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# Incentives to Quality and Investment: Evidence from Electricity Distribution in Italy*


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**Abstract** – This paper investigates the relationship between output-based incentives for service quality and the use of capital and non-capital resources to meet regulatory targets in the electricity industry. To conduct the empirical analysis we use a dataset collected with the support of the Italian energy regulatory authority, comprising micro data on monetary incentives and physical assets for the largest electricity distribution operator in Italy (86% of the market). Our results show that physical assets and operational expenditures do affect service quality. Moreover, when we investigate causality in the relationship between incentives to quality and the use of capital and non-capital resources, we find that incentives Granger-cause capital expenditures (and not vice-versa). Finally, our results reveal an asymmetric effect of rewards and penalties on capital expenditures' decisions across areas with different quality levels. From these findings, we derive several policy implications.



***Keywords*** – Electricity distribution, Incentive regulation, Investment, Service quality

***JEL Classification***: L51, L94



* For comments on earlier versions of this paper we thank the Editor, Michael Crew, two anonymous referees, Alberto Iozzi, Tooraj Jamasb and David E.M. Sappington and participants at the *2nd Conference on the Regulation of Infrastructure Industries,* EUI – Florence School of Regulation (Florence, 2013), the *Mannheim Energy Conference,* ZEW, University of Mannheim (Mannheim, 2013) and the 7th Meeting of the *Network on Economics of Regulation and Institutions* (Turin, 2014). Technical and financial support from the Italian Regulatory Authority for Electricity, Gas and Water is kindly acknowledged. The opinions expressed in this paper do not represent the official position of the Italian Regulatory Authority and do not commit the Authority to any course of action in the future. Similarly, the opinions expressed in this paper do not represent the official position of *Enel Distribuzione* and do not commit *Enel Distribuzione* to any course of action in the future.

## 1. Introduction

Since the introduction of structural reforms in energy network industries, a major concern of incentive regulation has been to encourage firms to focus on inputs - i.e. operational and capital expenditures- and to enhance productive efficiency and service quality. Only few directly measurable outputs were typically associated with an explicit definition of performance targets and with specific monetary incentives. In most cases, output-based incentives were employed to reduce network losses and/or to improve service quality (Jamasb and Pollit, 2007; Joskow, 2008). In Italy, the energy regulatory authority (*Autorità per l'energia elettrica, il gas e il servizio idrico,* AEEGSI) has been applying output-based regulation to indicators of service quality since 2000.

In the past few years, energy regulators have started to focus on additional goals, such as sustainability and innovation, and rely on output-based incentives that reward/penalize companies depending on their ability to reduce their environmental impact or to enable the integration of new technologies (e.g. dispersed generation or electrical vehicles), and so on. The *Revenue, Innovation, Incentives and Output* (RIIO) model, recently adopted in the UK (Ofgem, 2010), is probably the best-known example, but other European regulatory agencies are moving in this direction.[1] In the US, where virtually all states have adopted ad-hoc regulatory incentives, specific output-based targets include energy efficiency and environmental sustainability.[2]

This paper empirically investigates the relationship between output-based incentives for service quality and the use of capital and non-capital resources by the largest electricity distribution operator (86% of total distributed energy) in Italy. The primary aim of the paper is to understand whether rewards and penalties are both needed to spur such expenditures and, in turn, service quality, or if rewards (and penalties) simply push (and withdraw) money towards companies for their past superior (inferior) performance, without affecting their expenditure decisions. Our analysis can thus provide insights to national regulators on how incentive payments may be calibrated in order to prevent unnecessary transfers from consumers to firms (and vice versa). Output-based regulatory mechanisms are indeed complex to implement and require significant regulatory resources (powers, budget and skills) for data collection and monitoring, as well as periodical adjustments over time

[1] As for Italy, see Lo Schiavo et al. (2013).

[2] For an overview of the regulatory regimes in the US electric utility industry on alternative output based goals in the US, see IEE (2013).

(Joskow, 2008; Jamasb et al. 2012). From a policy perspective, our analysis is therefore relevant in view of the direct regulatory costs of current and future regulatory frameworks.

Among EU national regulators, the Italian Authority (AEEGSI) has been a frontrunner in the introduction of specific quality-based incentive schemes in electric distribution. To test the effect of output-based incentives, we use micro data on electricity distribution, collected with the support of the AEEGSI through a dedicated survey on the activity of the largest distributor in Italy, *Enel Distribuzione*, which operates throughout the national territory. The company is part of *ENEL* group, the former electricity state monopolist, privatized and publicly listed in 1999. Although the company is formally state-controlled, almost 75% is publicly traded (67% in 2009), so its behavior, including its responsiveness to regulatory and incentive policies is similar to that of privately controlled quoted firms.[3] The dataset is a comprehensive and balanced panel of *Enel Distribuzione*'s 115 distribution Zones (or units), which includes unit-level accounting data from 2004 to 2009 and, more importantly for us, the amounts annually received as rewards (paid as penalties) for service quality – data that are generally available only to national regulatory agencies. The information on incentive (rewards and penalties) payments is a key feature of this paper, allowing us to investigate, differently from previous studies, if incentive payments affect the capital and non-capital expenditure decisions and whether this effect is asymmetric between rewards and penalties and differs among areas with different quality levels.

Another distinctive feature in the case of *Enel Distribuzione* is the detail of the technical micro data, which allows us to measure the technical changes adopted by the company after the introduction of quality regulation in Italy (see, Cerretti et al., 2005 and Valtorta et al., 2009). In general, it is difficult to identify quality-specific investments as many if not most technical and structural applications have multiple purposes. The fact that the company's response to quality-specific incentives is (in part) measurable is a step forward with respect to the existing literature. In particular, AEEGSI has collected unit-level micro data on the type, location and timing of several technical interventions carried out by *Enel Distribuzione* over the territory it serves. Such detailed micro-level information is not available for any other jurisdiction served by alternative distributors in Italy and, to our knowledge, has not been exploited for similar analyses in other countries.

[3] Notably, the ownership share held by the state through municipalities in the other Italian distributors is always larger than 50%, for example, A2A – Milan with 54%, ACEA - Rome with 51%, AEM (now IREN) – Genoa and Turin with 54%.

The recent economic literature has focused on the relationship between input-based incentive regulation (e.g. price/revenue caps), quality-specific incentives and the level of service quality. In a comprehensive survey, Sappington (2005) highlights that the introduction of minimum quality standards and/or rewards and penalties schemes is needed to secure a desirable level of service quality in presence of high-powered incentive mechanisms. Consistently, the empirical evidence shows that the introduction of quality standards prompts firms to achieve cost savings without adversely affecting quality (Reichl et al., 2008; Ter-Martisoryan and Kwoka, 2010).

Differently from previous work that looked into the effect of the presence of quality regulation in the form of a dichotomous variable (Ter-Martisoryan and Kwoka, 2010), we employ here the annual monetary amounts actually assigned to (paid by) each distribution unit as a result of its quality performance, within an output-based mechanism. Our reasoning starts with the assumption that output-based incentives are expected to influence performance (with respect to the regulated output) by driving firms to invest in capital assets and/or additional operating expenses – ideally maintenance costs – in order to meet the regulatory target (Jamasb et al., 2012). In theory (Sappington, 2005; De Fraja and Iozzi, 2008), the firm's decision to exert an effort is conditional on (marginal) incentives being larger (in absolute value) than firm's (marginal) costs of (providing) quality. Given that incentives reflect consumer willingness to pay for quality, this mechanism should lead regulated firms to deliver welfare-maximizing levels of performance. In this paper, our purpose is to test the relationship between quality-related incentives and firm investment.

Previous empirical work has related the level of regulatory incentives (per unit of quality improvement) with the estimated per unit cost of quality improvement (Jamasb et al., 2012; Coelli et al., 2013). Finding that actual unitary incentives are higher (lower) than estimated per unit costs, the authors infer that firms are likely (not likely) to improve service quality.

We differ from this approach in that we analyze the actual strategy of a large distribution firm. Specifically, we investigate whether incentives to quality affect the firm's decision to invest in capital and operational expenditures in order to improve quality (a mechanism that may recall industrial policy interventions that offer tax incentives for R&D and innovation in manufacturing firms). Incentives are assigned at the end of the year, based on the observed performance. Therefore, it may happen that not only *expected* rewards/penalties incentives, but also rewards *received* or penalties *paid* at the end of the year positively affect future investments, in that they generate cash *in*-flows or *out*-flows that ultimately influence firm's decisions.

Based on the regulatory setting in place in Italy, in the econometric analysis we account for this articulated timing of the incentive procedure and carry out the analysis proceeding along three steps.

First, we provide empirical evidence that quality as measured by the average duration of service interruptions (i.e. the indicator of service quality that has been subject to regulatory control in Italy for the longest time) is affected by investments in physical assets and by operational expenses (an item that aggregates maintenance as well as operational costs). This result is in line with Ter-Martirosyan and Kwoka (2010), who show that, for the U.S., maintenance expenditures positively affect the same quality indicator. This first step serves the specific purpose to verify that, by increasing the available fixed assets and equipment and/or the aggregate operational expenditures, firms succeed in improving their quality performance.

Second, we analyze the relationship between capital and operational expenditures and regulatory incentives. By employing the Granger (1969) and Sims (1972) causality test, we show that past incentives positively affect current capital expenditures, which suggests a causal relationship from output-based incentives to firm investment, but not vice versa. In contrast, we find no evidence of a causal relationship between past incentives to quality and current operational expenses.

Finally, we test whether the impact of output-based incentives on the investment rate survives after controlling for other determinants. To this end, we estimate a dynamic accelerator model of investment with financial effects, which includes lagged regulatory incentives among the explanatory variables. Furthermore, in order to investigate potential asymmetries between positive and negative incentives, we decouple rewards and penalties within the investment analysis. Our findings show that penalties (paid) play a significant role in the decision to invest, especially so if the unit's quality performance is very low. Received rewards appear, instead, to affect the investment decision only in areas with top quality performance, but not in the remaining areas. Interestingly, therefore, neither rewards nor penalties seem to affect the investment decision in distribution units with average quality performance. Our results actually throw some light on the role of positive monetary incentives. Rewards do compensate the unit for having achieved a desirable level of performance – hence quality incentives are not assigned in vain -, but one should not necessarily expect that the same rewards unambiguously prompt the unit to further improve on it.

