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Low-powered vs high-powered incentives: Evidence from German electricity networks[☆]

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ABSTRACT

We propose a difference-in-differences approach to estimating the impact of incentives on cost reduction in the context of German electricity networks. When subject to a lower-powered regulation mechanism, relatively more efficient operators pile up more costs in the year used to determine future prices. This pattern is consistent with the idea that incentives matter: higher-powered incentives lead to cost reduction. The results are also consistent with an equilibrium where more efficient firms pool with less efficient ones under the threat of ratcheting.

1. Introduction

The regulation of electric utilities is a topic of great research interest and practical relevance. In the past few decades, theoretical and empirical scholars, as well as policy makers, have addressed various issues related to mechanism design and cost-efficiency incentives, especially in the presence of information asymmetries between regulator and regulated firm. At the risk of oversimplifying, one might say that, in terms of the investment incentives provided, regulation mechanisms can be high-powered or low-powered. In a high-powered incentive mechanism, price caps are largely independent of firms' costs. This provides regulated firms high incentives for cost reduction, but at the cost of setting prices that may be too high or too low. In a low-powered incentive mechanism, prices are set in line with the regulated firms' costs; this prevents major misalignments between prices and costs, but at the cost of providing low incentives for cost reduction.

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The trade-off between high- and low-powered incentive mechanisms is largely an empirical question: do cost-reduction incentives really matter? Do regulated firms subject to higher-powered regulation mechanisms invest more in cost reduction?

The German system for regulating electricity distribution system operators (DSOs) provides a natural setting for addressing these questions. A legal exemption in the German incentive regulation system effectively results in two different regulatory regimes, one with higher-powered incentives than the other. Specifically, the default regulatory mechanism unfolds over a five-year period. While revenue caps are initially based on the DSOs' own costs, caps gradually decrease over time and are eventually determined by the industry's most cost efficient firm (which the regulator identifies beforehand by means of efficiency analyses). In this sense, the default regulatory regime is a hybrid of cost-based regulation (first year) and yard-stick regulation (last year of the regulatory period).[1]

Small DSOs (those with less than 30,000 connected consumers) can opt for an alternative regulation regime. As in the default regime, revenue caps are initially based on the DSOs' own costs. However, unlike the default regime, where prices adjust toward the fifth-year yardstick cap, under the alternative system prices adjust at an exogenously given rate. In this sense, the alternative regulatory regime provides lower incentives for cost reduction: even fifth-year prices remain a function of first-period costs. This regime is thus based to a larger degree on cost-based regulation than the default regime and disregards the individual DSOs' true cost efficiency when demanding cost reductions. The default regime relying on a yardstick element is thus much closer to the theoretical ideal of a price cap regulation determining exogenous prospective price targets (while also being cost-based with respect to the initial base costs).[2]

The German regulatory system is idiosyncratic in several ways. However, the relation between high-powered incentives and cost reduction is of more general interest. In order to better understand the essential features, we develop a simple model of regulation and cost reduction. We derive three results, all corresponding to testable predictions. First, everything else constant, firms under the low-powered regime (the "revenue-cap" regime, or simply r) inflate their costs to higher levels. Second, this cost inflation is particularly significant for firms that are more efficient to begin with (and for which the scope for cost inflation is greater). Third, cost inflation is particularly significant for operating expenditures (as opposed to capital expenditures), given that the former can more easily be "targeted" at one specific year.

To test these predictions, we propose a difference-in-differences (DiD) approach. The first level of difference in our DiD analysis compares the base year, that is, the year which determines subsequent years' caps, to the years when this cost-inflation incentive is absent. The second level of difference in our DiD analysis compares DSOs subject to a high-powered mechanism (the "yardstick" regime, or simply y) to DSOs subject to a low-powered mechanism (the "revenue-cap" regime, or simply r).

The DiD approach allows us to control for potentially confounding factors such as a heterogeneous expansion of power plants for decentralized renewable electricity generation. Moreover, it enables us to account for the potential selection bias due to the non-random assignment of treatment. We argue that the participation choice of small DSOs is driven by expected gains that depend on time-invariant unobservables (such as propensity to take regulatory risks). The average treatment effect on the treated can then still be consistently estimated with DSO-specific effects (Blundell and Dias, 2009).

