Output-based incentive regulation in electricity distribution: evidence from Italy

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Abstract

Incentive regulation in electricity distribution is expected to enlarge its scope, from an input-oriented instrument to one that includes additional, output-based incentives. This creates a potential conflict with more traditional concerns for productive efficiency. In the case of Italy, together with input-oriented instruments, output-based incentives have been applied to indicators of quality for over a decade. Using micro-data from the largest Italian distribution company, we conduct an assessment of the effects of this regulatory framework. The aim of this word is threefold. First, we measure performance in terms of cost-efficiency and find that similar cost-reducing efforts were exercised in all distribution units. Second, we measure performance with respect to the overall regulatory framework. Using quality-related rewards and penalties, we find that more cost-efficient areas were also more successful in earning rewards/avoiding penalties: favorable external conditions have similar, positive effects on both cost and quality performance. Using the cost of the energy not supplied, we find no evidence of a conflict between cost efficiency and social cost efficiency. Results indicate, however, that is preferable to use social costs when measuring a single unit's performance. From these results we derive specific policy indications.

Keywords: Data Envelopment Analysis, Electricity distribution, Incentive regulation, Malmquist index, Quality of supply.

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1. Introduction

Current technical changes in electricity distribution networks prompted a lively debate, in Europe and elsewhere, on how incentive regulation should evolve. Since liberalization, regulatory incentives have focused almost exclusively on the use of inputs (operational and capital expenditures). Current concerns for network innovation and sustainability are being addressed, instead, with incentives that focus on outputs measures of companies' performance (network reliability, environmental impact, ability to connect dispersed generation, etc.). The best-known example in this regard is the new regulatory scheme recently adopted by Ofgem, the *Revenue, Innovation, Incentives and Output* (RIIO) model (Ofgem, 2010); the Italian regulatory authority and other regulatory agencies, for instance the Australian energy regulator, are moving in this direction as well (AEEG, 2011a; ACCC/AER, 2012).

On the one hand, given the regulator's asymmetry of information, output-based regulation has an important advantage: leaving the decision on the use of the resources to the regulated firm, it minimizes inefficiencies in the use of inputs. On the other hand, it forces the regulated firm to increase expenditures, to meet the additional goals set by the regulator (in contrast with the cost efficiency objective). Moreover, it presents implementation complexities and requires adequate regulatory powers, budget and skills (Glachant et al., 2012).

In the case of Italy, together with incentives aimed at productive efficiency, output-based incentives have been applied to indicators of quality for over a decade. Under the current regulatory reform, this represents an interesting case to investigate how a regulated firm responds to such a incentive scheme. The debate around this issue is, indeed, quite recent (Coelli et al., 2013; Growitsch et al., 2010; Jamasb et al., 2012).

Moreover, when network operators are required to meet potentially conflicting objectives, also the assessment of their performance becomes more complex. Since the adoption of incentive regulation in infrastructure industries, benchmarking analysis has been extensively used to measure firms' efficiency (Jamasb and Pollit, 2001; Joskow, 2008; Haney and Pollit, 2009). Nevertheless, the question of including additional output measures of performance (e.g., quality of supply) has been scarcely explored by regulatory authorities and academics as well.

Finally, as for Italy in particular, anecdotic evidence indicates that after a period of rapid increase in performance, the level of quality varied at a much slower pace, while the rules for assigning output-based incentives have remained unchanged.[2] Although from a technological perspective such a trend is to be expected, it has also prompted the question of how this regulatory scheme should evolve in the future.

In this paper we address all three issues mentioned above.

We investigate how the largest Italian electricity distribution company has responded to the input-based and output-based incentives provided by the current regulatory framework. To our knowledge, this is the first assessment of this incentive regime since its introduction in the year 2000. To this end, we exploit on an original dataset, constructed with the support of the Italian regulatory authority (*Autorità per l'energia elettrica e il gas*, AEEG), by means of a dedicated data collection. It is a comprehensive and balanced panel for 115 distribution units (Zones), tracked from 2004 to 2009, which includes the amounts annually received in rewards (paid in penalties) for exceeding (failing to meet) quality-specific targets.

As for the analysis, we rely on a benchmarking approach and contribute to the debate regarding the inclusion of additional measures of performance. Specifically, we use two alternative measures of quality that provide different and complementary information regarding the efficiency of the observed distribution unit: in one case, efficiency is estimated in terms of response to regulatory incentives; in the second, in terms of social costs. While latter was used in previous literature, the former has never been studied. From a methodological perspective, we apply a recent approach based on a two-stage, semi-parametric Data Envelopment Analysis (DEA) and bootstrapping techniques, where technical efficiency is estimated in the first stage and then regressed on a set of external variables in the second stage (Simar and Wilson, 2007). We also study the evolution of performance over time by means of Malmquist indices.

Our main finding is that the presence of quality regulation has not significantly altered the distribution units' behavior: those that responded well to cost efficiency incentives, responded equally well to quality-related incentives and vice versa. After all, favorable external variables that have a significant and positive effect on cost efficiency (area size, load composition and network design) also influence the ability of a distribution unit to exceed the targets imposed by quality regulation.

[2] In the first regulatory period (2000-2003) the national average duration of interruptions per customer decreased by over 60 minutes; in the second period (2004-2007) the improvement amounted to less than 20 minutes and, in the third period (2008-2011), to about 10 minutes.

Nevertheless, this response to regulatory incentives appears in contrast with the long term objective of quality regulation in Italy (convergence in performance). Hence, on the basis of the evidence provided throughout the paper, we derive two policy suggestions for the development of quality regulation, respectively, in the medium and in the long term.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature on benchmarking analysis in electricity distribution; Section 3 outlines the Italian regulatory framework; Section 4 presents the empirical methodology; Section 5 describes the dataset and presents our choice of variables for the benchmarking analysis; Section 6 discusses results in the context of the existing literature and derives policy implications; Section 7 concludes.

2. Selected literature review

A relatively small number of papers analyzes efficiency in the electricity distribution sector using a benchmarking model which includes an indicator of service quality. While Table 1 summarizes all the main contributions with these characteristics, we concentrate here on five studies based on panel data.[3]

TABLE 1 ABOUT HERE

A first strand of literature focuses on performance measurements and explores one main question, namely, the potential trade-off between cost savings and the level of service quality at firm level (i.e. the effects of incentive regulation on service quality). Additional questions explored in this literature regard: (*i*) the use of an integrated cost-and-quality benchmarking model vs. a cost-only approach, when assessing the progress of an incentive regulation regime and (*ii*) the analysis of productivity changes over time. The existing empirical studies do not provide clear cut evidence on any of these issues.

[3] Benchmarking studies in electricity distribution which include a measure of quality, but rely on a cross-sectional sample, include the work by Jamasb and Pollit (2003) on 1999 international data, by von Hirschhausen et al. (2006) on 2001 German data (where quality is measured by network losses), and by Growitsch at al. (2009) on 2002 international data (where quality is measured by customer minutes lost).

Using a panel of 14 electricity distribution utilities in the UK (tracked from 1991/92 to 1998/99) Giannakis et al. (2005) find that efficiency scores of cost-only DEA models do not show a high correlation with those of quality-based models (where quality is measured by the number and duration of service interruptions). In other words, cost-efficient firms do not necessarily exhibit high service quality. Malmquist indexes indicate, however, that improvements in service quality have made a significant contribution to the sector's total productivity change. The authors conclude that is "desirable to integrate quality of service […] in benchmarking […] of electricity networks" (Giannakis et al., 2005, page 2269). Coelli et al. (2007) measure the efficiency of 92 French electricity distribution units (tracked from 2003 to 2005), all belonging to the same distribution company. By employing both a stochastic frontier and a DEA approach, they show that the inclusion of the quality variable (number of interruptions) has no significant effect on estimated efficiency scores. They deduce that including a quality aspect in an efficiency benchmarking is "unlikely to have a substantial effect upon price regulation outcomes" (Coelli et al., 2007, page 17). Productivity changes are the main focus of the work by Miguéis et al. (2012). Employing a sample of 127 Norwegian distribution companies (tracked from 2004 to 2007) the authors estimate both efficiency scores and Malmquist indexes using a multiple-output, single input DEA model. Several topological and geographical variables are included as outputs and quality is included as an input which adds to the utilities' costs (i.e. quality is measured by the value of the Energy Not Served – ENS). Contrary to Giannakis et al. (2005), the authors find no evidence of a significant technology change over time (but do not estimate a cost-only model). Also, none of the factors considered in a second-stage regression is found to have a significant effect on efficiency scores.