The paper is organized as follows. Section 2 provides the relevant details of the Italian regulatory framework. Section 3 describes the research design and the empirical methodology. Section 4 illustrates the dataset and the variables used in the estimations. Section 5 presents the estimates from the regression analyses and discusses the results. Section 6 concludes and derives policy implications.

## 2. Regulatory incentives in the Italian electricity distribution sector

The structure of the Italian electricity distribution sector has been quite stable for the past ten years. At the end of 2013, it counted 136 Distribution System Operators (DSO) that delivered a total volume of 269 TWh. In 2009, the last year observed in this analysis, there were 140 DSOs, which delivered 280 TWh. The largest firm and historical incumbent operator, *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%), serving the urban areas of Milan, Rome and Turin, respectively. Even today, none of the other operators delivers more than 1% of total distributed energy.

Since 2000, the regulatory framework includes both input-based and output-based incentives: the former have the main objective to stimulate productive efficiency, the latter to ensure an adequate level of service quality. As for productive efficiency, a price cap mechanism applies to operational expenditures, requiring them to decrease annually by an *X* efficiency factor. Differently, depreciation and the cost of capital pass through directly to consumers. The cost of capital is remunerated with a fixed rate of return, estimated with a Weighted Average Cost of Capital (WACC) methodology.[4]

Service quality regulation encompasses several dimensions, ranging from commercial quality aspects (e.g., appointment scheduling) to highly specific technical characteristics (e.g., voltage dips). Different quality dimensions are controlled using different approaches (Fumagalli et al., 2007). Output-based incentives are specifically employed in Italy to regulate continuity of supply, i.e., the occurrence of service interruptions, with two main

[4] For the second tariff period (2004-2007) WACC was set 6.8% and the *X* factor at 3.5%. For the third tariff period (2008-2011) the WACC was increased to 7% and the *X* factor was decreased to 1.9%. For the current, fourth tariff period (2012-2015) the WACC is set at 8.6% for the first two years and at 6.4% for the remaining two years; the *X* factor is set at 2.8%. Details on the choice of the WACC and *X* factors in the energy sector in Europe can be found in Cambini and Rondi (2010). Specific investment benefits have been introduced to support, for instance, the deployment of low-loss transformers and to promote automation and control of active grids (Lo Schiavo et al., 2013)

objectives: *(i)* to improve continuity levels and *(ii)* to reduce the differences in continuity levels observed across different geographical regions.

To this end, AEEGSI requires DSOs to measure, on an annual basis, the average number and duration of service interruptions per customer. For a given distribution unit and year, the average duration of long interruptions (longer than 3 minutes) per consumer is indicated with the acronym SAIDI (System Average Interruption Duration Index) and calculated as:

$$SAIDI = \sum_{k=1}^{M} \frac{D_k N_k}{N_{tot}}$$

where the sum extends over all $M$ interruptions in a year ($k$ = 1…$M$) , $D_k$ is the duration of interruption $k$ (in minutes), $N_k$ is the number of consumers affected by interruption $k$, and $N_{tot}$ is the total number of consumers served in the distribution unit.[5]

This indicator is measured, separately, in the 300 and more *territorial districts* that cover 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.[6] For each district, AEEGSI defines an annual target (more on this below) and requires companies to report, each year, the difference between the actual indicator and the target. Economic incentives ($INC_{j,t}$) per district $j$ and year $t$ are calculated, as follows:

$$INC_{j,t} = DeltaSAIDI_{j,t} \cdot (C_1 \frac{res\_energy_{j,t}}{8.76} + C_2 \frac{nonres\_energy_{j,t}}{8.76}) \quad (1)$$

where:

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[5] In addition to SAIDI the Italian regulation requires distribution companies to report the average number of long interruptions per customer, known by the acronym SAIFI (System Average Interruption Frequency Index), as well as the average number of short (shorter than 3 minutes and longer than 1 second) interruptions per customer: this index is called MAIFI (Momentary Average Interruption Frequency Index). The average number of long (short) interruptions per consumer is calculated as:

$$SAIFI\ (MAIFI) = \sum_{k=1}^{M} \frac{N_k}{N_{tot}}$$

where notation is as above. From 2000 to 2007 rewards and penalties were applied to SAIDI only. From 2008 onwards, rewards and penalties apply to SAIDI as well as to another indicator calculated as the sum of SAIFI plus MAIFI (total number of interruptions, long and short ones).

[6] Each of the Enel’s units (Zones) includes two or three districts, typically of different density levels (see also Section 4).

- $DeltaSAIDI_{j,t}$ (in minutes) is the difference between the target and the actual SAIDI for district $j$ in year $t$; actual and target SAIDIs do not include notified interruptions nor events that are not under the responsibility of the distributor (more on this below);
- $C_1$ and $C_2$ are unitary incentives set by AEEGSI at, respectively, 18 c€/(minute·kW) and 36 c€/(minute·kW): they reflect the different willingness to pay for quality of, respectively, residential and non-residential customers, as estimated by means of a customer survey (AEEGSI, 2007);
- $res\_energy_{j,t}$ and $nonres\_energy_{j,t}$ are, respectively, residential and non-residential energy consumption per district $j$ and year $t$ (in MWh).

Several remarks are in order. First, AEEGSI sets targets using a formula that implies a convergence in performance of all districts with equal population density to the same quality level, the so-called *national standard*, in the medium term (12 years from 2004 for SAIDI). This implies that targets are increasingly demanding every year, until the district's performance reaches the set national standard, and that greater quality improvements are required by districts reporting lower levels of performance when the medium-term target was set. The motivation of this scheme is that the Italian legislation requires distribution tariffs to be the same across the entire national territory: the same quality has to be associated to the same level of customer expenditure. This also implies that annual rewards received (or penalties paid) for each district are collected into a single account. At the end of the year, if the account has a surplus, this is equally distributed to consumers by a decrease in the distribution tariff. Vice versa, if the account has a deficit, the distribution tariff is increased. In this manner, costs (savings) for higher (lower) levels of quality are socialized among consumers, while quality-related incentives remain district-specific for the regulated companies.[7]

Second, the national standard of performance is differentiated per population density so that more densely populated districts are expected to provide higher levels of continuity, i.e. a higher quality. In other words, regulation accounts for technical differences in urban, suburban and rural distribution districts.[8]

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[7] In the time span of our analysis, the average household has paid an extra cost due to quality increments of about 2 €/year. The cost of continuity regulation was accounted for in the distribution charges of the electricity bill. For the average household the latter amounts to around 500 €/year.

[8] Urban networks present, compared to rural networks, shorter feeders, a higher share of underground cables and a higher level of redundancy. These structural characteristics favor continuity of supply.

Finally, we observe that registered interruption events are classified per cause and origin of the fault (e.g., transmission network, Force Majeure, etc.). Although our dataset includes, separately, the average duration and number of (long and short) interruptions for all events, in this paper we consider only events that, according to the regulatory definition, fall under the responsibility of the distributor.[9] All other interruptions do not contribute to the regulated part of the total SAIDI and do not enter in the calculation of rewards and penalties. For this reason, they are excluded also from our empirical analysis.

## 3. Research design

The focus of this paper is on the effectiveness of output-based incentive schemes. Specifically, we explore whether incentives affect the use of those resources that are most likely to affect performance with respect to the regulated outputs.

Differently from previous work (Jamasb et al., 2012; Coelli et al., 2013), we empirically study the relationship between annual monetary incentives and the observed level of expenditures. To this end, several issues need to be considered.

First, because an increase in expenses can be associated both with an increase and with a decrease in quality (Jamasb et al., 2012) there is an ambiguity issue. On the one hand, the longer and more frequent the interruptions, the higher will be the expenses incurred to repair the faults, including personnel related costs (we refer to these as corrective costs). On the other hand, expenses (i.e. preventive costs) will increase whenever the firm implements specific actions (e.g. more frequent maintenance interventions, structural changes in the network, etc.) aimed at improving service quality. The nature of the relationship between performance, incentives and expenditures is laid out in Figure 1. As shown in the diagram, we expect that physical equipment in year *t* defines the level of quality in the same year, while the effect of new investments in year *t* will become evident in subsequent years (as they are expected to ameliorate future quality). The same holds for maintenance expenditures (in that their effect is to be seen in the future). Differently, operational expenditures in year *t* can be influenced by the level of quality in year *t*, but also influence the level of quality, at

[9] In particular, the Italian regulation makes a distinction between interruption events and exceptional interruption events or, better, “exceptional time periods”. Since 2004 these events (time periods) are identified using a statistical methodology which, originally, identified an extreme region in the daily SAIDI (and SAIFI) plane, where such exceptional events (periods) belonged to. The boundaries of this region were originally defined for each district using thresholds of means and standard deviations of daily SAIDIs (for details see Fumagalli et al., 2009). Such exceptional events (thus including extreme weather) are considered as caused by Force Majeure.

the same time. Finally, Figure 1 shows that quality levels, calculated at the end of each year, determine rewards/penalties for the same year; as such, monetary incentives can enter the decision making for expenditures made in the subsequent year.

This implies that there is also a causality issue. As we set out to explore whether incentives influence investment or operational expenditures and, in turn, quality, we need to consider that quality does determine the rewards or the penalties, i.e. the incentives granted to the firm by the regulator. Hence, the need to test the direction of causality between the incentive scheme and the investment or maintenance plans.