We use data on 150 German DSOs over the period 2010–2013. Revenue caps for the regulatory period 2014–2018 are based on each DSO's cost in 2011, the base year. We compare costs in the base year to costs in the other years of the first regulatory period. Our base results show no difference between the y and r regimes. However, when we restrict to more efficient firms, we estimate (with precision) that the r regime implies a 3 to 5% inflation in DOS costs during the base year. If we further distinguish operating from capital expenditures, then we find a higher effect on the former (4 to 6%) and no significant effect on the latter.

Overall, these results are consistent with the basic idea that incentives matter: If a regulated firm can keep a greater fraction of its cost savings, then cost savings are greater. The fact that the effect is particularly strong for firms that are more efficient is consistent with two different ideas, both of which we discuss in detail in the theory section of the article: First, more efficient firms have a greater ability to add wasteful expenditures to their cost base. Second, in a world of asymmetric information and sequential regulation without regulator commitment, efficient regulated firms have an incentive to pool with inefficient firms: the ratchet effect (Laffont and Tirole, 1993).

The paper is organized as follows. The next section discusses related literature. Section 3 provides an overview of the German regulatory setting; a stylized theoretical model; and a set of testable hypotheses. Our empirical approach is explained in Section 4, and the results are presented and discussed in Section 5. Section 6 concludes.

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[1] See Shleifer (1985) for yardstick regulation. See also Averch and Johnson (1962) and Finsinger and Kraft (1984) for cost-plus regulation and its incentive for wasteful spending.

[2] There is some disagreement — both in economics literature and in regulatory practice — regarding the usage of the term "price cap". Beesley and Littlechild (1989) and Laffont and Tirole (1993) stress its proximity to cost of service (or rate of return) regulation. However, in theory a completely exogenous price cap makes the firm the residual claimant of its profits (Cabral and Riordan, 1989). In this sense, yardstick regulation is the practical counterpart of this theoretical extreme. In regulatory practice — and in the empirical literature — the term "price cap" often refers to an incentive scheme subject to periodical regulatory audits, which effectively make a firm's price a function of its (historical) cost (Littlechild, 1986, also cf. Section 2 below). Price cap regulation is then effectively a low-powered mechanism (especially if the regulatory lag is short). In our case, the alternative regime is closer to this historical own-cost based approach, whereas the default regime determines final period's price targets based on cost data exogenous to the firm. The German regulator calls both regimes "revenue-cap regulation" ("Erlösobergrenze" in the Incentive Regulation Ordinance (IRO)). So as to avoid further confusion, we use the terms "revenue-cap" regime for the low-powered; and "yardstick" regime for the high-powered scheme.

2. Related literature

Since the 1980s, and following the United Kingdom's lead, a number of countries implemented various forms of incentive regulation. (Until then, utilities were typically subject to cost-based regulation (US) or were state owned (UK and Europe).) This institutional development was accompanied by a renewed research interest, both theoretical and empirical, on the economics of regulation.

At the theoretical level, earlier contributions regarding price-cap regulation include Cabral and Riordan (1989) and Biglaiser and Riordan (2000). Cabral and Riordan (1989) show that tougher price caps may increase cost-reduction incentives. Biglaiser and Riordan (2000) argue that price-cap regulation leads to more efficient capital replacement decisions compared to naive rate-of-return regulation.

More recently, a series of authors have looked at price-cap regulation in the context of capacity expansion. Dobbs (2014) considers a monopoly firm's optimal capacity expansion when subject to a price cap. Evans and Guthrie (2012) studies the effect of scale economics on equilibrium investment and on optimal price-cap regulation. Willems and Zwart (2018) derive an optimal regulation mechanism for irreversible capacity expansion by a firm with private information about capacity costs. While these papers are related to the issue discussed in this paper, they do not address the central question in which we are interested, namely the effect high-powered incentive regulation on cost efficiency.