More recent papers have taken a different perspective. The main focus is no longer on the effect of incentive regulation on the level of service quality, but on the impact of quality regulation on firm performance, in terms of cost efficiency or in terms of quality provision. Such a change is clearly motivated by a wider adoption of quality regulation in European countries.

Growitsch et al. (2010) use a panel dataset for 131 Norwegian distribution network operators observed over the period 2001 (the year quality regulation was introduced) to 2004. Comparing the efficiency scores of a cost-only and a cost-and-quality DEA model they find no systematic differences between the two (quality is measured by the value of the ENS). Their results suggest that the introduction of quality regulation in Norway did not have a strong impact on firm's performance nor it conflicted with cost efficiency of electricity distributors. Coelli et al. (2013) employ a parametric distance function approach and a panel of 92 distribution units, all belonging to the main distribution company in France (tracked from 2003 to 2005). They conduct a study of the production technology and propose a methodology to estimate the operating cost of preventing one interruption. Their suggestion is to calculate this cost using more recent data and to use it to predict the efficacy of the quality-related incentives introduced in France in 2009.

Our analysis of the Italian distribution sector is closer to the more recent empirical studies, i.e. it concerns distribution units that have been subject to price *and* quality incentive regulation and focuses on assessing the progress of both regulatory regimes. Our paper contributes to the literature in several ways. First, this appears to be the first study to examine the Italian distribution sector after the introduction of incentive regulation in the year 2000.[4] Second, we propose two different (monetary) valuation of service quality for inclusion in the cost-and-quality benchmarking models. One measure has been used in studies on Norwegian data (the value of the ENS). The other is novel and it is the rewards and penalties actually paid by or received from the regulatory authority for, respectively, exceeding or failing to meet the quality targets set for each distribution unit. Third, we use a recent methodology to analyze the determinants of the heterogeneity in performance in both the cost-only and the cost-and-quality models. To this end, we consider several explanatory variables that were either identified in previous studies, or that we identified as potentially significant on the basis of additional tests performed on our database. Finally, we devote particular attention to policy implications.

3. The regulatory framework

In Italy, in 2009, there were over 150 Distribution System Operators (DSO), 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%), *Acea Distribuzione* (3.6%) and *Aem Torino Distribuzione* (1.3%); the other

[4] Benchmarking analyses on Italian data are all prior to this date (e.g., Scarsi, 1999).

operators held marginal quotas (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, investments and service quality. As for productive efficiency and investments, operational expenditures are required to decrease with an X efficiency factor while, starting from the second regulatory period (2004), the cost of capital is directly passed through to consumers.[5] Note that the decision to pass-through all capital expenses was taken by the government and not by the regulator (Law n. 290/2003). Moreover, since 2008, several, specific investments benefit from an increase in Weighted Average Capital Cost for period of 8 to 12 years (a plus 2% over the ordinary return). These include investments in low-losses transformers and in automation and control of active grids.[6]

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.[7] This indicator, SAIDI, is measured separately in more than 300 territorial districts, covering the entire national territory.[8] Rewards and penalties are calculated per district on an annual basis, as a function of the difference between a target-SAIDI and the actual-SAIDI (targets are defined separately for each territorial district and year). The distribution tariff is unique across the entire national territory and it is adjusted yearly on the basis of companies' performances: it

[5] For the second tariff period the Weighted Average Capital Cost (WACC) was set at 6.8% and the X factor at 3.5%. For the third period (2008-2011) the WACC was increased to 7% and the X factor was decreased to 1.9%. Details on the choice of the WACC and X factors in the energy sector can be found in Cambini and Rondi (2010).

[6] Further details on the evolution of the Italian regulatory framework can be found in Lo Schiavo et al. (2013).

[7] 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).

[8] 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.

increases when, on average, quality has improved more than required (rewards earned by all districts in the country are greater than total penalties paid) and vice versa.

Because of the uniqueness of the distribution tariff, beginning with the second regulatory period, target-SAIDIs are calculated using a formula that assumes a convergence in performance of all districts with equal population density to the same quality level (the national standard) in the medium term (12 years) – there are three levels of density and better continuity is expected in more densely populated areas. This approach enables the regulator to set more ambitious targets for districts that are initially under-performing with respect to national standards and vice versa. Also, in line with the indications of the literature, the results of a customer survey are used to define penalties and rewards (Sappington, 2005). Two different valuations of quality are considered, to reflect the different willingness to pay (WTP) for quality of residential and non-residential customers (see Section 5.1).

4. Methodology

For the purpose of this study we employ a two-stage DEA estimation, based on the semi-parametric approach proposed by Simar and Wilson (2007). Accordingly, technical efficiency is estimated in a first stage and regressed on a set of external variables in a second stage. This accounts for possible sources of inefficiency heterogeneity among different units of observation. Moreover, bootstrapping techniques are used in both stages to overcome other issues related to the traditional procedure, i.e. the uncertainty associated with DEA efficiency scores in the first stage and their serial correlation in the second stage.

More specifically, assuming that all units of observation share the same production technology, the first stage is devoted to the estimation of the technology frontier and to the measurement of each unit's efficiency, as their distance from the same frontier. Given a distribution unit which uses a set of inputs ($\mathbf{x}$) to produce a set of outputs ($\mathbf{y}$) via a known production technology, the unit's efficiency is measured as an input distance function (Shephard, 1970).[9] This is defined on the input set $L(\mathbf{y})$ as:

[9] 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.

$$d(\mathbf{x}, \mathbf{y}) = max\{\rho : (\mathbf{x}/\rho) \in L(\mathbf{y})\} \qquad (1)$$

where $L(\mathbf{y})$ represents the set of all input vectors, **x,** which can produce the output vector, **y,** and ρ is the input distance measure, i.e., for a each distribution unit $1/\rho$ represents the amount by which the observed inputs can be proportionally reduced, while still producing the same output level. The distance function will take a value which is greater than or equal to one if the input vector **x** is an element of the feasible input set, $L(\mathbf{y})$, that is:

$$d(\mathbf{x}, \mathbf{y}) = max\{\rho : (\mathbf{x}/\rho) \in L(\mathbf{y})\} \qquad (2)$$

The distance function will take a value of unity if the input vector is located on the inner boundary of the input set (Coelli et al, 2005).

Normally, the production technology is unknown and its estimation is required. This can be done using different approaches. The well-known advantages of using DEA include the absence of any assumptions on the functional form of the production frontier and the possibility to simultaneously use multiple inputs and outputs. Thus, in the first stage, we employ DEA to construct the frontier surface using linear programming methods and to compute technical efficiency scores (they are obtained as a by-product of the frontier construction process). Assuming that each unit of observation i uses K inputs to produce M outputs, we indicate with **X** the KxN matrix of inputs, whose columns are the input vectors $\mathbf{x}_i$ of all N units. Similarly, we indicate with **Y** the MxN matrix of outputs that contains the N output vectors $\mathbf{y}_i$. The input-oriented, Constant Returns to Scale (CRS) frontier is estimated by solving N linear programs of the following form:

$$\begin{aligned} & \max_{\rho, \lambda} \rho \\ & \text{s.t.} \\ & \quad -\mathbf{y}_i + \mathbf{Y}\lambda \geq \mathbf{0} \\ & \quad \frac{\mathbf{x}_i}{\rho} - \mathbf{X}\lambda \geq \mathbf{0} \\ & \quad \lambda \geq \mathbf{0} \end{aligned} \qquad (3)$$

where $1 \leq \rho \leq \infty$ and $\boldsymbol{\lambda}$ is an Nx1 vector of constants.[10]

One of the well known limitations of DEA is its potentially biased estimation due to the uncertainty associated with sampling variation. We control for the uncertainty of DEA scores in the first stage by estimating their bias and confidence intervals using a consistent bootstrap approximation of the efficiency distribution (Simar and Wilson, 2000).