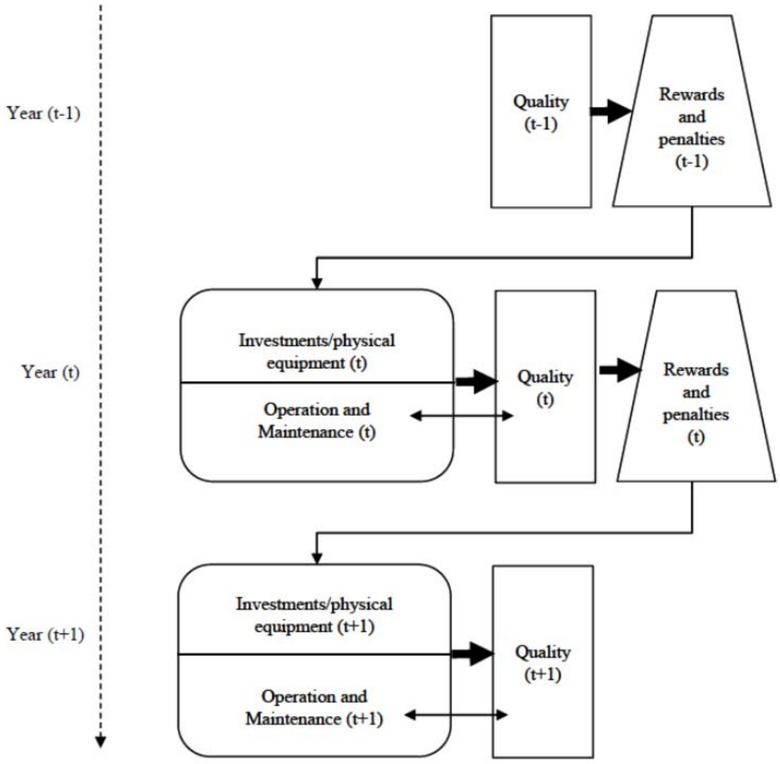


**Figure 1** – Incentives, expenditures and quality

The third issue deals with the organization of distribution, as companies, including *Enel*, often manage several electricity distribution units. Therefore, when only firm-level data are available, it is not easy to match the firm (operator)'s attempt to improve service quality in a specific unit with the performance of the single distribution unit. The peculiar nature of our micro data allows us to cope with this problem in that we have access to both accounting data and physical characteristics of the capital endowment of all distribution units (Zone) of the operator, i.e. *Enel Distribuzione* (see Section 4 for a detailed description of the dataset).

Hence, we can match these unit-level data with output quality data achieved in each unit. Another key feature of this dataset is that each distribution unit accounts for an individual and separate managerial decision entity within the company, so it is not inappropriate to view them as firms or quasi-firms.

Finally, the usual measurement problems that arise in calculating the investment rate (i.e. the ratio of gross fixed investment to capital stock at replacement value) for standard manufacturing firms become even more complicated when applied to a distribution service operator. Ideally, we need sensitive accounting data at the distribution unit level, but the available accounting monetary values to calculate the investment rate (i.e. the capital expenditures and fixed capital stock)) are usually aggregated at firm level (see above). In addition, in our empirical analysis, we intend to investigate the relationship between the quality-related investments with a particular kind of "output", i.e. customer minutes lost. Again, our micro dataset provides the solution, making available at unit-level the technical data on several physical components of the distribution network (e.g., the number of automated secondary substations), which can be directly related to higher continuity levels, hence to higher quality.

To deal with the first and second issues, i.e. ambiguity and causality of the impact of expenses, our research strategy proceeds in three steps.

In the first step, we investigate the relationship between the continuity of supply (SAIDI) and firms' capital and non-capital resources. One novelty of our approach is that we proxy for capital expenditures with a number of *physical* characteristics of the distribution network (e.g. the number of automated secondary substations) that is generally considered as specifically influencing the number of power interruptions and lost minutes. An additional advantage of this strategy is that it enables us to connect supply continuity with the actual physical assets employed in the *distribution unit*.

In the second step, we explore the issue of causality between output-based regulatory incentives and the use of resources that are supposed to affect the level of quality (i.e. the determinants of continuity of supply analyzed in the first step). To this purpose, we consider capital expenditures and operational expenditures, both expressed in monetary values since we now relate them to monetary incentives. To establish the direction of causality between capital or operational expenditures and regulatory output-based incentives, we apply the Granger (1969) and Sims (1972) weak-causality test, which tests whether an increase in incentives is followed by an increase in capital (or operational) expenditures or vice versa.[10] The test allows for three alternative possibilities. First, it may be that past incentives prompt the unit's manager to upgrade the network (i.e. the service), in which case we can say that incentives Granger-cause capital (or non-capital) expenditures. Alternatively, it could be that, following past increases (or decreases) in capital or operational spending, the unit/firm will be granted a reward (or a penalty). In this case, we can say that it is firm's expenditures which Granger-cause incentives. Finally, we may find evidence of circularity, i.e. two-way causality, where an increase in (capital or operational) expenditures is followed by an increase in incentives, and vice-versa.

The third step builds on the results of the Granger causality test. Considering that the specification of the Granger model just focuses on the dynamic relationship between investment and incentives, it can be argued that the relationship may be driven by unobserved variables. For example, incentives are definitely either a cash-flow entry (rewards) or a cash-flow exit (penalties) and investments are related with cash flows. To account for the complexity of the investment decision with a more comprehensive approach, we investigate the impact of quality-related incentives on investments estimating an accelerator investment model that controls for financial and demand factors (Bond et al., 2003). The objective of this analysis is twofold. First, we test whether the dynamic effect of incentives on investment survives when we control for other determinants. Second, we test whether penalties and rewards present similar or asymmetric effects on the investment rate.

## 4. The sample and the data

We built the dataset with the support of the Italian energy regulatory authority, by means of a dedicated data collection. It is a comprehensive and balanced panel for 115 distribution units (called Zones) that belong to *Enel Distribuzione*, tracked from 2004 to 2009. Given *Enel*'s market share (86% in 2009) and its presence over the entire national territory, our data provides a good representation of the Italian electricity distribution sector.

The dataset includes unique technical and accounting micro data for each of the 115 units (or Zones). Continuity indicator (SAIDI) as well as the amounts annually received in rewards (paid in penalties) are available, instead, per *district*, which are geographical areas smaller

[10] See Arellano (2003, Ch. 6) for details regarding the use of Granger causality tests in the context of a panel setting. Granger causality tests were recently used to examine several regulatory issues such as tariff rates, leverage, investment, intensity of regulation, regulatory independence, etc. (Edwards and Waverman, 2006; Bortolotti et al., 2011; Cambini and Rondi, 2012).

than *Enel*’s managerial *units*, so that each Zone includes two to three (clearly identifiable) districts, typically of different density levels. To ensure coherence with technical and accounting data, we used the number of low voltage consumers in each district as weights to compute for each Zone the continuity indicator as well as quality-related incentives.[11] Such details about the duration and frequency of interruptions, as well as the amounts of rewards received and penalties paid per district are not publicly available data and were directly provided by the AEEGSI.

### *4.1. Data and summary statistics*

By effect of the current regulatory setting (see Section 2), our sample is composed of units of observation that are subject to (input-based) incentives to reduce operational costs, but also relatively free to choose the desired level of investment. Rewards or penalties associated with quality performance increase or decrease the amount of revenues collected by the distribution unit, depending on whether it meets (or fails to meet) the regulatory quality targets.

In the observed time span, both price and quality regulation evolved across two regulatory periods (2004-2007 and 2008-2009). Apart from a few, expected adjustments, the general regulatory framework remained the same within the entire period of observation.[12]

By looking at service continuity data from 2004 to 2009, we observe a decreasing rate of improvement in performance over time. As illustrated in Figure 2 (on the right), the average duration of long (longer than 3 min.) interruptions per consumer (actual SAIDI) registered the largest improvements in the years 2005 and 2006; after that, only smaller changes in quality are visible. A similar trend (Figure 2, on the left) can be observed for the average number of long interruptions per consumer (actual SAIFI). While from a technological perspective such a trend is to be expected, it also provides an interesting environment for exploring the effectiveness of the output-based incentive scheme.

[11] By combining district-wide data into Zone-wide data, the relation between population density and continuity of supply (duration and frequency of interruptions, but also penalties and rewards) becomes considerably less precise.

[12] Even so, in our empirical analysis we do test for differences across the two periods. We thank an anonymous referee for this suggestion.

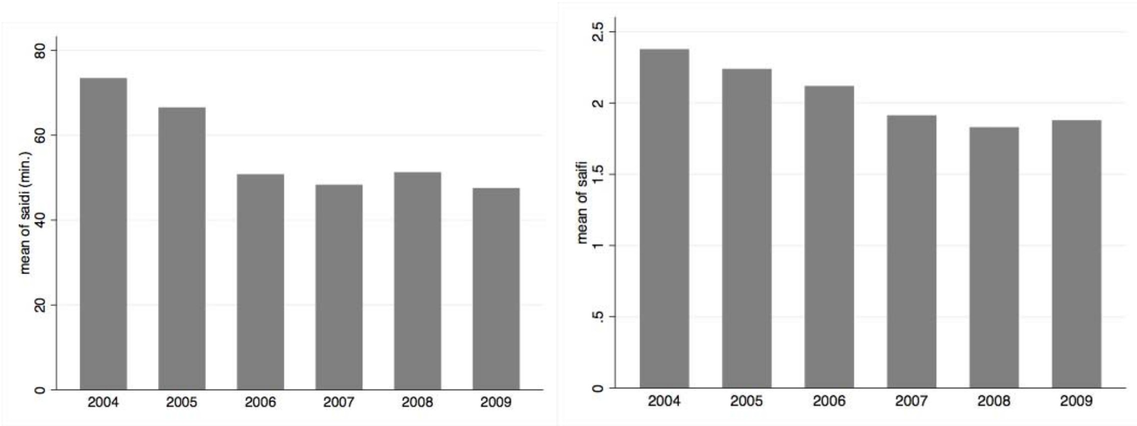


**Figure 2 –** Actual SAIDI (right) and SAIFI (left) over the observed period

Our measure of quality performance is the average duration of long interruptions per consumer (variable *SAIDI*).[13] We opt for SAIDI because this is the key variable of the regulatory incentive scheme for the entire observation period, whereas monetary incentives for the number of interruptions (SAIFI) were introduced only in 2008. Accordingly, to measure output-based incentives we use a variable which is equal to the amount received in rewards or paid in penalties for meeting (failing to meet) SAIDI-related targets (*INC*) – adjusted for inflation by using the Consumer Price Index at 2005 and excluding SAIFI-related incentives. *INC* can assume positive and negative values, depending on the quality performance in each year. Hence, we also define a *REWARD,* equal to positive values of *INC* (and zero otherwise) and *PENALTY,* equal to negative values of *INC* (and zero otherwise). Note that, over the observed period, the occurrence of positive values (rewards) has always outnumbered the occurrence of negative values (penalties).

To investigate potential determinants of the variable *SAIDI*, we use capital and non-capital resources, i.e. fixed capital assets and operational expenditures, as well as control variables to account for specific characteristics of the distribution unit.