At the empirical level, the central question regards the impact of incentive regulation on the regulated firm's cost-reduction effort, and ultimately on their efficiency levels. Newbery and Pollitt (1997) and (Domah and Pollitt, 2001) show that the introduction of incentive regulation promoted productivity and service quality among UK electricity utilities. Greenstein et al. (1995) and (Ai and Sappington, 2002) demonstrate that incentive regulation in the US telecommunications sector encouraged cost-reducing investment. Results by Majumdar (1997) further indicate that this positively affected technical efficiency. More recent evidence by Cambini and Rondi (2010), who examine EU energy utilities from 1997 to 2007, shows that investment rates tend to be higher under incentive than under cost-based regulation. Seo and Shin (2011) find a positive effect of incentive regulation on productivity in the US telecommunications industry during the period 1988–1998.[3]

Despite the variety of industries and data sets considered, a common pattern among virtually all of the empirical studies is the comparison of firm efficiency before and after the adoption of incentive regulation.[4] For example, different US states adopted price-cap regulation at different points in time, which provides a right-hand side explanatory variable for a firm investment regression. By comparison with this strand of the literature, the strength of our empirical approach is that it consists of a differences-in-differences approach with a regression-discontinuity flavor based on an essentially exogenous feature of regulation: that the alternative (low-powered) regulatory regime is only an option for DSOs with less than 30,000 connected consumers.

Beyond this general characterization, two papers are particularly germane to ours and deserve special mention. Like us, Cullmann and Nieswand (2016) study the investment behavior of German DSOs. They measure an increase in investment after the introduction of incentive regulation, especially in the base year. Whereas their results are consistent with our evidence, they do not make a case for a causal effect in the way we do. Moreover, they do not distinguish the different regulatory regimes (low- and high-powered) as we do. Agrell et al. (2005), in turn, is similar to our article in that they provide a dynamic framework with which to compare revenue-cap and yardstick regulation. They use data on Swedish electricity utilities from 1996 to 2000 and focus on the value of yardstick regulation in reducing uncertainty regarding price cap levels. However, their different regulatory regimes are based on (out of sample) counterfactual simulations, while our results are based on historical data.

3. Setting

In this section we provide a brief description of the German incentive regulation; develop a simple formal model that encapsulates the main features of the various regulatory systems; and derive a series of theoretical results which imply specific testable predictions.

3.1. Incentive regulation in Germany

In 2009, Germany switched from a cost-based to an incentive-based regulation regime of electricity network access charges. In this section, we explain its functioning in general terms, leaving for Appendix A.2 the more detailed description of the Incentive Regulation Ordinance (IRO) which led to the regulatory change.

Similarly to many other countries, the German regulator imposes revenue caps on its more than 800 electricity Distribution System Operators (DSOs). The idea is that, by setting allowed prices over a period of time, firms become residual

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[3] For largely qualitative analysis of the effects of incentive regulation, see also Braeutigam and Panzar (1993), Crew and Kleindorfer (1996), Crew and Kleindorfer (2002), Joskow (2008), Liston (1993), Guthrie (2006), Vogelsang (2002). Kridel et al. (1996) and (Sappington and Weisman, 2010) provide detailed surveys of the empirical literature.

[4] There also exists a strand of empirical literature investigating the effect of deregulation. See Fabrizio et al. (2007), Davis and Wolfram (2012) and Cicala (2015) for studies of US electric generating plants. Knittel (2002) also finds evidence that regulation allowing plants to capture some of the rents from cost savings is related to higher technical efficiency.

claimants of any cost reductions during the regulatory period, and are thus highly incentivized to become more cost efficient. Against this efficiency benefit, one must also consider that the cap itself is at least partly based on the firm's cost, which in turn creates some incentives for wasteful expenditures.

The extent of the cost-reduction and cost-padding incentives depends on how revenue caps are computed and applied. In Germany we find two different regulatory regimes: a default regime and an alternative regime. The alternative regime was introduced by the regulator in an attempt to reduce bureaucratic costs: it is characterized by less reporting requirements. This simpler regime can only be chosen by DSOs with less than 30,000 connected consumers (which corresponds to more than 75% of all German DSOs).

