targets).[17]

Choosing, instead, the variable $op\_costsENS_{it}$, we include, in a single variable, the costs incurred by the DSO and the costs sustained by customers for service quality; in other words, we obtain a “social” cost representation of the non-capital inputs (that is also independent from the regulatory targets).[18] Moreover, although we can hardly predict the changes in efficiency scores between the cost-only and the cost-and-quality model (geographical distances are both decreased and amplified when adding ENS to operational costs), we are still in the position to identify Zones that present a trade-off between costs and quality (in both directions). Finally, we can also observe the change (if any) in the efficiency rankis given by the two models and identify Zones that are stably efficient (or inefficient) in both representations.

V. RESULTS

In this Section we discuss the results of the two benchmarking models estimated using the input and output variables selected in Section IV (and summarized in Table V). More

[17] In terms of quality, this model partially compensate for heterogeneity in service areas (remember that regulatory targets for quality are scaled according to customer density per territorial district).

[18] This is in line with the choice made in [12].

Table V
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 €)	$LVcons_{it}$

specifically, efficiency scores derive from an input-oriented, CRS DEA model applied to 114 Zones belonging to Enel Distribuzione and were computed, using the FEAR Software Package, with respect to a different frontier for each of the six years of the observed period [20].[19]

A concise representation of the results is given in Table VI where we report average scores by year and geographical areas, for Model 1 (cost-only) and Model 2 (cost-and-quality).[20] As expected, on average, efficiency in the North of Italy is higher than in the rest of the country (in both models) and the geographical differences with respect to Zones in the Center and in the South are always statistically significant (at 1% confidence level). 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). Moreover, the (small) increase in Enel's average scores over time (in both models) must be interpreted as a reduction of the zonal differences over the observed period.

In Table VI we also report the difference (in percentage) between the efficiency scores obtained in the cost-only model and in the cost-and-quality model. This value is significantly different from zero (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). Considering average differences for the three geographical areas, it is also clear that the South of Italy is the area where the inclusion of quality engenders the largest change: the average difference over time is, in this case, equal to -2.66% and significant at 1% confidence level. We thus conclude that, for our dataset, the inclusion of quality in the benchmarking model provides a more detailed picture of Enel's zonal efficiency.

This evidence is in line with the conclusions reached in [9] (for a panel of 14 UK utilities observed over eight years) and in [10] (for a cross-section of utilities from eight European countries).[21] On the contrary, our results differ from the findings presented in [18] where the authors analyze a data set which is quite similar to the one employed in this study (92 French distribution units, all belonging to the same distribution company, observed over three years) but conclude that quality has no significant effect upon their average efficiency scores. Our results differ also from those derived in [12] (for a panel of 131 Norwegian utilities observed over a period of four years), where the authors estimate two models which are quite similar to the ones we employ in this study (they use total expenditures or total expenditures plus the cost of the ENS as inputs); nevertheless, their work shows no systematic differences between the results of the two models.

[19]One Zone had to be dropped because of a major asset divestiture in 2006.

[20]Bootstrapped results are not discussed in this paper but are available from the authors upon request.

[21]In [9] the authors apply a Stochastic Frontier Analysis (SFA) method.

Table VI
EFFICIENCY SCORES

Enel	**Model 1**	**Model 2**	**% diff. (2-1)**
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 Enel	*0.78*	*0.77*	*-0.02*
Average North	*0.83*	*0.82*	*-0.01*
Average Center	*0.77*	*0.76*	*-0.01*
Average South	*0.74*	*0.72*	*-0.03*

We now turn to consider, specifically, each Zone: as mentioned, we are interested in measuring changes in rank between Models 1 and 2. When a Zone presents a higher rank in Model 2 (where efficiency is estimated relative to "social" costs) than in Model 1, it means that it is rewarded by the inclusion of quality and vice versa. On average over time, the inclusion of quality allows 46 Zones to reach a higher rank, this result suggesting that, in these Zones, higher costs are justified by higher levels of quality. Conversely, 57 Zones are penalized by the inclusion of quality (i.e. their rank in Model 2 is lower than in Model 1), this suggesting that lower costs were attained at the expenses of quality. In the remaining 11 cases, zonal ranks are not influenced by the inclusion of quality; these are typically extremely efficient or extremely inefficient Zones. The overall rank correlation between Model 1 and 2 is 0.88.

Finally, in Table VII we characterize "efficient" and "non efficient" Zones. A Zone is defined as "efficient" ("non-efficient") if the average value over time of its efficiency scores (estimated through Model 1) is higher (lower) than the median value of the sample. Our results show that efficient Zones are described by one of the following: a low ratio of capital inputs over energy consumptions, a low ratio of non-capital inputs over energy consumption, 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 per customer is relatively large (or $perc\_res_{it}$ is relatively low) and in Zones where territorial density is higher; conversely, less efficient Zones are characterized by a lower average consumption per consumer and by a lower territorial density (differences are significant at 1% confidence level).

VI. CONCLUSIONS

Incentive regulation in electricity distribution is soon expected to enlarge its scope, from a cost efficiency instrument to one that includes objectives such as innovation and sustainability; moreover, regulators are keen to structure incentives in these directions as additional regulated outputs. Benchmarking analysis has been in use for years to assess companies' performance; nonetheless, it is still unclear if and how additional

Table VII
DESCRIPTIVES FOR EFFICIENT AND NON-EFFICIENT ZONES

	$capital_{it}$/ $LVcons_{it}$	$capital_{it}$/ $energy_{it}$	op_cost_{it}/ $LVcons_{it}$
"non-eff."	1216.25	225.31	74.16
"eff."	927.41	139.02	63.25
	op_cost_{it}/ $energy_{it}$	$energy_{it}$/ $LVcons_{it}$	$LVcons_{it}$/ $area_{it}$
"non-eff."	13.89	5.68	157.28
"eff."	9.50	7.41	216.32

regulated outputs, such as quality (but then also sustainability and innovation), are to be included in 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 we argued that not all the representations of a DSO activity implied by these choices really capture the essence of an efficient DSO. In particular, we observed that, when using energy delivered and number of consumers as outputs, expressing inputs in monetary variables has several advantages over the option to express them in technical units. Similarly, we deemed more correct to express also quality in monetary terms.

The results of the analysis show that, for our dataset, higher efficiency in electricity distribution is found in areas characterized by high territorial density (confirming a well known result) and by high energy consumption per customer (a less explored evidence). Moreover, we found that average efficiency scores are affected by the inclusion of quality; also efficiency scores and ranks of individual zones indicate, for several observations, a trade-off between cost efficiency and quality.

In light of the existing literature we are not in the position to argue for the inclusion of quality in benchmarking models *per se* but, as an ever increasing number of European utilities collect continuity data, we can certainly recommend that the effect of quality should always be tested on the specific data set in use.

Finally, 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 challenges mentioned above and formulate policy indication for the future.

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