The set of physical asset components includes the share of underground cable over total network length (*UNDER*), the number of automated secondary substations per Low Voltage (LV) consumer (*AUTO_LVcons*) and the number of Petersen coils per LV consumer (*PC_LVcons*). The variable *UNDER* is commonly used in the literature to capture the type of the distribution territory (grounding of MV feeders is a standard choice in areas with higher population density) as well as the additional burden in terms of capital assets (Kuosmanen,

[13] As already mentioned, the variable *SAIDI* coincides with the regulated part of total SAIDI (e.g., it does not include notified interruptions, nor events that originated on the transmission network or that were caused by Force Majeure). Also, it was winsorized to exclude an outlier in the first year of observation.

2012). *UNDER* is closely related to continuity of supply, as underground cables are associated with a lower probability of fault. The number of automated secondary substations and of Petersen coils describes the infrastructural investments made by *Enel Distribuzione* as a response to continuity of supply regulation (Cerretti et al., 2005; Valtorta et al., 2009). Both have a positive effect on service quality: the former is supposed to decrease the fault selection time while the latter should reduce the number of interruptions.

Non-capital resources, i.e. operational expenditures, are defined as the sum of costs incurred for labor, services, materials and other costs (*OPEX*) – adjusted for inflation by using the Consumer Price Index at 2005. Specifically, the explanatory variable employed here (*OPEX_LVcons*) is constructed as the ratio of *OPEX* to the number of LV consumers.[14]

As a control for specific characteristics of the distribution unit, we employ the percentage of non-residential consumption (*PERC_NR*), i.e. the ratio of LV non-residential consumption plus medium voltage consumption over total consumption. This variable accounts for higher willingness to pay for quality and for higher revenues per customer and is typically associated with better continuity of supply.[15] In addition, as shown by Jamasb et al. (2012), also weather conditions may affect service quality. We thus include two weather variables sourced from the Italian National Statistic Institute (ISTAT): the yearly average amount of precipitation (*PRECIPITATION*)[16] and the yearly average minimum temperature (*MIN TEMP*).

To estimate Granger tests and investment equations the key variables are the investment rate, the unit-level control variables, and the regulatory incentives. For the investment rate, we start from the accounting values of gross fixed investment (capital expenditures) and fixed capital stock at replacement value to calculate the investment (*I*) to beginning of year capital stock (*K*) ratio ($IK_t$).[17] Additional control variables in the empirical investment model

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[14] Non-capital resources are represented in Ter-Martirosyan and Kwoka (2010) by two variables, operations expenses (that cover current firm operations) and maintenance expenses (that involve servicing the infrastructure). Our dataset does not allow us to distinguish between the two and we are bound to employ a single variable which, inevitably, aggregates preventive as well as corrective costs.

[15] Ter-Martirosyan and Kwoka (2010) employ average income per capita or per capita consumption with the same purpose. Other potentially interesting control variables, such as zonal density or the average length of feeders per substation report a high correlation with the variable *UNDER* (respectively, 0.666 and -0.575). Hence, they were not included in the analysis.

[16] The publicly available data from ISTAT are provided per administrative province, which closely matches *Enel*'s distribution units. Precipitation is defined as rain, snow, sleet or hail that falls on the ground and is measured in mm.

[17] Accounting data typically include only historic cost valuations of fixed assets (capital stock), which usually bear little relation to current replacement cost of long-lived fixed capital assets. Hence, we calculate the replacement cost of the capital stock using the perpetual inventory formula: $p_{t+1}K_{t+1} = p_tK_t(1\text{-}\delta)(p_{t+1}/p_t) + p_{t+1}I_{t+1}$, where $p_t$ is the domestic price index of investment goods in period *t* sourced by the ISTAT (the National Institute of Statistics), $K_t$ is the fixed capital stock in period *t*, $I_t$ is the investment flow in period *t*, and $\delta$ is the

are the operating cash flow (including depreciations, $\Pi_t$) and the revenues from sales ($S_t$) to the beginning of year capital stock ratio ($\Pi K_t$ and $SK_t$ respectively). Regulatory incentives enter the investment model as ratios over the beginning of year capital stock (respectively, $INCK_t$, $REWARDK_t$, $PENALTYK_t$), in the same way as operational expenditures enter the Granger test as ratios over the beginning of year capital stock ($OpK_t$).[18]

Finally, several variables are employed as external instruments: zonal density, measured by the number of LV consumers over network length (*DENSITY*), the area covered by forests (*FOREST*) and two dummy variables, one (*NORTH*) accounting for Zones located in the North of Italy (the more industrialized part of the country) and one (*COAST*) capturing the proximity to the sea.

Table 1 summarizes the variables' descriptions. Table 2 reports basic descriptive statistics and Table 3 reports average economic performance of distribution units in terms of investments, operational expenditures and incentives by SAIDI quartiles. The most relevant features of the distribution across SAIDI quartiles are not only the obvious negative relationship between continuity of supply and incentives, but, more interestingly for us, the negative relation between SAIDI, the investment rate and the operational expenses. Table 3 also highlights that the amount of incentives is not trivial with respect to investment and operational expenditures. Rewards represent 22.8% of investment outlays at the top quartile (best performers) and only 9.5% at the bottom quartile. Penalties are in practice nonexistent among top performers, and mount to almost 2% of the investment outlays for units with the lowest quality performance. Finally, with respect to operational expenditures, on average, incentives account for 10.1% of operational expenditures in the top quartile and for 2.2% in the bottom quartile.

## 5. Empirical strategy and estimation results

### *5.1 Determinants of continuity of supply (step one)*

To study the determinants of continuity of supply, we estimate a fixed-effects model, where *SAIDI* (in minutes) is the dependent variable. Explanatory variables include capital and non-capital resources, as well as control variables, as described in Section 4 (see Table 2). To proxy for capital resources, we consider only physical measures of equipment whose main

depreciation rate. The sector specific depreciation rate for the energy sector (4.4%) is derived from Bureau of Economic Analysis estimates reported in "Rates of Depreciation, Service Lives, Declining Balance Rates, and Hulten-Wykoff Categories".

[18] When taken as ratios to the beginning of year capital stock, variables *INC*, *REWARD*, *PENALTY* and *OPEX* are not adjusted for inflation.

purpose is to reduce the duration and frequency of *regulated* interruptions (that are key in the calculation of rewards and penalties). Indeed, our dataset does not provide separate monetary amounts spent on these assets alone. A well-known technical and accounting problem with distribution networks is that while a few quality-specific assets can be clearly identified, most structural interventions made by the distributor have multiple purposes. Using the physical measure of these (clearly identifiable) quality-specific interventions is particularly useful in this first step  Differently, when the focus of the analysis shifts to the *monetary* value of the economic incentives, we switch to using the aggregate value of fixed capital assets and to a more standard, accounting-based definition of the investment rate (from Section 5.2 onwards). For non-capital resources, instead, because, the nature of the data does not allow us to focus on quality-specific measures of operational expenses.  As a result, have to rely on aggregated accounting values.

The model takes the following form:

$$SAIDI_{i,t} = \alpha_0 + \alpha_1 UNDER_{i,t} + \alpha_2 AUTO\_LVcons_{i,t} + \alpha_3 PC\_LVcons_{i,t} + + \alpha_4 OPEX\_LVcons_{i,t} + \alpha_5 PERC\_NR_{i,t} + \alpha_6 PRECIPITATION_{i,t} + \alpha_7 MIN\_TEMP_{i,t} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where *i* indicates the distribution unit (Zone) and *t* the year. The model includes Zone, $\mu_i$, and year, $\lambda_t$, dummies, and an error term, $\varepsilon_{it}$. As usual, firm fixed effects account for all time invariant observable and unobservable variables.[19]

In Table 4, Column (1) and (2) present the results of two simple specifications where we include the physical asset components and the operational expenses separately along with the unit-specific control variables, while Column (3) reports the results when we include both. Overall, the results show that specific, quality-related capital resources positively affect the level of service. In particular, the effect is statistically significant for the share of underground lines (*UNDER*) and for the number of automated secondary substations (*AUTO_LVcons*) – both exhibit the expected negative signs. As for the lack of significance of *PC_LVcons*, this might depend on the fact that Petersen coils are installed to reduce the

[19] Given the presence of a number of potentially relevant time invariant territorial characteristics, we started the empirical analysis by estimating a random effects panel model. However, although the random effects estimates are more efficient than fixed effects estimates, in order to be valid, one must ensure that the individual invariant component in the error term is not correlated with regressors. To test for the consistency of the random effects coefficients we thus employed the Hausman (1978) specification test, but in all specifications the results pointed us to use fixed effects estimation.

number of interruptions: their effect on their duration is therefore only indirect. Differently, in Column (2), we find that operational expenditures (*OPEX_LVcons*) have a significant and positive effect on *SAIDI*. We interpret this as a prevalence of corrective costs in our aggregate variable, i.e. operational costs related to the need to respond to interruptions in the service. As for control variables, we find an unexpected positive sign on the share of non-residential energy consumption (*PERC_NR*) and on the minimum temperature variable (*MIN TEMP*). However, their estimated coefficients are both statistically insignificant.[20] In contrast, the second weather variable (*PRECIPITATION*) has a positive and significant coefficient, meaning that more intense precipitation in a Zone has a negative effect on service quality.

To account for potentially (unobserved) factors correlated with changes in regulatory period, we interact all independent variables with a dummy (*REGII*) that takes value 1 for all observations in years 2008 and 2009. Results are reported in Column (4). We find that the interacted technical variables are all insignificant, meaning that their effect on the dependent variable does not differ across the two regulatory periods. The only significant interaction is with operational expenses, which appears to have negatively affected service quality in 2008 and 2009, possibly due to a prevalence of preventive costs (Jamasb et al., 2012). However, the sum of the coefficients on linear and interacted operational expenditures terms remains positive, confirming our previous results.

Finally, to test the robustness of our fixed effect estimates, we account for the potential endogeneity in this dynamic relationship. We thus include the lagged *SAIDI* in the regression and, we use the Arellano and Bond (1991) and Arellano and Bover (1995) linear generalized method of moments (GMM) estimators to deal with the dynamic panel bias and the potential endogeneity of other regressors.[21] To check the validity of the instrument set, we then calculate the two-step Sargan-Hansen statistic under the null hypothesis of joint validity of the instruments and report the resulting p-values in Table 4 – Columns (5) and (6).[22] However, the Hansen test does not provide information on the strength, or relevance, of the

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[20] As a robustness check, we also estimated the above models normalizing the independent variables with respect to the power sold (MWh). Our results remain consistent with those in Table 4. For this reason, and to save space, we do not report them in the paper, but make them available upon request.