Under both regimes there is a designated base year (three years before the regulatory period) during which firm costs are audited. The estimate of the firm's cost determines the revenue cap at the start of the five-year regulatory period. The revenue cap then declines in each subsequent year.[5]

The differences between the two regimes pertain to the way the cap is adjusted over time. Under the default regime, an industry efficiency frontier (yardstick) is estimated by the regulator.[6] By the end of the regulatory period, all firms are set a revenue cap corresponding to this efficiency frontier. That is, any inefficient costs have to be reduced by then. Until then, each firm's revenue cap declines linearly from the first year's level (which, as we have seen before, is determined by the firm's cost during the designated base year).

Under the alternative regulatory regime, by contrast, the initial revenue cap is adjusted at an exogenous rate, which the regulator sets uniformly for all DSOs.[7] In other words, whereas under the default regime the final cap is determined exogenously, under the alternative regime it is the adjustment rate that is determined exogenously thus being independent of their true cost efficiency.

Both the default and the alternative regimes include elements of cost-based regulation as well as elements of price-based regulation. However, the extent of cost-reduction incentives is greater under the default regime: under this regime revenue caps during the last period are exogenously given, as in pure yardstick regulation. By contrast, under the alternative regime revenue caps in every period are a function of the firm's cost audit during the base year.

To put it differently, in the first period both regimes are essentially cost-based regimes. By contrast, in the last period the yardstick regime is a high-powered regime (exogenous cap) whereas the alternative regime is a low-powered regime (cost based). For this reason, we refer to the default regime as a high-powered regime (even though, in all periods but the last, it includes elements of cost-based regulation).

Our empirical strategy uses this difference in incentive power, together with a "natural" assignment to each system, to estimate the effects of regulation on cost reduction incentives.

3.2. A model of regulation and cost reduction

In order to better understand the effects of alternative regulatory mechanisms, we next develop a simple model of a regulated firm's cost-reduction strategy. The model's main purpose is to derive sharp testable implications which we then bring to the data. Moreover, as often happens with economic modeling, we hope to distill from the admittedly complex and idiosyncratic German regulatory system the features that are of more general interest, namely the degree to which each regime resembles high-powered or low-powered incentive regulation.

Suppose that the firm is regulated during two periods: the base period and the regulatory period (or final period). The timing is very simple: First, the regulated firm chooses a level of wasteful expenditures. Next the regulator determines the allowed revenue in each of the two periods.

Every model involves an element of simplification. We are interested in understanding the qualitative differences between two regulatory regimes. As mentioned in the previous section, the differences are greatest in the last year of the regulatory period. For this reason, we consider a simple two-period model where the first period is like the first period of the German regulatory process whereas the second period is like the last year of the German regulatory process.[8]

Given this setup, the two regulatory regimes work in the same manner during period 1 but not during period 2. Specifically, during period 1 revenue caps are set according to costs, whereas during period 2 revenue caps are set exogenously (default regime) or equal to first period revenue caps minus an exogenous x (alternative regime). We refer to the default

[5] Revenue caps basically comprise two components. A first component corresponds to costs that are beyond the DSOs' control, such as concession fees. A second component corresponds to controllable costs, i.e. the effective costs of network operation; this component is subject to cost-reduction targets (see Appendix A.2 for details.).

[6] The regulatory authority employs a combination of Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), using costs as input; and exit points, network length, annual peak load, and area served amongst others as outputs (see Appendix A.2 for details.)

[7] Similarly to the default regime, in the alternative regime DSOs are assigned an efficiency score: 87.5 percent in the first regulatory period (2009–2013) and 96.14 percent in the second regulatory period (2014–2018). While, starting from the second period, the score is defined as the mean over all previous scores, it is unknown how it was set in the first period. Due to the large number of small DSOs (which is one of the reasons to simplify regulation) it is unlikely that the regulator conducted an internal efficiency analysis beforehand. We thus assume that there is no direct link between the exogenous efficiency score and their true efficiency.