A second limitation of DEA is its deterministic nature (all the distances from the efficient frontier are assumed to be inefficiency). In this regard, we note that while parametric methods allow for a random unobserved heterogeneity among different units of observation, they also require several assumptions, regarding the specific functional form of the production function, the distribution form of the inefficiency and of the statistical noise. Estimated efficiency scores are, of course, sensitive to these specifications (Coelli et al., 2005).[11] Considering the purpose of our analysis and the characteristics of our dataset (which includes data from a single distribution company) a non-parametric approach was the preferred choice for the present work. Nevertheless, in the second stage, the efficiency of each unit of observation is regressed on a set of external variables. In other words, the bias-correct efficiency scores estimated in the first stage are used as dependent variables in a second stage regression analysis. To consistently estimate the regression parameters we apply a truncated regression and, following Simar and Wilson (2007), we also use a bootstrap approach for inference. The latter consistently accounts for the serial correlation structure of DEA efficiency scores.

Input distance functions are also used to measure productivity changes between two points in time. To this end, we resort to the Malmquist index (M) proposed by Caves et al. (1982). For each unit of observation, this can be expressed as:

$$M = \left[\frac{d^t(\mathbf{y}^t, \mathbf{x}^t)}{d^t(\mathbf{y}^{t+1}, \mathbf{x}^{t+1})} \times \frac{d^{t+1}(\mathbf{y}^t, \mathbf{x}^t)}{d^{t+1}(\mathbf{y}^{t+1}, \mathbf{x}^{t+1})} \right]^{1/2} \tag{4}$$

[10] Note that the distribution operator can choose its internal organization, in particular regarding the size of the distribution Zones: this motivates our choice of a CRS assumption (moreover, our results show an average scale efficiency always above 93%).

[11] This method is employed in several benchmarking studies regarding the electricity distribution sector, including Estache et al. (2004), Farsi and Filippini (2004), Farsi et al. (2006) and Growitsch et al. (2009).

where $d^t(\mathbf{y}^t, \mathbf{x}^t)$ is the input distance function in time period t in relation to the production technology at time t and $d^t(\mathbf{y}^{t+1}, \mathbf{x}^{t+1})$ is the input distance function in time period t in relation to the production technology at time $t+1$; $d^{t+1}(\mathbf{y}^t, \mathbf{x}^t)$ and $d^{t+1}(\mathbf{y}^{t+1}, \mathbf{x}^{t+1})$ are similarly defined.[12]

Malmquist indices can assume values that are smaller or greater than unity. A Malmquist index greater than one indicates a productivity growth from year t to year $t+1$; conversely an index M_i smaller than one indicates a productivity decline. Moreover, under the assumption of constant returns to scale, a Malmquist index can be decomposed in two components, or possible sources of productivity change: an efficiency change and a technical change (Färe et al., 1994). That is:

$$M = \frac{d^t(\mathbf{y}^t, \mathbf{x}^t)}{d^{t+1}(\mathbf{y}^{t+1}, \mathbf{x}^{t+1})} \times \left[\frac{d^{t+1}(\mathbf{y}^{t+1}, \mathbf{x}^{t+1})}{d^t(\mathbf{y}^{t+1}, \mathbf{x}^{t+1})} \times \frac{d^{t+1}(\mathbf{y}^t, \mathbf{x}^t)}{d^t(\mathbf{y}^t, \mathbf{x}^t)} \right]^{1/2} \tag{5}$$

The first component in (5) represents the efficiency change *EC* from year t to year $t+1$ and measures the extent to which a unit has moved closer to the frontier. The second component in (5) is the technical change *TC*. For a given sample, a *TC* greater than unity indicates an industry-level technological progress and vice versa.

5. Data set and cost models

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. Given the volume of energy distributed by *Enel* and the geographic extension of its distribution territory, it can be considered a good representation of the entire country.

As for technical variables, the dataset includes, for each Zone, 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), transformers' capacity for primary and secondary substations (in MVA) and network length (in km, for MV and LV, cable and overhead lines). Accounting data are given

[12] In practice, Malmquist indices require the estimation of two single period and two mixed period distance functions. To this end, we employ, with the necessary modifications, CRS DEA models of the type described in equation (3). Also Malmquist indices are computed using a bootstrap procedure.

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 (which include labor, services, materials and other costs).

In addition, 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).[13] 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. Continuity of supply data (indicators as well as rewards and penalties) were given per territorial district, which are geographically smaller than Zones. To ensure coherence with the other variables in the dataset, continuity data had thus to be calculated per Zone, aggregating district data. This means that, inevitably, the relation between population density and continuity of supply became less precise.

The benchmarking analysis is conducted on 114 units (one Zone was dropped because of a major asset divestiture), a sample size that is comparable with those of the most recent studies (see Section 2). All units of observation belong to the same distribution company as in Coelli et al. (2007) and Coelli et al. (2013), but are observed over a longer period (six vs. three years). In the following we motivate our choice of variables for the benchmarking models. While our choice of monetary variables as inputs (vs. physical units) is in line with the most recent literature, we provide a rather strong motivation for our preference. We also illustrate some descriptive statistics, derive hypotheses on estimation results and identify candidate determinants of inefficiencies.

5.1 Selected inputs and outputs

The selection of input and output variables is crucial to the validity of a DEA model. On the basis of previous work and our knowledge of the distribution activity, we define a first model with energy consumption ($energy_{it}$) and number of LV consumers ($LVcons_{it}$) as the outputs for Zone i in year t. As known, the energy requested by final users is not under the control of a DSO. Similarly, all requests for connection must be met by the distributor (within certain technical limits). Our choice

[13] Actual SAIDI used for regulatory purposes does not include interruption events that originated on the transmission network or that were caused by Force Majeure. The same assumption holds in this paper.

of inputs includes capital and non-capital variables (operating costs). Following Coelli et al. (2005), capital ($capital_{it}$) is measured using gross asset value (substations, feeders and points of connection) and not capital expenditures. This is to avoid penalizing a Zone for making recent investments. As for non-capital input, we included labor (the main voice), services, materials and other operating costs – and excluded depreciation and taxes ($opcost_{it}$).[14]

The use of monetary inputs is justified by the fact that we are observing a single company and therefore we can reasonably assume that the price of goods, services and labor is the same for all Zones. Moreover, we are studying performance with respect to regulatory incentives: since one of the primary aims of the regulation was to create stimuli for productive efficiency (in operating costs), the use of monetary variables as inputs seems appropriate.