[21] We use the dynamic System-GMM model developed by Arellano and Bond (1991) and Blundell and Bond (1998). This model estimates a system of level and first-differenced equations and uses lags of first-differenced variables as instruments for equations in levels and lags of variables in levels as instruments for equations in first-differences. For the estimation, we used the *xtabond2* Stata module created by Roodman (2006).

[22] The set of instruments includes lags of all the variables in the regression as well as a number of external variables that account for the unit-specific environment: the size of the service area in $km^2$ (*AREA*); the area covered by forests, in *ha* (*FOREST*), and a dummy variable denoting proximity to the sea (*COAST*).

instruments. Since no well-established criteria is available for evaluating the joint relevance of the instrument set (as for the standard two-stage least squares instrumental variable method), we follow the two-step procedure recently introduced by Wintoki *et al*. (2012) and calculate the Cragg-Donald Wald statistics, designed to test weak identification of the instrument set.[23]

Results in Columns (5) and (6) show that most of the variables keep the expected sign confirming previous results. *UNDER* remains negative and significant, *PRECIPITATION* enters with a positive and significant coefficient and the positive coefficient on *OPEX_LVcons* is not far from significance (p value = 0.12). Moreover, the GMM results show that the number of Petersen coils (*PC_LVcons*) has the expected negative and significant impact on *SAIDI* while *AUTO_LVcons* loses significance. Interestingly, we now find that both the share of non-residential energy consumption (*PERC_NR*) and the minimum temperature variable (*MIN TEMP*) enter significantly and with the expected negative sign in Column (5).

From a research perspective, our results add to previous literature by providing evidence on the role of specific, structural interventions on quality levels.[24] While grounding of feeders is a well-known, quality-enhancing strategy, to the best of our knowledge, the impact of network automation and neutral grounding has not been studied previously. We can use our GMM estimates to find some quantitative implications. For example, doubling the average number of Petersen coils per $10^4$ consumers, from 0.55 to 1.1, would lead to a decrease in SAIDI of around 3 minutes. By increasing the percentage of underground lines by one percentage point, the number of minutes lost per customer would decrease in the range of 2 to 4 minutes, depending on the specification; evaluated at the sample mean, this implies that SAIDI would decrease on average from 56 to 54-52 minutes per customer. Interestingly, one may also note that an increase of 100 mm of *PRECIPITATION* (from 783 mm to 883 mm at the sample mean) would increase SAIDI by about 2 minutes. Finally, the results for non-

[23] The procedure adapts the two-stage procedure to the GMM-System estimation method and relies on the critical values developed by Stock and Yogo (2005) for testing weak identification as used in the 2SLS framework. Following Wintoki *et al.* (2012), and adapting to the system structure of GMM-System, we perform the test on the *levels* of endogenous variables regressed on the instruments in *first-differences* and obtain the first Cragg-Donald (CD) Statistic. Then, we regress the *first-differences* of the endogenous variables on the instruments in *levels* and obtain the second CD statistic. We finally compare the CD statistics with critical values by Stock and Yogo (2005). In Table 6 – Panel A, the values of the CD test are well above the critical value of 10, which is the "rule of thumb" critical value suggested for assessing strength of the instruments. See also Fremeth and Shavers (2014) for a similar implementation of the test.

[24] Differences in quality performance across Italian distribution units are associated with network structure and type of consumers served (Cambini et al., 2014). Since the latter can hardly be modified, it is not surprising that quality improvements in Italy are mainly driven by structural interventions (e.g., grounding of feeders and network automation).

capital resources highlight the corrective role of operational costs, while evidence provided by Ter-Martirosyan and Kwoka (2010) supports the (preventive) effect of maintenance expenditures.

We now proceed to examine the direction of causality between output-based incentives and firm decisions on investment and operational expenditures. We are not aware of any previous work that uses Granger causality tests to this purpose.

### *5.2 The relationship between capital and non-capital expenditures and incentives (step two)*

To test the direction of the relationship between incentives and capital resources we perform a Granger test by estimating the following bivariate vector autoregressive VAR(2) model for incentives and investment rates:

$$IK_{i,t} = \alpha_{t-1} IK_{i,t-1} + \alpha_{t-2} IK_{i,t-2} + \beta_{t-1}^{INC} INC_{i,t-1} + \beta_{t-2}^{INC} INC_{i,t-2} + \mu_i + \lambda_t + \varepsilon_{it}^{IK} \tag{3}$$

$$INC_{i,t} = \alpha_{t-1}^{IK} IK_{i,t-1} + \alpha_{t-2}^{IK} IK_{i,t-2} + \beta_{t-1} INC_{i,t-1} + \beta_{t-2} INC_{i,t-2} + \mu_i + \lambda_t + \varepsilon_{it}^{INC} \tag{4}$$

where $IK_{it}$ is the ratio between gross fixed investment and the beginning of the year capital stock at replacement value, $INC_{it}$ is the inflation corrected amount of incentives, $\mu_i$ and $\lambda_t$ are the Zone and year dummies, and $\varepsilon_{it}^{IK}$ and $\varepsilon_{it}^{INC}$ are the error terms.

The hypothesis that, conditional on individual and time effects, incentives Granger-cause firm investments, but not vice versa, requires that $\beta_{t-1}^{INC}$ and $\beta_{t-2}^{INC}$ are positive and jointly significant in equation (3), while $\alpha_{t-1}^{INC}$ and $\alpha_{t-2}^{INC}$ are not significant in equation (4). In other words, it requires that past incentives ($INC_{i,t-1}$ and $INC_{i,t-2}$) contribute significantly to the investment rate in regression (3), while past investments ($IK_{i,t-1}$ and $IK_{i,t-2}$) do not contribute significantly to determine incentives in equation (4).

In order to control that the total effect of the incentives on investment is positive as well as significant, we test the joint significance of the once and twice-lagged coefficients as well as their sum and report the p-values of the Wald tests with the regression results in Table 5 – Panel A.

A main concern when estimating a dynamic model as in equations (3) and (4) is that the lagged dependent variables are endogenous to the fixed effects in the error term, thus giving rise to a dynamic panel bias. As before, we rely on the GMM estimators and we calculate the two-step Sargan-Hansen statistic under the null hypothesis of joint validity of the instruments and report the resulting p-values in Table 5 – Panel A.[25] To ensure that the lagged variables are valid instruments, we also present the AR(1) autocorrelation test for the first-differenced error terms.[26]

The results from estimating equations (3) and (4) are in the first two columns. The results in Column (1) show that only the twice-lagged incentive term is statistically significant. However, the Wald test indicates that the first and second lags of the incentives in Column (1) are jointly significant in explaining the investment rate. Moreover, quite importantly, the sum of their coefficients is positive and significant. In contrast, in Column (2), the lagged investment terms are insignificant and do not contribute, either individually or jointly, to explain the amount of incentives granted to the distribution Zone. The results of the test indicate that lagged incentives contribute significantly to determine the investment rate of a Zone, and not vice-versa. From a research perspective, our results add to the existing literature by establishing a direction in the causality between incentives provided by the regulatory authority (in previous periods) and the firm's investment decision.

We then turn to the relationship between incentives and operational expenses by using the following bivariate Granger causality test:

$$OpK_{i,t} = \alpha_{t-1} OpK_{i,t-1} + \alpha_{t-2} OpK_{i,t-2} + \beta_{t-1}^{INC} INC_{i,t-1} + \beta_{t-2}^{INC} INC_{i,t-2} + \mu_i + \lambda_t + \varepsilon_{it}^{OpK} \tag{5}$$

$$INC_{i,t} = \alpha_{t-1}^{OpK} OpK_{i,t-1} + \alpha_{t-2}^{OpK} OpK_{i,t-2} + \beta_{t-1} INC_{i,t-1} + \beta_{t-2} INC_{i,t-2} + \mu_i + \lambda_t + \varepsilon_{it}^{INC} \tag{6}$$

where $OpK_{i,t}$ is the ratio between the operational expenses in year *t* and the capital stock in year *t-1*. As before, our hypothesis requires that both $\beta_{t-1}^{INC}$ and $\beta_{t-2}^{INC}$ are positive and jointly significant in equation (5), while $\alpha_{t-1}^{OpK}$ and $\alpha_{t-2}^{OpK}$ are not significant in equation (6).

[25] The Sargan-Hansen test is robust, but may be weakened if there are too many instruments with respect to the number of observations (Roodman, 2006). Therefore we follow a conservative strategy using no more than one/two lags of the instrumenting variables (i.e. the third or fourth lags in our case), to assure that the number of instruments is not greater than the number of firms. The rather demanding time structure of the Granger test and of the GMM-System estimator is also the reason why the number of observations drops from 690 in Table 4 to 345 in Table 5 – Panel A (although of course all observations are used in the estimation).

[26] The AR(2) tests of the second-order correlation in the first-differenced residuals could not be calculated by STATA due to length of our time series. However, the purpose of the AR(2) test is to assess the validity of instruments lagged two years and in case of invalidity of the instrument, the third lag has to be used. As explained in the footnote above, the third lag of the variable is indeed the earliest instrument that we use, hence the AR(2) test is not relevant to us.

Results in Columns (3) and (4) of Table 5 – Panel A show that lagged incentives contribute significantly to explaining the variable *OpK*, but the two coefficients $\beta_{t-1}^{INC}$ and $\beta_{t-2}^{INC}$ bear opposite signs. While incentives granted one-year ago appear to increase operational expenses, incentives granted two years ago appear to reduce them. Not surprisingly, the sum of the two coefficients is not significantly different from zero, as shown by the test reported at the bottom of the column. When we look at the reverse relationship, i.e. whether past operational expenses significantly determine incentives, we find that the coefficients on lagged operational expenses are never significant in the regression where the dependent variable is the amount of incentives to the Zone.

Overall, the results in Columns (3) and (4) do not support any direction in the causality between incentives and operational expenses, possibly due to our inability to separate preventive from corrective costs within the operational expenses item.[27]

To further test the robustness of our analysis, we also run the Granger tests replacing *INC* (incentives) with *REWARDS* (i.e. positive incentive payments) as the main variable of interest. Results are reported in Table 5 – Panel B. The results show that (past) rewards do affect investment rate, but not vice versa. Once again, the evidence when we use operational expenses does not allow us to establish the direction of the causality between rewards and operational expenditures. Overall, this further evidence is consistent with the results in Table 5-Panel A.