[8] An alternative way of understanding our modeling strategy is to say that we conflate the designated base year with the first year of the regulatory period (and call this the base period); and we collapse years 2 through 5 during the regulatory period into one (and call it the regulatory period). That is, we assume all years are like year 5.

regime as high-powered regime (or "yardstick", or simply y) and to the alternative one low-powered regime (or "revenue cap" regime, or simply r).

For simplicity, we assume that firm output is exogenously given; and with no further loss of generality assume it to equal 1. The regulated firm's cost (total and per unit) in the base period, c_0, is given by

$$c_0 = \theta + w \tag{1}$$

where θ is firm efficiency (which we assume to be exogenously given) and w corresponds to wasteful expenditures. Moreover, the regulated firm's cost during the regulatory period is given by

$$c_1 = \theta \tag{2}$$

(Below we change this assumption by allowing base-period expenditures to have an effect on cost during subsequent periods.) Regardless of regulatory regime, allowed revenue during the base period is given by

$$R^\circ = \theta + e(\theta) f(w) \tag{3}$$

where $e(\theta)$ measures how effectively a type θ firm is able to turn wasteful expenditures into its cost base (everything else equal); and $f(w)$ measures how, independently of firm type, wasteful expenditures can be padded on to the cost base used by the regulator in setting revenue caps.

We make the important assumption that $e(\theta)$ is decreasing. As a higher θ implies that the firm is less efficient, we assume that less efficient firms find it harder to make wasteful expenditures count (in terms of making them part of the cost base).

As to $f(w)$, we assume that it is a positive, strictly increasing, strictly concave and bounded function defined in $\mathbb{R}^+$. The idea is that there are diminishing marginal effects in adding wasteful expenditures to the regulated cost base: first the firm will select expenditures that are easily passed on to the cost base. As more and more expenditures are added, the regulated firm eventually gets into highly dubious expenses (e.g., a third executive car).

Allowed revenue during the regulatory period (the second period in our model) depends on the regulatory system. Under the default yardstick regime (denoted system y), allowed revenue during the regulatory period is determined by industry best practice (as assessed by the regulator), a value that is exogenous with respect to the regulated firm's cost level. Under the alternative revenue-cap regime (denoted system r), allowed revenue is given by $R^\circ(1-x)$, where the regulator sets $x \in (0, 1)$ independently from the regulated firms' cost levels.

The regulated firm's objective function consists of firm profits over the two periods (for simplicity, we assume no discounting between periods):

$$\max_w \ \pi^\circ + \pi^s \tag{4}$$

where π° denotes profit during the base year, π^s denotes profit during the regulatory period, and s denotes the regulatory system in place ($s \in \{y, r\}$).

Given our assumptions, the profit functions are given by

$$\pi^\circ = R^\circ - c_0 = \theta + e(\theta) f(w) - (\theta + w) \tag{5}$$

$$\pi^y = R^y - c_1 = R^y - \theta \tag{6}$$

$$\pi^r = R^r - c_1 = R^\circ(1-x) - \theta \tag{7}$$

where R^y is exogenously given. Finally, we define

$$\Delta \equiv w^r - w^y \tag{8}$$

the difference, in terms of wasteful expenditures, between system r and system y. Our prior is that a high-powered regulatory regime (y) implies lower wasteful expenditures, so that $\Delta > 0$. We will show this theoretically, together with other implication of the model, and then test it empirically. Specifically, based on this simple model, we derive two basic propositions which reflect the core of our theoretical (and later empirical) analysis.

Proposition 1. $\Delta > 0$, *that is, wasteful expenditures are lower under the high-powered regulatory regime.*

(Proofs may be found in Appendix A.1.) Proposition 1 reflects what is perhaps the most basic result regarding regulation: incentives matter. Yardstick regulation, to the extent that it sets a revenue cap (during the regulatory period) which is not a function of the firm's cost, creates an extra incentive for firms to reduce costs: as far as the regulatory period is concerned, any cost increase translates directly into a profit decrease. By contrast, revenue-cap regulation has the property that revenue caps during every period are an increasing function of the firm's cost during the base period; and this creates additional incentives for the firm to increase its costs in the base year by means of wasteful expenditures.