Nevertheless, given the amplitude of our dataset, we considered building an alternative benchmarking model, where input variables were expressed in terms of physical units. In analogy with the "monetary" model, capital input was measured by transformer capacity (in MVA) and network length (in km), while operating costs were approximated by the number of employees. Nevertheless, this model was less convincing for various reasons. Recall that a DEA model finds the units of observation that are efficient with respect to a combination of input-output ratios. As for the number of employees, it seems reasonable to define efficient a distribution unit that minimizes the number of workers per consumer, or per energy delivered. Similarly, as for network length, it sounds reasonable to label as more efficient a distribution unit with less km of feeders per customer. On the contrary, it is more difficult to argue that a distribution unit is more efficient than another because 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 transformation capacity per MWh delivered is indeed efficient, there is no practical meaning in labeling as efficient a unit that minimizes its transformer capacity per customer (remember that we are including in the model only the number of LV customers). In sum, when using technical input variables it seemed

[14] This model does not account for variables that are beyond the influence of the company (observable heterogeneity). Typical external variables in the distribution sector include geographic and climatic factors (altitude, costal areas, snow, etc.). Previous studies have shown that these are not relevant for Italy (Scarsi, 1999). In this work we will explore only the effect of load-related and network-related variables that are outside the control of the distribution unit (see Section 5.3).

inevitable to incur in input-output combinations that had little practical significance (network length per MWh or transformer capacity per LV customer). Hence, we opted for the "monetary" model specified above.[15]

As for the inclusion of quality, and in line with the choice of a "monetary" model, we consider the two following options:

- to substitute $opcost_{it}$ with a new variable, $opcost\_RP_{it}$, sum of $opcost_{it}$ plus penalties paid and minus rewards received (*RP*); as a consequence, Zones that receive rewards (i.e. present higher levels of quality than requested by the regulator) are expected to be relatively more efficient;
- to substitute $opcos_{tit}$ with a new variable, $opcost\_ENS_{it}$, sum of $opcos_{tit}$ plus the cost of the ENS; in this way, Zones with lower levels of ENS are expected to be relatively more efficient.

To derive the cost of ENS (C_ENS_{it}) for Zone *i* and year *t* we employ:

- the actual value of $SAIDI_{it}$ per Zone *i* and year *t*;
- the WTP parameters indicated by the Italian regulatory authority: C_1 for residential users and C_2 for non-residential ones or, respectively, 18 and 36 c€/(min·kW) (AEEG, 2007);
- the residential (res_energy_{it}) and non-residential ($nonres\_energy_{it}$) consumption per Zone and year (in MWh).

From these, the cost of ENS is calculated as:

$$C\_ENS_{it} = SAIDI_{it} \cdot \left(C_1 \cdot \frac{res\_energy_{it}}{8.76} + C_2 \cdot \frac{nonres\_energy_{it}}{8.76} \right) \tag{6}$$

Note that also regulatory rewards and penalties are calculated, per district, as in equation (6). To this end, however, $SAIDI_{it}$ is replaced by the distance between the actual-SAIDI and the target-SAIDI for the district and year.[16]

In sum, as summarized in Table 2, we estimate three DEA models. With the *Cost-only* model we measure performance with respect to the regulation of inputs (cost

[15] Efficiency scores estimated using a "non-monetary" model are available from the authors upon request.

[16] In the regulatory practice, other information enter this calculation. For instance, annual rewards and penalties are capped and a two-year average value is used as the actual-SAIDI. All the details can be found in the Regulatory Orders n. 4/04 and 333/07 (AEEG, 2004; AEEG, 2007).

efficiency).[17] With the *CostRP* model we measure performance with respect to the overall regulatory framework, that includes price and quality incentive schemes (regulatory efficiency). With the *CostENS* model, performance is measured with respect to social costs, sum of the company's cost and the cost incurred by consumers for the ENS (social cost efficiency).

TABLE 2 ABOUT HERE

5.2 Descriptive statistics

Table 3 shows the descriptive statistics of the input and output variables used in the three models. Table 4 provides yearly average values of the same variables, as well as their annual, relative standard deviations (in %).[18] Statistics include also several quality indicators; note that *RP* is the only variable that assumes both positive (rewards) and negative (penalties) values.

TABLE 3 ABOUT HERE

TABLE 4 ABOUT HERE

In terms of outputs, average energy consumption has increased from 2004 to 2008 and decreased in 2009 because of the economic crisis. Also the number of consumers has grown in the observed period (an internal recalculation by *Enel* explains why this number is lower in 2008). As for inputs, the total gross value of the assets has steadily increased, while we observe a reduction in operating costs between 2004 and 2008 (and an increase in 2009), mainly due to a reduction in labor costs over the same period (partially compensated by increasing costs for services). Differences among Zones (relative standard deviations) remain fairly stable over time.

While trends in *opcost_RP* and *opcost_ENS* are well explained by changes in the operating cost variable, it is interesting to look more closely at quality indicators.

[17] In practice, the revenues of a distribution unit are modified by quality-related rewards and penalties. Hence, the cost model leaves out costs (and benefits) that derive from quality regulation.
[18] The relative standard deviation is obtained by multiplying the standard deviation by 100 and dividing this product by the average value of the variable.

SAIDI values steadily improved over the observed period.[19] More specifically, the first three years of data reveal a significant decline in customer minutes lost, from a zonal (arithmetic) mean of 73.56 min. in 2004 to 51.06 min. in 2006. In the following years we do not observe a comparable trend: SAIDI in 2009 was equal to 47.73 min. and an increase was registered in 2008.

As for *RP*, Table 4 shows that, on average, net rewards have constantly increased in the second tariff period (2004-2007). An initial large reduction in customer minutes lost, even if followed by relative stability, explains why incentives have continued to growth: a large initial improvement normally ensures that a district meets the quality targets for the rest of the tariff period. On the contrary, in the years 2008 and 2009, *RP* were significantly lower because of two effects: first, the recalculation of the starting point that, at the beginning of each tariff period, fixes the initial target-SAIDI at the same level of the actual-SAIDI for all districts and, second, the absence of a significant decline in customer minutes lost. Average *RP* values show also particularly large relative standard deviations.

The cost of ENS (*C_ENS*) follows the trend in customer minutes lost: significant reductions in 2005 and in 2006, relatively smaller decreases in 2007 and in 2009 as well as an increase in 2008. Zonal differences (relative standard deviations), are similar at the beginning and at the end of the sample period (they present a minimum in 2005 and a peak in 2007).

5.3 Hypotheses on benchmarking results and determinants of inefficiencies

Considering first the *Cost-only* model, the relative standard deviations in Table 4 suggest that cost-efficiency might not be particularly high, nor significantly converge over time. Nevertheless, we need to consider the possibility that differences across Zones are related to variables outside the control of the DSO.

For instance, the surface covered in squared kilometers (*area*) is a measure of network dispersion: operating costs (manly maintenance activities) as well as capital costs (length of LV lines) are normally linked to the size of the area served (Coelli et al., 2007). Hence, we expect lower efficiency in larger areas.

Moreover, standard deviations of the ratios of capital and non-capital inputs over number of LV consumers are higher than the corresponding ratios over energy

[19] SAIDI data presented an outlier with an extremely high value (698 min.) in 2004. To avoid bias in the analysis the variable was winsorized in the upper tail (Dixon, 1960).

consumption.[20] Assuming a rationale conduct on the part of the DSO, we make the hypothesis that distribution costs are strongly driven by the number of customers served. Consequently, we expect that Zones where the single customer consumes relatively more energy will make a "better" use of their inputs and, therefore, will be more efficient. This effect can be captured by the ratio of non-residential consumption over total consumption (*nonres_cons*, in %). A similar effect was found by Scarsi (1999) and Filippini and Wild (2001).

Finally, we consider also the average length of feeders per substation (*f_length*), calculated as the ratio of network length (in km, for MV lines) over transformer capacity for primary substations (in MVA).[21] Although the variable is ultimately defined by investment choices, the number of substations installed is driven by the capacity which is necessary to serve the load and it can be modified only in the long term. Its impact on efficiency is ambiguous: a higher transformer capacity constitutes an additional burden in terms of capital assets, however it might be fully justified by a higher demand. The same variable is also closely related to continuity of supply: a higher number of substations ensures a higher level of redundancy (less consumers affected by the same fault, or for a shorter period of time).[22]

As for the *CostRP* model, three observations are in order. First, *RP* present the largest relative standard deviations in Table 4. Second, as argued above, a good explanatory variable for SAIDI is the average length of feeders per substation. Third, in addition to changes in SAIDI, regulatory incentives depend on the composition of the load (see equation (6)). Altogether, we expect average efficiency scores in the *CostRP* model to differ from those in the *Cost-only* model and, specifically, to present lower values. We also expect that the determinants of inefficiency will include load composition and network design.