### *5.3 The impact of quality-related incentives and the asymmetric effect of penalties and rewards (step three)*

In this section, we expand the scope of the analysis of the relationship between investment and incentives. We first test if past incentives still affect investment after controlling for other potential determinants and we then investigate whether penalties and rewards have similar or asymmetric effects on investment.

We conjecture that rewards and penalties received act as a signal (more or less effective) of the adequacy of the capital expenditure decisions made by the firm to control continuity of supply: a reward indicates that firm decisions were more than adequate (above the regulatory expectations) and vice versa. Hence, we expect penalties do stimulate investments:

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[27] We recall that previous literature has found (weak) evidence that quality standards (not necessarily output-based incentives) result in greater maintenance expenditures (Ter-Martisoryan and Kwoka, 2010). We must postpone further investigation until this distinction in the data becomes available.

even if the firm (on a rational basis) had not spent on quality in the previous period, it should be more prone to invest after receiving a penalty. As for rewards, we have equal expectations for both types of responses. On the one hand, a premium might reinforce the firm's willingness to take additional measures to reduce outages. On the other hand, it may also induce the firm simply to maintain the same level of quality performance.

For a basic empirical model, we rely on the micro econometric literature on company investment. We include the *lagged investment ratio* to account for capital stock adjustment, and *demand growth*, measured by the change in sales to capital stock ratio [$\Delta(SK_t)$], to account for the accelerator effect and for future investment opportunities. [28] Moreover, to control for *financing constraints* due to imperfect capital markets and asymmetric information, we add the operating cash flow to capital stock ratio ($\Pi K_t$).[29]

We augment this model by adding the monetary incentives, normalized with respect to beginning of the year capital stock at replacement value. We start with the aggregate incentive variable ($INCK_t$), which can take positive or negative values, then we test the effect of rewards ($REWARDK_t$) and finally we turn to penalties ($PENALTYK_t$), all of which entered separately in the investment specification. The baseline specification is the following:

$$IK_{i,t} = \alpha_0 + \alpha_1 IK_{i,t-1} + \alpha_2 \Delta SK_{i,t} + \alpha_3 \Pi K_{i,t} + \alpha_4 INCK_{i,t-1} + \lambda_t + \mu_i + \varepsilon_{it} \quad (7)$$

where $INCK_{i,t-1}$ is alternatively replaced by $REWARDK_{i,t-1}$, $PENALTYK_{i,t-1}$; $\lambda_t$ and $\mu_i$ are the Zone and year dummies, while $\varepsilon_{it}$ is the error term.

To estimate the dynamic investment model in equation (7) with panel data, we rely on the linear generalized method of moments (GMM) estimator.[30] We report the two-step Sargan-Hansen statistic under the null hypothesis of joint validity of the instruments, the difference in Hansen test of exogeneity (which compares full and restricted models to assess the orthogonality of the instruments) and the AR(1) and AR(2) autocorrelation tests for the first-differenced error terms. Moreover, we calculate the Cragg-Donald Wald statistics, designed to test weak identification of the instrument set.

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[28] Recall that revenues from tariffs (i.e. sales) also cover quality-related costs for the provision of target SAIDI.

[29] See, for example, Hubbard (1998) for a comprehensive survey of company investment models estimated with panel data, Fazzari et al. (1988) for a seminal contribution, Lyon and Mayo (2005) for an application to the US electric utility industry and Cambini and Rondi (2010) for an application to EU energy companies.

[30] The set of instruments includes lags of investment, sales, cash flow and incentives (or rewards or penalties) to capital stock ratios as well as a number of external variables that account for the unit-specific environment: the percentage of the non residential energy consumption (*PERC_NR*); zonal density, measured by the number of LV consumers over network length (*DENSITY*); the area covered by forests, in *ha* (*FOREST*), and a dummy variable indicating Zones in the North of the country (*NORTH)*.

We report the results in Table 6 – Panel A. In Column (1) we examine the effect of the aggregate incentive variable and in Columns (2) and (3) we test the separate effect of rewards and penalties.[31] In all Columns, both demand growth and the cash-flow to capital ratio enter with a positive and significant coefficient, suggesting that demand and financial factors do matter for the investment decisions. Moreover, the lagged investment term is positive and not too far from significance in most specifications. Having established that the usual control variables work as expected, we turn to the effect of the output-based incentive scheme, which is the focus of the paper.

In Column (1), the effect of the aggregate measure of monetary incentives ($INC_t/K_{t-1}$) is positive, but the coefficient is insignificant, possibly because the effects of rewards and penalties cancel each other out in this specification, i.e. after controlling for other determinants of investment. To pin down the effect of the output-based incentives policy we thus follow an alternative route and test, separately, the role of reward and penalties. If both types of incentives are "successful" in fostering capital expenditures, we should find that *REWARDK* carries a positive sign, while *PENALTYK* should enter with a negative coefficient. This is what we find when we look at Columns (2) and (3) in Table 6 – Panel A. However, while the negative coefficient on *PENALTYK* is statistically significant (with a p-value of 0.022), the coefficient on *REWARDK* is positive but insignificant. This indicates that the firm is more sensitive to negative, than to positive incentives.

These findings reveal an asymmetric effect of rewards and penalties, as rewards do not seem to affect significantly the firm's investment decision while penalties apparently do. To throw some light on this result, in Table 6 – Panel B we divide the sample in subgroups according to different levels of quality performance, i.e. by SAIDI quartiles, and then test whether rewards and penalties present a differentiated impact whenever Zones report different quality performance.[32] In Column (1), we analyze the effect of regulatory incentives in Zones with the SAIDI indicator below 32 minutes (top quartile in terms of service quality). Results show that rewards do matter in top quality Zones, affecting the investment rate. When we turn to Zones in the range of intermediate quality performance (second and third quartiles) we find that neither rewards (Column 2) nor penalties (Column 3) display a significant effect on investment. Finally, when we look at the sub-sample of units with the lowest quality of service (above 73.9 minutes), we find that the coefficient on *PENALTYK* is

[31] We also checked the fixed effect results from the static version of the investment model and we found that they hold. Results are available on requests.
[32] We thank an anonymous referee for suggesting us this further analysis.

negative and significant, which, recalling that the variable is entered with a negative sign, means that penalties have a positive effect on the investment rate. If we translate the estimated coefficients into quantitative effects, we find that a 1 percentage point increase in the reward to capital stock ratio for high performing units would lead to a 0.4% increase in the investment rate; evaluated at the sample mean, this implies an increase from 6.6% to 7%. Turning to penalties, and taking into account that they are on average quite lower than rewards (see Tables 2 and 3), we find that by doubling the mean *PENALTYK* to less performing units from 0.35% to 0.70%, the investment rate would increase by 0.5 percentage points; that is, evaluated at the mean, from 5.8% to 6.2% (not far from the investment rate of the best performing units).

Not only this is a novel result from a research perspective, but it also conveys interesting policy insights into output-based regulation.[33] We find that the Italian incumbent distributor does respond to the signal provided by penalties received the year before by deploying capital resources to improve service quality. In other words, penalties paid in the past are effective in inducing the firm to exert effort aimed at improving quality, and especially so if it operates in area with a low quality performance. As for rewards, we interpret the lack of statistical significance in the majority of areas as an indication that *ENEL Distribuzione* views positive monetary incentives as a signal that their level of output is adequate. Accordingly, rewards granted the year before are less likely to lead the firm to invest further (i.e. to exercise an additional effort).

## 6. Conclusions and policy implications

We use detailed micro data on service quality (duration of service interruptions), monetary incentives and physical assets for the largest Italian electricity distributor to shed some light on the relation between quality-based incentives and the incumbent's decisions about capital and operational expenditures in order to meet given regulatory targets. This analysis is relevant, not only because it aims at throwing some light on the practical implementation of output-based regulatory mechanisms, but also because regulators are currently expanding the set of regulatory outputs that are subject to incentive mechanisms.

[33] Using a different empirical approach, Poudineh and Jamasb (2015) find that the cost of energy-not-supplied seems relevant in explaining the investment behavior of Norwegian electricity distribution companies. However, their result suggests that investments have mainly been of a corrective nature rather than a preventive one (they are a response to outages in the same time period).

We begin by providing empirical evidence that investments in specific quality-related physical assets are effective in enhancing the level of service quality. This adds to previous literature that focused on the effect of operational expenditures. Then, we concentrate on the direction of the causality in the relationship between incentives to quality and the use of capital and non-capital resources. We find that incentives Granger-cause capital expenditures (and not vice-versa). Finally, we proceed to verify whether incentives continue to affect firms' decision to invest, after we account for other potential determinants of the investment rate. We do so also by considering the effect on investment of positive and negative incentives, i.e. reward and penalties, separately. Our results show that (paid) penalties are more effective than rewards in prompting the incumbent to invest capital resources to improve their performance. When we divide the sample in subgroups of zones with different levels of service quality, we find that penalties have a significant and positive effect on the investment rate in zones with low quality performance but not where the service quality is intermediate quality. As for rewards, we find that they positively and significantly affect investment decisions in zones that report top service quality performance, but not within distribution units with intermediate quality.  The lack of significance of both rewards and penalties in intermediate quality areas suggests that monetary incentives do not provide any relevant signal to the regulated firm and that rewards are viewed as a premium for achieving a desirable level of performance, not as a stimulus to exert an additional effort. Overall, the evidence of an asymmetric role of quality-related incentives suggests that penalties and rewards should separately analyzed when assessing the effectiveness of an output-based regulatory policy.

Our results question the usefulness of maintaining a two-side (positive and negative) incentive scheme over the entire range of output levels, as well as the use of both types of incentives over a relatively wide output range, where they seem to be not effective (or no longer effective). These considerations appear relevant in light of the complex implementation of these incentive schemes and the associated costs incurred in practice by the regulatory authority.

On the policy ground, our results suggest that regulators might consider whether to assign incentives only to top or bottom quality units or, given the length of the investment process, perhaps assign them less frequently, i.e. not every year, but eventually only once in every regulatory period. Such policy would preserve the incentive mechanism and at the same time, it would reduce the occurrence of incentive assignments and, possibly, the cost of quality regulation.