Proposition 2. *Suppose that* $f(w) = \log(w)$. *Then* $d\Delta/d\theta < 0$, *that is, the effects of a high-powered regulatory regime are greater the more efficient a firm is.*

Intuitively, more efficient firms are better able to turn wasteful expenditures into their cost base. As such, these firms are greatly affected by a change in regulatory regime. We note that the condition that $f(w)$ is logarithmic is sufficient (and greatly simplifies the proof of Proposition 2) but not necessary.

We next consider a model extension that allows for the distinction between operating and capital expenditures. One important difference between these two types of expenditures is that capital expenditures during the base year have an effect on firm costs for a number of periods, including the regulatory period. The distinction is important: whereas w-operational expenditures lead to cost padding, w-capital expenditures contribute to cost padding but also to an increase in cost during the period when the firm is a residual claimant of any cost reductions. In other words, the wasteful expenditure effect of cost-based regulation should be lower for capital expenses.

To formalize this argument, we now split the value of w into two different components:

$$w = w_o + w_k \tag{9}$$

From the model's point of view, the crucial difference between w_o and w_k is that the former can be chosen to apply during the base period only, whereas the latter leads to multi-period commitment, which we model by assuming the same value of w_k in both periods.

The regulated firm's problem is now given by

$$\max_{w} \ \pi^\circ + \pi^s + \alpha\,(w_o + w_k) \tag{10}$$

The profit functions are now given by

$$\pi^\circ = R^\circ - c_0 = \theta + e(\theta)(f_o(w_o) + f_k(w_k)) - (\theta + w_o + w_k) \tag{11}$$

$$\pi^y = R^y - c_1 = R^y - (\theta + w_k) \tag{12}$$

$$\pi^r = R^r - c_1 = R^\circ(1 - x) - (\theta + w_k) \tag{13}$$

Similarly to our previous analysis, we define

$$\Delta_k \equiv w_k^r - w_k^y \tag{14}$$

$$\Delta_o \equiv w_o^r - w_o^y \tag{15}$$

We can then derive the following result:

Proposition 3. $\Delta_o > \Delta_k$. *In words, the effects of incentive regulation are greater in reducing wasteful operating expenses than in reducing wasteful capital expenses.*

Finally, we note that the above model considers one regulation cycle only. As we explain in detail in the next section, there have already been two regulation cycles since the reform of the German electricity regulation system; and more cycles are expected to take place. More generally, in a repeated-regulation context with no long-term commitment on the part of the regulator, theory predicts that ratcheting will then take place. Specifically, the regulator infers from a high performance an ability to repeat a similar performance in the future and becomes more demanding. Consequently the firm has an incentive to keep a low profile (Laffont and Tirole, 1993, p. 664).

Specifically, Laffont and Tirole (1993) provide conditions such that, under asymmetric information regarding the regulated firm's cost efficiency, some measure of pooling of types takes place in the first period (see their Propositions 9.1 and 9.2). By pooling we mean that more efficient types signal the same cost level as less efficient types. This is consistent with the idea of more efficient DSOs inflating costs by more than less efficient DSOs (that is, efficient DSOs pooling with inefficient DSOs, at least partially).

Laffont and Tirole (1993) do not provide results comparing the extent of pooling across different regulatory mechanisms. However, intuitively the incentive for pooling in the first regulation round should be greater the more cost-based future regulation rounds will be. For this reason, we would expect pooling to be greater under the alternative revenue-cap regime.

We thus have an alternative reason why cost padding is greater for more efficient firms, that is, an alternative interpretation for Proposition 2's prediction.

3.3. Testable predictions

Propositions 1–3 imply a series of related testable predictions. First, in the base year DSOs in the low-powered revenue-cap regime should show higher expenditures compared to DSOs in the high-powered yardstick regime (everything else constant). Second, this effect should be particularly strong among more efficient firms. Third, this effect should be particularly strong for operating expenditures (as opposed to capital expenditures).