The *CostENS* model is similar to the one studied by Growitsch et al. (2010), which employs the same outputs, but a single input, sum of capital and operational expenses, plus the costs of ENS. While Growitsch et al. (2010) find no significant differences in

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[20] On average, the capital ratio on energy consumption has a relative standard deviation equal to 29.60% while the relative standard deviation of the capital ratio on number of customers is 43.63%. The corresponding values for the operating costs are, respectively, 14.82% and 37.23%.

[21] Dividing by the number of primary transformers per Zone would have been more appropriate, but our database does not include this information.

[22] The Appendix shows that a good explanatory variable for SAIDI at MV level is, indeed, the average length of feeders. Moreover, *f_length* presents also a high correlation with the percentage of underground lines. Grounding of long feeders is not necessarily cost efficient, but underground cables are normally associated with a lower probability of fault.

average efficiency between their cost-only and a cost-and-quality models, descriptive statistics in Table 4 do not immediately indicate an expected outcome for our database. Nevertheless, the fact that *C_ENS* is calculated as in equation (6) suggests that differences across Zones might be, again, related to the average length of feeders and to the composition of the load.

6. Results

In this section we focus, first, on the *Cost-only* model and analyze distribution units' performance in terms of cost efficiency (i.e. we study the effect of input-based incentives). To this end, we investigate also the role of external variables and estimate productivity changes over time. Secondly, we analyze the combined effect of input-based and output-based (quality-specific) regulation, using the two cost-and-quality models. Also in this case we consider possible determinants of inefficiency (and estimate productivity changes over time). For each model we discuss our results in light of previous studies and we interpret our findings in terms of their policy implications.

Efficiency scores derive from the estimation of input-oriented, CRS DEA models, and are bias corrected via bootstrap replications. Specifically, they are calculated with respect to a different frontier for each of the six years of the observed period, using the FEAR Software Package (Wilson, 2008). The latter computes efficiency scores according to Shephard (1970), i.e. as input distance functions. All numerical elaborations presented in the paper are based on these values. Differently, in presenting and our results we report input efficiency measures according to Farrel (1957), i.e., as the reciprocal of the Shephard efficiency score. This representation is chosen to facilitate comparison with previous studies.

6.1 Cost-only model

A concise representation of the results for the *Cost-only* model is given in Table 5 where we report the arithmetic average of bias-corrected efficiency scores, by year.

The average unbiased efficiency over the period is 0.750 (0.736 in 2004 and 0.771 in 2009), indicating that, given their input, *Enel*'s Zones could increase their output by 25%. These results are partially consistent with the findings of the literature. They are below average scores obtained by Giannakis et al. (2005) and Coelli et al. (2007), on data from, respectively, the UK and France (around 82%). However, they are above the scores obtained by Growitsch et al. (2010) on Norwegian data (between 56% and 63%, depending on the year). Of course, comparison with previous studies should be taken carefully because of the different choices made in terms of input and output variables: Giannakis et al. (2005) and Coelli et al. (2007) include an additional output (area size/network length), while Giannakis et al. (2005) and Growitsch et al. (2010) use total expenditures (TOTEX) as an input.[23]

TABLE 5 ABOUT HERE

As all Zones belong to the same company and are subject to the same regulatory incentives we are interested in exploring the determinants of the observed inefficiencies. Moreover, given that inefficiencies can be the result of bad managerial practices as well as of external conditions, it is important, from a regulatory perspective, to separate the two effects. To this end, we resort to a second-stage regression analysis, using bias-corrected efficiency scores (BC_d_{it}) as the dependent variable. The model includes three independent variables – area size (*area*), load composition (*nonres_cons*), average length of feeders (*f_length*) – and takes the following form:

$$BC\_d_{it} = \alpha_0 + \alpha_1 \cdot nonres\_cons_{it} + \alpha_2 \cdot area + \alpha_3 \cdot f\_length_{it} + \lambda_t + \epsilon_{it} \quad (7)$$

where λ_t are year fixed effects and ε_{it} is the error term. Results are obtained using a truncated regression with bootstrap replications for the bias correction and for the confidence intervals.

The results reported in Table 6 support the hypothesis that the heterogeneity observed across distribution units is associated with external factors (a positive coefficient suggests a larger distance from the efficient frontier and vice versa). As expected, a larger area size and a lower percentage of non-residential consumption positively affect a unit's performance in terms of cost efficiency. The same holds also for shorter feeders.

[23] Using TOTEX as a the only input (TOTEX model) we obtain an average unbiased efficiency of 0.672 (between 0.651 and 0.683, depending on the year of observation). The correlation among efficiency scores in the *Cost-only* model and in the TOTEX model is equal to 0.843.

TABLE 6 ABOUT HERE

Before analyzing performance over time, note that the residuals of equation (7) represent the portion of efficiency that remains unexplained after the correction for the external factors, used as independent variables. It is possible to use these residuals to level the external variables and derive an adjusted efficiency that is not influenced by the external conditions in which each Zone operates. Employing, with the necessary modifications, the procedure proposed by De Witte and Moesen (2010), we obtain an average adjusted efficiency over the observed period equal to 0.854 (0.832 in 2004 and 0.886 in 2009). In other words, after accounting for several determinants of heterogeneity, our results appear fully consistent with previous studies that use data from a single company. In terms of policy, this is a positive result: although inefficiencies are still present, managerial performance appears quite homogeneous across all *Enel*'s Zones.

The question, however, remains on the effect of the regulation of inputs over time, or on the company's response to regulatory incentives aimed at productive efficiency. To properly discuss this matter and on the basis of the original *Cost-only* model, we examine productivity changes over time. Average Malmquist indices and their components (efficiency change and technical change) are reported in Table 7.

TABLE 7 ABOUT HERE

During the observed period, there is evidence of a decrease in productivity and both the efficiency and the technical component are, on average, lower than one. In other terms, from the perspective of productive efficiency, our analysis shows no significant improvements over time (there are no costs reductions that can be passed on to consumers). This is consistent with results obtained by Miguéis et al. (2012) and also with the Italian regulatory framework. The tariff scheme provides incentives for the DSO to achieve higher efficiency in operating costs but allows a pass-through of capital expenses and depreciation. In practice, it appears that savings in operating costs have been masked by renovation or expansion of distribution assets, a strategy that is expected to bring benefits to consumers only in the longer term.

6.2 Cost-and-quality models

To study the effects of price and quality regulation we employ two different measures of quality: regulatory rewards and penalties (*CostRP* model) and the cost of the ENS (*CostENS* model). The arithmetic average of the bias-corrected efficiency, for each model and year is reported in Table 8. Before discussing each model in detail, a few general remarks are in order.

TABLE 8 ABOUT HERE

Average efficiency scores observed over the entire period are lower in the *CostRP* model than in the *Cost-only* model (0.700 vs. 0.750); conversely, differences between average efficiency in the *Cost-only* and the *CostENS* model are minimal (0.743 vs. 0.750).

Table 9 presents the score and ranking (in parentheses) correlation coefficients across the three models. Score correlations between the *Cost-only* and the *CostRP* model are equal to 86.9% and those between the *Cost-only* and the *CostENS* models, to 82.8%. Notably, the lowest score correlation (77.2%) is between the two cost-and-quality models. The same holds also for ranking correlations.