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## Table 1. Variables' descriptions

| Variable name | Label | Description |
|---|---|---|
| *SAIDI* | System Average Interruption Duration Index | Average duration of long, unplanned interruptions per customer (in minutes). |
| *INC* | Regulatory incentives | Amounts received in rewards or paid in penalties (the variable assume either a positive or a negative sign). In constant euros (base 2005). |
| *REWARD* | Rewards | Equal to the variable *INC* if this is positive (and zero otherwise). In constant euros (base 2005). |
| *PENALTY* | Penalties | Equal to the variable *INC* if this is negative (and zero otherwise). In constant euros (base 2005). |
| *UNDER* | Percentage of underground cable | Ratio of underground cable length over total network length. |
| *AUTO_LVcons* | Number of automated secondary substations per Low Voltage (LV) consumer | Ratio of the number of automated secondary substations over the number of LV consumers. |
| *PC_LVcons* | Number of Petersen coils per LV consumer | Ratio of the number of Petersen coils over the number of LV consumers. |
| *PERC_NR* | Percentage of non-residential energy consumption | Ratio of LV non-residential energy consumption plus Medium Voltage (MV) energy consumption to total energy consumption. |
| *OPEX* | Operational expenditures | Sum of costs incurred for labor, services, materials and other costs. In constant euros (base 2005). |
| *OPEX_LVcons* | Operational expenditures per LV consumer | Ratio of operational expenditures to the number of LV consumers. In constant euros (base 2005). |
| *PRECIPITATION* | Precipitation | Yearly average amount of rain, snow, sleet, or hail that falls to the ground (in mm) |
| *MIN TEMP* | Minimum temperature | Yearly average minimum temperature (in Celsius degrees) |
| *IK* | Investment rate | Ratio of investments (*I* in *t*) to the beginning of year capital stock, at replacement value (*K* in *t*-1). |
| *ΠK* | Operating cash flow to capital stock ratio | Ratio of operating cash flow (*Π* in *t*) to the beginning of year capital stock, at replacement value (*K* in *t*-1). |
| *SK* | Sales to capital stock ratio | Ratio of sales (*S* in *t*) to the beginning of year capital stock, at replacement value (*K* in *t*-1). |
| *OpK* | Operational expenditures to capital stock ratio | Ratio of operational expenditures (*OPEX* in t) to the beginning of year capital stock, at replacement value (*K* in *t*-1). |
| *INCK* | Incentives to capital stock ratio | Ratio of incentives (*INC* – not adjusted for inflation – in year *t)* to the beginning of year capital stock, at replacement value (*K* in year *t*-1). |
| *REWARDK* | Rewards to capital stock ratio | Ratio of rewards (*REWARD* – not adjusted for inflation – in year *t*) in year *t* t to the beginning of year capital stock, at replacement value (*K* in year *t-1*). |
| *PENALTYK* | Penalties to capital stock ratio | Ratio of penalties (*PENALTY* – not adjusted for inflation – in year *t*) to the beginning of year capital stock, at replacement value (*K* in year *t-1*). |
| *COAST* | Proximity to the sea | Dummy variable that takes the value 1 when a Zone is close to the sea |
| *NORTH* | North of Italy | Dummy variable that takes the value 1 when a Zone is located in the North of the country |
| *AREA* | Dimension of the service area | Total area covered (in $km^2$) |
| *DENSITY* | Consumer density | Ratio of number of LV consumer to network length |
| *FOREST* | Area covered by forest | Hectares of land covered by forest |

## Table 2 – Summary statistics

| Variable | Mean | Std. Dev. | Min | Max | N. Obs. |
|---|---|---|---|---|---|
| *SAIDI* (minutes) | 56.34 | 31.56 | 10.42 | 194.28 | 690 |
| *INC* (M€) | 0.87 | 1.13 | -3.07 | 8.77 | 690 |
| *REWARD* (M€) | 0.90 | 1.09 | 0.00 | 8.77 | 690 |
| *PENALTY* (M€) | 0.03 | 0.18 | 0.00 | 3.07 | 690 |
| *UNDER* (%) | 0.71 | 0.12 | 0.46 | 0.97 | 690 |
| *AUTO_LVcons* (n./$10^2$ consumers) | 2.80 | 0.076 | 0.123 | 0.849 | 690 |
| *PC_LVcons* (n./$10^4$ consumers) | 0.549 | 0.379 | 0.00 | 2.34 | 690 |
| *PERC_NR* (%) | 0.72 | 0.08 | 0.51 | 0.85 | 690 |
| *OPEX* (M€) | 17.19 | 8.52 | 4.13 | 50.48 | 690 |
| *OPEX_LVcons* (€/consumer) | 65.04 | 10.87 | 43.20 | 112.52 | 690 |
| *PRECIPITATION* (mm) | 782.90 | 173.51 | 406 | 1378.7 | 690 |
| *MIN TEMP* (°C) | 8.81 | 2.86 | -1.5 | 15.2 | 690 |
| *IK* | 0.06 | 0.02 | 0.00 | 0.26 | 575 |
| *ΠK* | 0.24 | 0.10 | 0.07 | 0.96 | 575 |
| *SK* | 0.34 | 0.11 | 0.14 | 1.15 | 575 |
| *OpK* | 0.14 | 0.03 | 0.06 | 0.40 | 690 |
| *INCK* | 0.009 | 0.010 | -0.012 | 0.087 | 575 |
| *REWARDK* | 0.009 | 0.010 | 0.00 | 0.087 | 575 |
| *PENALITYK* | 0.0003 | 0.0013 | 0.00 | 0.012 | 575 |
| *AREA* ($km^2$) | 2480.22 | 1445.81 | 130.92 | 7274.35 | 690 |
| *COAST* | 0.54 | 0.50 | 0 | 1 | 690 |
| *NORTH* | 0.42 | 0.49 | 0 | 1 | 690 |
| *DENSITY* (consumers/km) | 28.71 | 11.68 | 13.07 | 82.94 | 690 |
| *FOREST* (ha) | 106,310 | 98,638 | 2,519 | 422,772 | 690 |

## Table 3 – Average level of the main economic variables by service quality defined as SAIDI quartiles

| *Service Quality (SAIDI, minutes)* | *Investment/ Capital Stock (IK)* | *Operation Exp./ Cap. Stock (OpK)* | *Incentives/ Cap. Stock (INCK)* | *Incentives/ Op.Ex/ (%)* | *Rewards/ Investment (%)* | *Penalties/ Investment (%)* |
|---|---|---|---|---|---|---|
| *SAIDI* < 32 | 0.066 | 0.149 | 0.015 | 10.1 | 22.8 | 0.002 |
| 32 ≤ *SAIDI* < 47.7 | 0.062 | 0.140 | 0.010 | 7.1 | 18.3 | 0.074 |
| 47.7 ≤ *SAIDI* < 73.9 | 0.058 | 0.143 | 0.005 | 3.5 | 12.8 | 0.79 |
| *SAIDI* ≥ 73.9 | 0.058 | 0.138 | 0.003 | 2.2 | 9.5 | 1.92 |

## Table 4. Technical and economic determinants of continuity of supply (SAIDI)

| Dep. Variable: *SAIDI* | (1) Physical Equipment | (2) Operational expenditures | (3) Physical Equipment and Operational expenditures | (4) Controlling for regulatory periods | (5) Physical Equipment | (6) Physical Equipment and Operational expenditures |
|---|---|---|---|---|---|---|
| | **Fixed Effects** | | | | **GMM** | |
| UNDER | -426.91** | - | -334.46* | -268.24 | -469.00*** | -260.52** |
| | (211.86) | - | (195.97) | (235.99) | (125.75) | (132.81) |
| AUTO_LVcons | -51.83** | - | -52.91** | -57.54** | -10.82 | -36.56 |
| | (4.21) | - | (22.07) | (26.47) | (19.19) | (26.02) |
| PC_LVcons | -3.584 | - | -1.854 | -1.223 | -6.274* | -6.687** |
| | (4.21) | - | (4.078) | (3.913) | (3.464) | (3.363) |
| OPEX_LVcons | - | 1.162*** | 1.056*** | 1.041*** | - | 0.451 |
| | - | (0.324) | (0.309) | (0.314) | - | (0.290) |
| PERC_NR | 118.62 | 144.08 | 146.02 | 186.11 | -129.31*** | -109.93*** |
| | (131.41) | (125.39) | (126.12) | (137.43) | (22.74) | (22.74) |
| PRECIPITATION | 0.025*** | 0.025*** | 0.023*** | 0.023*** | 0.020*** | 0.019*** |
| | (0.007) | (0.008) | (0.007) | (0.007) | (0.006) | (0.006) |
| MIN TEMP | 2.486 | 1.775 | 1.635 | 2.001 | -1.235** | -0.824 |
| | (2.16) | (1.960) | (2.026) | (2.069) | (0.62) | (0.532) |
| $SAIDI_{t-1}$ | - | - | - | - | 0.453*** | 0.478*** |
| | - | - | - | - | (0.065) | (0.059) |
| UNDER*REGII | - | - | - | -0.98 | - | - |
| | - | - | - | (17.00) | - | - |
| AUTO_LVcons*REGII | - | - | - | 15.00 | - | - |
| | - | - | - | (21.72) | - | - |
| PC_LVcons*REGII | - | - | - | -1.982 | - | - |
| | - | - | - | (3.870) | - | - |

| | | | | | | |
|---|---|---|---|---|---|---|
| OPEX_LVcons*REGII | - | - | - | -0.583** | - | - |
| | - | - | - | (0.265) | - | - |
| Constant | 256.62 | -156.74 | 99.32 | 23.79 | 152.78*** | 98.64*** |
| | (182.04) | (94.12) | (183.55) | (219.50) | (25.61) | (35.52) |
| Unit dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.358 | 0.368 | 0.383 | 0.392 | - | - |
| AR(1) | - | - | - | - | 0.000 | 0.000 |
| AR(2) | - | - | - | - | 0.332 | 0.418 |
| Sargan-Hansen Test (p value) | - | - | - | - | 0.202 | 0.171 |
| Cragg-Donald weak identification test statistic (levels) | - | - | - | - | 11.3 | 7.31 |
| Cragg-Donald weak identification test statistic (first-diff) | - | - | - | - | 33.29 | 26.47 |
| Observations | 690 | 690 | 690 | 690 | 575 | 575 |
| Number of units | 115 | 115 | 115 | 115 | 115 | 115 |

All variables are defined in Table 1. Robust standard errors in parentheses:
*** p<0.01, ** p<0.05, * p<0.1

**Table 5 – Panel A. Granger Tests: relationship between investment and incentives and between operational expenditures and incentives**

| *Investment and Incentives* | | | | *Operational expenditures and Incentives* | | | |
|---|---|---|---|---|---|---|---|
| Dep. Variable: *IK* | | Dep. Variable: *INC* | | Dep. Variable: *OpK* | | Dep. Variable: *INC* | |
| $\alpha_{t-1}$ | -0.324 | $\alpha^{IK}_{t-1}$ | -38.178 | $\alpha_{t-1}$ | 0.819*** | $\alpha^{OpK}_{t-1}$ | 13.768 |
| | (0.418) | | (37.644) | | (0.301) | | (13.318) |
| $\alpha_{t-2}$ | -0.160* | $\alpha^{IK}_{t-2}$ | -8.880 | $\alpha_{t-2}$ | 0.121*** | $\alpha^{OpK}_{t-2}$ | 5.230 |
| | (0.086) | | (8.290) | | (0.035) | | (5.843) |
| $\beta^{INC}_{t-1}$ | -0.001 | $\beta_{t-1}$ | 0.202 | $\beta^{INC}_{t-1}$ | 0.002* | $\beta_{t-1}$ | 0.259** |
| | (0.002) | | (0.135) | | (0.001) | | (0.107) |
| $\beta^{INC}_{t-2}$ | 0.005** | $\beta_{t-2}$ | 0.348 | $\beta^{INC}_{t-2}$ | -0.003*** | $\beta_{t-2}$ | 0.105 |
| | (0.002) | | (0.221) | | (0.001) | | (0.071) |
| Constant | 0.082** | Constant | 3.099 | Constant | 0.025 | Constant | -2.465 |
| | (0.035) | | (3.021) | | (0.043) | | (2.378) |
| P-value test on H$_0$: $\beta^{INC}_{t-1} = \beta^{INC}_{t-2}$ =0 | 0.038 | P-value test on H$_0$: $\alpha^{IK}_{t-1} = \alpha^{IK}_{t-2}$ =0 | 0.558 | P-value test on H$_0$ $\beta^{INC}_{t-1} = \beta^{INC}_{t-2}$ =0 | 0.007 | P-value test on H$_0$: $\alpha^{OpK}_{t-1} = \alpha^{OpK}_{t-2}$ = 0 | 0.582 |
| P-value test on H$_0$: $\beta^{INC}_{t-1} + \beta^{INC}_{t-2}$ = 0 | 0.079 | P-value test on H$_0$: $\alpha^{IK}_{t-1} + \alpha^{IK}_{t-2}$ = 0 | 0.299 | P-value test on H$_0$: $\beta^{INC}_{t-1} + \beta^{INC}_{t-2}$ =0 | 0.597 | P-value test on H$_0$: $\alpha^{OpK}_{t-1} + \alpha^{OpK}_{t-2}$ = 0 | 0.301 |
| Obs. [Nr. Unit] | 345 [115] | Obs. [Nr. Unit] | 345 [115] | Obs. [Nr. Unit] | 345 [115] | Obs. [Nr. Unit] | 345 [115] |
| Hansen test | 0.648 | Hansen test | 0.293 | Hansen test | 0.513 | Hansen test | 0.027 |
| AR1 | 0.910 | AR1 | 0.218 | AR1 | 0.100 | AR1 | 0.014 |

All variables are defined in Table 1. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10

**Table 5 – Panel B. Granger Tests: relationship between investment and rewards and between operational expenditures and rewards**

| *Investment and Rewards* | | | | *Operational expenditures and Rewards* | | | |
|---|---|---|---|---|---|---|---|
| Dep. Variable: *IK* | | Dep. Variable: *REWARD* | | Dep. Variable: *OpK* | | Dep. Variable: *REWARD* | |
| $\alpha_{t-1}$ | -0.204 | $\alpha_{t-1}^{IK}$ | -27.167 | $\alpha_{t-1}$ | 0.655* | $\alpha_{t-1}^{OpK}$ | 30.819 |
| | (0.407) | | (33.877) | | (0.379) | | (26.279) |
| $\alpha_{t-2}$ | -0.187* | $\alpha_{t-2}^{IK}$ | -8.177 | $\alpha_{t-2}$ | 0.089*** | $\alpha_{t-2}^{OpK}$ | 6.705 |
| | (0.112) | | (9.495) | | (0.028) | | (8.150) |
| $\beta_{t-1}^{INC}$ | -0.002 | $\beta_{t-1}$ | 0.294** | $\beta_{t-1}^{INC}$ | 0.002 | $\beta_{t-1}$ | 0.331** |
| | (0.003) | | (0.128) | | (0.002) | | (0.146) |
| $\beta_{t-2}^{INC}$ | 0.007** | $\beta_{t-2}$ | 0.311 | $\beta_{t-2}^{INC}$ | -0.002** | $\beta_{t-2}$ | 0.012 |
| | (0.003) | | (0.237) | | (0.001) | | (0.088) |
| Constant | 0.067** | Constant | 2.240 | Constant | 0.047 | Constant | -4.601 |
| | (0.033) | | (2.699) | | (0.049) | | (4.350) |
| P-value test on H0: $\beta_{t-1}^{INC} = \beta_{t-2}^{INC} = 0$ | 0.020 | P-value test on H0: $\alpha_{t-1}^{IK} = \alpha_{t-2}^{IK} = 0$ | 0.668 | P-value test on H0 $\beta_{t-1}^{INC} = \beta_{t-2}^{INC} = 0$ | 0.096 | P-value test on H0: $\alpha_{t-1}^{OpK} = \alpha_{t-2}^{OpK} = 0$ | 0.448 |
| P-value test on H0: $\beta_{t-1}^{INC} + \beta_{t-2}^{INC} = 0$ | 0.027 | P-value test on H0: $\alpha_{t-1}^{IK} + \alpha_{t-2}^{IK} = 0$ | 0.407 | P-value test on H0: $\beta_{t-1}^{INC} + \beta_{t-2}^{INC} = 0$ | 0.881 | P-value test on H0: $\alpha_{t-1}^{OpK} + \alpha_{t-2}^{OpK} = 0$ | 0.268 |
| Obs. [Nr. Unit] | 286 [112] | Obs. [Nr. Unit] | 286 [112] | Obs. [Nr. Unit] | 286 [112] | Obs. [Nr. Unit] | 286 [112] |
| Hansen test | 0.643 | Hansen test | 0.158 | Hansen test | 0.496 | Hansen test | 0.125 |
| AR1 | 0.720 | AR1 | 0.122 | AR1 | 0.144 | AR1 | 0.033 |

All variables are defined in Table 1. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.10

**Table 6 – Panel A: Investment analysis - GMM estimations**

| Dep. Variable: $IK_{i,t}$ | (1) Incentives | (2) Rewards | (3) Penalties |
|---|---|---|---|
| $IK_{i,t\text{-}1}$ | 0.107 | 0.105 | 0.118 |
| | (0.089) | (0.089) | (0.085) |
| $\Delta SK_{i,t}$ | 0.133*** | 0.133*** | 0.134*** |
| | (0.024) | (0.024) | (0.022) |
| $\Pi K_{i,t}$ | 0.066*** | 0.068*** | 0.081*** |
| | (0.018) | (0.019) | (0.015) |
| $INCK_{i,t\text{-}1}$ | 0.241 | - | - |
| | (0.196) | - | - |
| $REWARDK_{i,t\text{-}1}$ | - | 0.233 | - |
| | - | (0.207) | - |
| $PENALTYK_{i,t\text{-}1}$ | - | - | -1.552** |
| | - | - | (0.679) |
| Constant | 0.033*** | 0.033*** | 0.030*** |
| | (0.006) | (0.006) | (0.006) |
| Unit dummies | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes |
| AR1 *(p-value)* | 0.006 | 0.006 | 0.005 |
| AR2 *(p-value)* | 0.556 | 0.559 | 0.735 |
| Hansen test of over-identification *(p-value)* | 0.454 | 0.477 | 0.673 |
| Diff-in-Hansen test of exogeneity *(p-value)* | 0.900 | 0.802 | 0.922 |
| Number of Instruments | 25 | 25 | 27 |
| Cragg-Donald weak identification test statistic (levels) | 31.49 | 31.19 | 40.88 |
| Cragg-Donald weak identification test statistic (first-diff) | 67.50 | 61.36 | 75.89 |
| Observations | 460 | 460 | 460 |
| Number of units | 115 | 115 | 115 |

All variables are defined in Table 1. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.10

**Table 6 – Panel B: Investment analysis - GMM estimations with Subsamples**

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.10$

| Dep. Variable: $IK_{i,t}$ | **(1)** *High performance units* (SAIDI ≤ 32) **I Quartile** | **(2)** *Average performance Units* (32 < SAIDI < 73.9) **II-III Quartile** | **(3)** *Average performance Units* (32 < SAIDI < 73.9) **II-III Quartile** | **(4)** *Low performance Units* (SAIDI ≥ 73.9) **IV Quartile** |
|---|---|---|---|---|
| $IK_{i,t-1}$ | 0.099 | 0.173 | 0.112 | 0.342 |
| | (0.072) | (0.199) | (0.152) | (0.276) |
| $\Delta SK_{i,t}$ | 0.160*** | 0.169*** | 0.168** | 0.585** |
| | (0.021) | (0.066) | (0.085) | (0.245) |
| $\Pi K_{i,t}$ | 0.074** | 0.186** | 0.189*** | 0.074 |
| | (0.030) | (0.080) | (0.071) | (0.077) |
| $REWARDK_{i,t-1}$ | 0.417** | -0.226 | - | - |
| | (0.212) | (0.185) | - | - |
| $PENALTYK_{i,t-1}$ | - | - | -0.704 | -1.459* |
| | - | - | (1.015) | (0.767) |
| Constant | 0.030*** | 0.003 | 0.006 | 0.017 |
| | (0.008) | (0.016) | (0.017) | (0.026) |
| Unit dummies | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes |
| AR1 *(p-value)* | 0.009 | 0.054 | 0.047 | 0.053 |
| AR2 *(p-value)* | 0.744 | 0.907 | 0.832 | 0.780 |
| Hansen test *(p-value)* | 0.155 | 0.365 | 0.414 | 0.107 |
| Diff-in-Hansen test of exogeneity *(p-value)* | 0.100 | 0.115 | 0.226 | 0.355 |
| Number of Instruments | 25 | 21 | 21 | 21 |
| Observations | 138 | 238 | 236 | 86 |
| Number of units | 44 | 83 | 83 | 36 |

All variables are defined in Table 1. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.10$