TABLE 9 ABOUT HERE

Table 10 illustrates changes in ranking of single Zones between the *Cost-only* and the two cost-and-quality models. Calculations are made using an average scores, per Zone, over the observed period and then dividing the observations in four quartiles. The *CostRP* model does not modify the ranking found in the *Cost-only* model, particularly at the extremes. Rankings are modified for 4% of 'very cost-efficient' Zones, 21% of 'very cost-inefficient' Zones and 34% or less of 'cost-inefficient' and 'cost-efficient' Zones. Altogether, out of 114 Zones, only 14 score better and 14 worse. Similarly, including the cost of ENS in the benchmarking model does not significantly modify the ranking of 'very cost-inefficient' (21%) and 'very cost-efficient' Zones (32%). Zones in the intermediate ranges appear, instead, to be impacted relatively more (48% of 'cost-inefficient' and 46% 'cost-efficient' Zones). On average, out of 114 Zones, 22 score better and 20 worse.

TABLE 10 ABOUT HERE

6.2.1 CostRP model

Efficiency scores for the *CostRP* model are consistent with the hypothesis of a larger dispersion in input data. Together with the relative stability in the ranking order this indicates that, on average, Zones that are more cost efficient are also good performers in terms of exceeding regulatory targets for quality (i.e. they have been rewarded by the regulatory mechanism). Also the converse is true: lower cost efficiency appears to be associated with lower cost-and-quality efficiency. Changes observed over time (2008 and 2009 present higher average values than previous years) are consistent with the fact that rewards and penalties decrease at the beginning of each regulatory period (a convergence in performance was to be expected).[24]

With respect to the literature, our results are in line with those found by Coelli et al. (2007): the *cost-only* model has, at least partially, captured the quality aspect of the distribution units. In terms of policy, we infer that in the period under observation the presence of quality regulation has not significantly altered the behavior of the distribution units: those that responded well to cost efficiency incentives responded equally well to quality-related incentives and vice versa. Another interpretation is that the company has responded strategically to the regulatory regime, extracting larger gains from both price and quality regulation in some distribution Zones and smaller ones (or none) in others.[25]

The absence of a different response to cost and quality regulatory incentives (or the adoption of a strategic behavior on the part of the distribution company) might be motivated by fact that the same external conditions that favor cost efficiency also influence the ability of distribution unit to attract larger rewards. To test this hypothesis we perform a second stage analysis of the bias-corrected efficiency scores obtained in the *CostRP* model, using the same independent variables employed in equation (7). Results, obtained with a truncated regression (with bootstrap replications for the bias correction and for the confidence intervals), are reported in the first

[24] Malmquist indices estimated for the *CostRP* model exclude, however, any performance change over time (the mean over the period is equal to 1.001).

[25] We thank an anonymous reviewer for this insight.

column of Table 11. They reveal that a smaller area size, a higher percentage of non-residential consumption and shorter feeders are associated with smaller distances from the efficient frontier. In sum, external factors that favor cost efficiency also ensure that the distribution unit collects regulatory rewards (i.e., maintains SAIDI below the regulatory target).

TABLE 11 ABOUT HERE

Nevertheless, the fact that a distribution unit responds in the same manner to input-based and to output-based incentives leads an allocation of quality-related incentives that appears in contrast with the long term objective of quality regulation (i.e. convergence of SAIDI). To support these statement we compute the average annual SAIDI reduction and the average annual rewards and penalties assigned to each Zone. Table 12 illustrates these data by different quintiles of the 2004 SAIDI index, i.e. ordered by the initial level of quality. Additional information includes the number of times when no rewards nor penalties were assigned and the external variables (area size, share of non-residential load and average feeder length).

TABLE 12 ABOUT HERE

We observe that Zones in the first quintile attained relatively small quality improvements (0.64 min./year) and yet, collected almost as many rewards as Zones whose annual SAIDI improvements were significantly larger (above 3 min./year) – clearly rewards were magnified by the share of non-residential load in the same areas. In any case, it appears that significant resources were allocated to reward cost-efficient distribution units (see external variables in Table 12) for providing nearly the same level of quality that they delivered in 2004.

At the same time, Zones in the last two quintiles attained the largest improvements in SAIDI (6.09 min./year and 12.52 min./year, respectively) but were able to attract less then average rewards. Although annual SAIDI targets are more demanding for poor performing areas, it appears that rewards were also limited by a lower share of non-residential load. Moreover, these Zones more frequently met, instead of exceeding, the regulatory targets, i.e. they received no rewards (or penalties). In sum, lower resources were allocated to Zones that presented higher values of SAIDI in

2004 as well as the external characteristics of less efficient areas (see external variables in Table 12).

Altogether, this raises some doubts on the efficacy of the current regulatory mechanism to reach convergence in SAIDI in the long term. Regulatory incentives for quality were never meant as a compensation for quality-related expenditures. Nevertheless, our analysis provides strong motivations for the modification of this principle and in favor of an incentive scheme where rewards are preferably assigned to areas with less favorable external conditions. The role of network structure in defining the level of quality also suggests that those incentives should be mainly directed at supporting capital expenditures.

In line with these findings, a change in prospective has been introduced in quality regulation for the fourth tariff period. Since January 2012 rewards to high performing territorial districts (SAIDI close to the national standard) have been significantly reduced, while those to underperforming ones can largely increase if substantial improvements in SAIDI are achieved (AEEG, 2011b).

Note that what appears as a radical change in perspective implies also a strong commitment to meet one of the regulatory objectives set in 2004. As this commitment approaches its natural end (in 2015), results from the *CostENS* model suggest taking a different course of action.

6.2.2 CostENS model

Also for the *CostENS* model, average efficiency scores (0.743) are in line with previous studies. Using SOTEX (TOTEX plus the cost of ENS) as the only input Growitsch et al. (2010) find average scores that are between 57% and 62%, depending on the year;[26] Miguéis et al. (2012) report, instead, average scores above 84% (but their model includes additional outputs).

Consistent with previous work (Growitsch et al., 2010) is also the fact that average performance in terms of cost efficiency and average performance in terms of social

[26] Using SOTEX as a the only input (SOTEX model) we obtain an average unbiased efficiency of 0.669 (between 0.642 and 0.698, depending on the year of observation). The correlation among efficiency scores in the *CostENS* model and in the SOTEX model is equal to 0.870.

cost efficiency do not significantly differ in our database. Although this does not imply that they can not be improved, at least, it excludes a conflict between them.[27]

Nevertheless, a relatively low score correlation with the *CostRP* model (Table 9) and the observed changes in ranking correlations with respect to the *Cost-only* model (Table 10) suggests that the *CostENS* model provides a different perspective on cost-and-quality efficiency. To illustrate this point, we conduct a second-stage analysis on bias-corrected efficiency scores from the *CostENS* model, using the same independent variables as in equation (7). Results, obtained with a truncated regression (with bootstrap replications for the bias correction and for the confidence intervals) are reported in the second column of Table 11.

We find that favorable geographical conditions (smaller area) and network design (shorter feeders) continue to have significant and positive effect on distribution units' performance. Differently, a higher share of non-residential load continues to have a positive effect on performance but becomes less significant: given the same cost efficiency level, two Zones can be equally social-cost efficient if one presents a relatively high value of SAIDI and a relatively low share of non-residential load and the other, instead, a lower SAIDI but a higher share of non-residential load.

From a research perspective, we infer that while the *CostRP* model is best suited to study how distribution units have responded to the regulatory regime, the *CostENS* model appears as a more equitable choice when assessing their performance in terms of (social) cost efficiency and the cost of ENS should be included in benchmarking of distribution networks.

From a policy perspective, we observe that current quality targets in Italy are not differentiated on the basis of the cost of ENS in a given area. In turn, this is used to calculate rewards and penalties. Therefore, customer valuations of different levels of quality (their WTP) enter the distributor's choice in setting the level of SAIDI, i.e. will induce a distribution unit to set different levels of SAIDI in areas with a different composition of the load. We infer that a regulatory objective which requires convergence in SAIDI performance is inherently at risk whenever the benefit of meeting it does not outweigh its cost from a company's perspective.

[27] Changes observed over time even suggests a converge of performance (see Table 8). Malmquist indices estimated for the *CostENS* model exclude, however, any performance change over time (the mean over the period is equal to 0.977).

Consequently, our policy suggestion for the longer term is to redefine the convergence objective in terms of the costs of ENS. This will provide a better understanding (also in the public opinion) of the progress of quality regulation and, at the same time, remove the incentive to provide the same level of SAIDI in areas where the composition of the load does not justify the cost. While this would mean accepting a higher SAIDI where the load is mostly residential, in the end it would benefit consumers, by ensuring that the level of expenditures in electricity distribution does not increase beyond what is socially efficient.

7. Conclusions

Regulation of electricity networks is changing, moving from a productivity-oriented instrument to one that includes additional, longer term objectives, generally pursued with the introduction of output-based incentives. This has prompted interest for the assessment of firms' response to output-based incentives, mostly because of their potential conflict with more traditional concerns for productive efficiency.

In this paper we study the effect of input-based and output-based regulatory incentives on the performance of the largest Italian electricity distribution company. Specifically, our focus is on assessing progress in terms of cost efficiency and in the provision of quality. To this end, we rely on a recent statistical approach, based on DEA and bootstrapping techniques, which enable the estimation of technical efficiency in the first stage and the study of possible sources of efficiency heterogeneity in the second stage. We also employ Malmquist indices to study changes in performance over time.

As for performance in terms of cost efficiency, as implied in the regulation of inputs, we find that, once we account for the external characteristics of each distribution unit (area served, load composition and network topology), similar efforts were exercised across all *Enel*'s Zones. They were restrained, however, by the need to renovate and to expand the distribution system.

As for performance with respect to the overall regulatory framework we find that the presence of (output-based) quality regulation has not significantly modified the behavior of the distribution units: those that responded well to cost efficiency incentives responded equally well to quality-related incentives and vice versa. Indeed, the same external conditions that favor cost efficiency also influence the ability of a distribution unit to exceed the targets imposed by quality regulation. This behavior, however, appears in contrast with the long term objective of convergence in SAIDI performance.

Finally, in line with previous literature, we find that average performance in terms of cost efficiency and in terms of social cost efficiency do not significantly differ. Nevertheless, a comparison with the results obtained with different specifications of the benchmarking model indicates that is preferable to include the cost of ENS when assessing a single unit's performance.

Altogether, the evidence presented in this paper calls for a new course of action in quality regulation. Specifically, in order to reach convergence in the desired output (SAIDI), the Italian incentive scheme needs to allocate more resources where quality improvements are difficult to achieve rather than on rewarding good quality performance. As the composition of the load or the area served can hardly be modified, incentives should be directed at improving the network design. While the national regulator has already taken a step in this direction, our analysis suggests also a different conduct. A convergence objective redefined in terms of the cost of ENS (rather than SAIDI) would account for differences in load composition and might reduce the need to modify the network in areas where consumers' valuation of quality does not justify the cost.

In this perspective, further work should concentrate on studying the relationship between quality-related incentives and expenditure decisions in the electricity distribution sector. Also, an estimation of the company's cost for quality improvements would be useful to assess the efficacy of the policy suggestions proposed in this paper.

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Table 1. Benchmarking with quality in electricity distribution

	Input variables	Output variables	Quality variables	Database	Benchmarking approach
Jamasb and Pollit (2003)	OPEX; TOTEX; (Network length)	Energy supplied; Num. customers; (Network length)	Energy losses	Cross-section 1999 International	DEA, COLS and SFA
von Hirschhausen et al. (2006)	Labour; Network length; Peak load capacity	Energy supplied; Num. customers; Inverse density index	Energy losses	Cross-section 2001 National	SFA and DEA
Growitsch et al. (2009)	TOTEX	Energy supplied; Num. customers	CML	Cross-section 2002 International	SFA
Giannakis et al. (2005)	OPEX; TOTEX	Energy supplied; Num. customers; Network length	NINT and TINT	Panel 1991/92 – 1998/99 National	DEA and Malmquist Index
Coelli et al. (2007)	Capital replacement value, OPEX	Energy supplied; Num. customers; Network length	NINT	Panel 2003-2005 One company	SFA and DEA
Miguéis et al. (2012)	SOTEX	Energy supplied; Num. customers, others	Cost of ENS	Panel 2004-2007 National	DEA and Malmquist Index
Growitsch et al. (2010)	TOTEX, SOTEX	Energy supplied; Num. customers	Cost of ENS	Panel 2001-2004 National	DEA
Coelli et al. (2013)	Capital replacement value, OPEX	Energy supplied; Num. customers; Area size	NINT	Panel 2003-2005 National	SFA, Parametric Linear Programming

Note: CML: Customer Minutes lost; NINT: Number of Interruptions; TINT: Duration of interruptions; ENS: Energy Not Served; OPEX: Operating expenditures; TOTEX: Operating and capital expenditures; SOTEX: TOTEX plus Cost of ENS.

Table 2. Input and output variables in DEA models

DEA Model	Input	Output
Cost-only	capital (€) opcost (€)	energy (GWh) LVcons
CostRP	capital (€) opcost_RP (€)	energy (GWh) LVcons
CostENS	capital (€) opcost_ENS (€)	energy (GWh) LVcons

Table 3. Descriptive statistics on input and output DEA variables

Variable	Mean	Std. dev.	Minimum	Maximum	Zones
energy (GWh)	1,756	1,162	307	5,876	114
LVcons	264,456	140,351	60,275	693,154	114
capital (mln€)	263.89	121.58	78.54	705.47	114
opcost (mln€)	17.21	8.56	4.13	50.48	114
SAIDI (min)	56.55	31.58	10.42	194.28	114
RP (mln€)	0.89	1.16	-3.19	9.05	114
C_ENS (mln€)	3.17	2.34	0.14	15.30	114
opcost_RP (mln€)	16.33	8.36	3.66	48.77	114
opcost_ENS (mln€)	20.38	10.39	4.37	57.75	114

Table 4. Descriptive statistics on input and output DEA variables: mean and relative standard deviation (%) per year

	2004	2005	2006	2007	2008	2009
energy (GWh)	1,685	1,719	1,782	1,787	1,826	1,736
	67.08%	66.48%	66.43%	66.59%	66.58%	64.96%
LVcons	257,460	260,344	264,054	269,183	266,781	268,912
	53.26%	53.24%	53.26%	53.29%	53.18%	53.17%
capital (mln€)	246.54	253.16	259.92	265.94	275.35	282.45
	45.94%	45.95%	45.80%	45.98%	46.00%	46.02%
opcost (mln€)	19.17	17.11	17.50	15.83	15.59	18.08
	48.85%	47.96%	48.29%	49.86%	50.11%	50.50%
SAIDI (min)	73.56	66.83	51.06	48.59	51.54	47.73
	50.65%	55.03%	51.57%	58.35%	47.07%	51.63%
RP (mln€)	0.55	1.02	1.38	1.58	0.47	0.33
	105.57%	104.45%	105.83%	98.42%	121.65%	193.56%
C_ENS (mln€)	4.03	3.54	2.95	2.79	3.03	2.69
	74.02%	64.78%	72.77%	78.14%	68.23%	74.51%
opcost_RP (mln€)	18.62	16.1	16.12	14.25	15.12	17.76
	49.39%	48.52%	50.00%	53.57%	50.24%	51.15%
opcost_ENS (mln€)	23.19	20.65	20.45	18.61	18.62	20.77
	49.34%	48.18%	49.95%	52.15%	51.39%	52.24%

Table 5. Efficiency scores in the *Cost-only* model

Year	**Mean**	**Std. dev.**	**Min**	**Max**
2004	0.736	0.085	0.500	0.889
2005	0.715	0.079	0.514	0.883
2006	0.751	0.076	0.541	0.901
2007	0.767	0.072	0.539	0.918
2008	0.760	0.072	0.502	0.922
2009	0.771	0.073	0.581	0.937
Mean	*0.750*	*0.079*	*0.500*	*0.937*

Efficiency scores are bias corrected via boostrap (2000 replications)

Table 6. Second stage regression (*Cost-only* model)

	Efficiency scores	
area	0.026	***
	(0.005)	
nonres_cons	- 0.267	***
	(0.082)	
f_lenght	0.019	***
	(0.003)	
2004	0.069	***
	(0.020)	
2005	0.111	***
	(0.018)	
2006	0.041	**
	(0.018)	
2007	0.011	
	(0.017)	
2008	0.023	
	(0.017)	
const.	1.350	***
	(0.069)	
n.obs	684	
n. Zones	114	

***, **, and * indicate, respectively, significance levels of 1%, 5%, and 10%

Table 7. Malmquist indices (*Cost-only* model)

Year	Malmquist	EF	TC
2004-05	0.893	1.023	0.873
2005-06	1.005	0.957	1.050
2006-07	0.887	1.981	0.904
2007-08	0.990	1.008	0.982
2008-09	1.154	0.992	1.164
Mean	*0.986*	*0.992*	*0.995*

Indices are bias corrected via boostrap (2000 replications)

Table 8. Efficiency scores in *CostRP* and *CostENS* models

	***CostRP* model**				***CostENS* model**			
Year	**Mean**	**Std. dev.**	**Min**	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**
2004	0.703	0.089	0.457	0.878	0.689	0.106	0.382	0.897
2005	0.664	0.094	0.447	0.877	0.706	0.107	0.423	0.918
2006	0.676	0.102	0.417	0.915	0.749	0.089	0.503	0.938
2007	0.675	0.101	0.414	0.905	0.752	0.089	0.470	0.926
2008	0.733	0.080	0.468	0.922	0.778	0.091	0.502	0.953
2009	0.748	0.079	0.543	0.927	0.786	0.082	0.545	0.975
Mean	*0.700*	*0.096*	*0.414*	*0.927*	*0.743*	*0.100*	*0.382*	*0.975*

Efficiency scores are bias corrected via boostrap (2000 replications)

Table 9. Score and ranking (in parenthesis) correlations among DEA models

	Cost-only	***CostRP***	***CostENS***
Cost-only	1		
CostRP	0.869 *** (0.859)	1	
CostENS	0.828 *** (0.842)	0.772 *** (0.803)	1

***, **, and * indicate, respectively, significance levels of 1%, 5%, and 10%

Table 10. Changes in raking order

		Cost only							
		Very efficient		*Efficient*		*Inefficient*		*Very inefficient*	
Cost-RP	*Very efficient*	25	86%	4	14%	0	0%	0	0%
	Efficient	4	14%	19	68%	5	17%	0	0%
	Inefficient	0	0%	5	18%	19	66%	5	18%
	Very inefficient	0	0%	0	0%	5	17%	23	82%
	Tot.	29	100%	28	100%	29	100%	28	100%

		Cost only							
		Very efficient		*Efficient*		*Inefficient*		*Very inefficient*	
Cost-ENS	*Very efficient*	23	79%	6	21%	0	0%	0	0%
	Efficient	5	17%	15	54%	7	24%	1	4%
	Inefficient	1	3%	5	18%	15	52%	8	29%
	Very inefficient	0	0%	2	7%	7	24%	19	68%
	Tot.	29	100%	28	100%	29	100%	28	100%

Percentage values are rounded

Table 11. Second stage analysis (*CostRP* and *CostENS* models)

	***CostRP* model**		***CostENS* model**	
area	0.041	***	0.038	***
	(0.008)		(0.008)	
nonres_cons	-0.565	***	-0.201	*
	(0.105)		(0.119)	
f_length	0.029	***	0.021	***
	(0.004)		(0.005)	
2004	0.102	***	0.243	***
	(0.023)		(0.034)	
2005	0.203	***	0.203	***
	(0.024)		(0.031)	
2006	0.187	***	0.094	***
	(0.027)		(0.024)	
2007	0.192	***	0.086	***
	(0.025)		(0.025)	
2008	0.041	*	0.027	
	(0.021)		(0.026)	
const.	1.511	***	1.199	***
	(0.090)		(0.105)	
n.obs	684		684	
n. Zones	114		114	

***, **, and * indicate, respectively, significance levels of 1%, 5%, and 10%

Table 12. Average annual SAIDI reduction and RP by SAIDI 2004 quintiles

Quintiles	SAIDI 2004	Annual SAIDI reduction	Annual Rewards	Annual Penalties	Zero RP	*area*	*nonres_cons*	*f_length*
	[min]	[min]	[mln€]	[mln€]	[N. obs.]	[km^2]	[%]	[km/MVA]
Q1	18.70 - 40.56	0.64	1.08	0.15	0	$1789*10^3$	0.77	3.33
Q2	40.56 - 59.83	3.08	1.15	0.45	1	$2825*10^3$	0.74	3.59
Q3	59.83 - 77.39	3.81	1.34	0.41	8	$2468*10^3$	0.72	4.02
Q4	77.39 - 98.18	6.09	0.88	0.48	11	$2541*10^3$	0.68	4.57
Q5	98.18 - 194.28	12.52	0.89	0.40	24	$2826*10^3$	0.68	5.18
Mean	-	*5.17*	*1.08*	*0.42*	-	*$2487*10^3$*	*0.72*	*4.13*

Appendix

In this Appendix we analyze the determinants of the continuity indicator SAIDI and, in particular, we focus on interruptions that occur at Medium Voltage (MV) level (a measure that include most of the customer minutes lost in a given area). To this end, estimate the following model (Model A):

$$SAIDI\_MV_{it} = \alpha_0 + \alpha_1 f\_length_{it} + \alpha_2 km\_MV_{it} + \alpha_3 nonres\_cons_{it} + \lambda_t + \epsilon_{it} \tag{A.1}$$

The dependent variable is the SAIDI indicator used in the paper, net of interruptions events that originated on the low voltage network (*SAIDI_MV*). The explanatory variables are the average length of feeders per substation (*f_length*), network length at MV level (*km_MV*) and the percentage of non-residential energy consumption over total consumption (*nonres_cons*). Annual dummy variables are included to control for time-variant fixed effects (λ_t).

As explained in Section 5.3, a larger value for the variable *f_length* is expected to increase SAIDI. Similarly, a longer network indicates a more dispersed distribution area and is expected to be associated with longer interruption durations (longer supply restoration times). On the contrary, a larger share of non-residential load is expected to be associated with lower values of SAIDI (non-residential consumers have a higher valuation of quality).

Results, obtained with a Random Effect model, are reported in Table A.1: Model A-I includes only the technical variables (*f_length* and *km_MV*); Model A-II considers also the composition of the load (*nonres_cons*).

In Model A-I, the coefficient on *f_length* is, as expected, positive and statistically significant; differently, the coefficient for the variable *km_MV* has the expected sign, but it is statistically insignificant. Model A-II confirms the effect on *SAIDI_MV* of the variable *f_length*, althought at a lower significance level; it also shows that a higher share of non-residential load has the expected negative and significant effect upon SAIDI at MV level. Finally, the annual dummy variables indicate that the variable *SAIDI_MV* decreased over the observed period.

Table A.1 Determinants of continuity indicator SAIDI at MV level

	Model A-I	**Model A-II**
f_length	3.132***	1.620*
	(0.953)	(0.956)
km_MV	0.002	0.001
	(0.001)	(0.001)
nonres_cons	-	-97.531***
	-	(24.720)
2004	26.043***	25.641***
	(2.505)	(2.560)
2005	19.127***	19.310***
	(2.132)	(2.125)
2006	4.661***	5.231***
	(0.896)	(0.908)
2007	1.938**	2.714***
	(0.851)	(0.852)
2008	1.194	2.238*
	(1.229)	(1.201)
const.	13.022***	91.062***
	(4.998)	(19.340)
N. obs.	684	684
N. Zones	114	114

***, **, and * indicate, respectively, significance levels of 1%, 5%, and 10%