4. Empirical approach

In this section we discuss our empirical approach and describe how our dataset was created.

4.1. Identification strategy

The low-powered regime r can only be chosen by small DSOs, specifically those with less than 30,000 connected consumers (which corresponds to more than three quarters of all German DSOs). Almost all of the smaller DSOs opted for the r regime. Our identification strategy is to compare DSOs greater than 30,000 (y regime) to DSOs smaller than 30,000 (r regime) difference-in-differences (DiD) approach.

The validity of the DiD approach relies on the common-trend assumption, the assumption that, absent the treatment (r vs y regime), similar DSOs would follow similar trends. For this reason, we restrict our analysis to DSOs with similar efficiency scores. As firms in the r regime face a homogeneous efficiency score of 87.5% in the first regulatory period, we restrict our attention to DSOs in the y regime having official efficiency scores between 82.5 and 92.5%.[9] We also employ several measures to ensure the validity of the common-trend assumption (see Section 4.4 below).

As incentive regulation was introduced in Germany in 2009, we observe DSO choices during two regulation cycles. The majority of smaller DSOs (more than 90%) opted for the r regime the first time around; and of the ones that did not, many did so the second time around (given that they did not grow and lost eligibility).[10] In this sense, our empirical design has a certain regression-discontinuity flavor: large DSOs choose the y regime and small DSOs choose the r regime, where the threshold is exogenously determined. However, despite the clear cutoff point (30,000 consumers), a "pure" regression discontinuity approach would be statistically fragile as there are hardly any DSOs just around the threshold.

In contrast to a standard regression-discontinuity approach, DiD has the advantage of addressing the possible selection bias arising from the non-random assignment of treatment: Assuming that decision-making is based on time-invariant unobservables (e.g., propensity to take regulatory risks), such DSO-specific effects cancel out in a DiD approach with fixed effects.[11] Blundell and Dias (2009) show that the average treatment effect on the treated can be consistently estimated using OLS.

In addition to the treatment effect of the r versus the y regime, we are also interested in the effect of DSO efficiency level, that is, whether the treatment depends on the regulated firm's efficiency level. As DSOs in the r regime are not subject to benchmarking, we must conduct our own analysis in order to assess DSO efficiency level. We thus replicate the official efficiency analysis of the German incentive regulation and follow the guidelines laid down by the IRO.

4.2. Dataset

841 German DSOs were subject to the IRO in the regulatory period 2009–2013. Of these, 184 were regulated under the yardstick regime (y), and the remaining 657 (all smaller DSOs) under the revenue-cap regime (r). Regarding the process of data collection, we should note that most small DSOs in Germany are still vertically integrated. For this reason, data on their network-operation expenditures can only be obtained by making use of accounting unbundling obligations which require them to publish a separate balance sheet for electricity distribution activities. As these obligations are legally binding only since 2011 and as we strive for a sample containing also data from before the base year, we can only rely on DSOs that report data regarding the previous year in their balance sheets of 2011.[12]

These data requirements imply that our sample is a strict subset of the population.[13] Specifically, we constructed an initial balanced panel of 150 DSOs from 2010 to 2013. However, as mentioned earlier, we restrict attention to DSOs under the y regime with cost-reducing targets comparable to DSOs in the r regime. This further restricts our panel to 131 DSOs, out of which 31 fall into the high-powered yardstick regime (y) and 100 into the low-powered revenue-cap regime (r).[14]

DSOs in our sample serve up to 430,000 exit points with the first half of firms serving less than 19,000 points. They distributed about 77 TWh of electricity and maintained about 134 thousand kilometers of low-voltage lines in 2011. This amounts to about 16 and 11% of the respective total numbers for Germany.

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[9] We obtain equally significant results when narrowing the interval to 85–90%, which, however, reduces the number of DSOs in the y regime from 31 to 19. In another set of regressions, we further restrict revenue-cap regulated DSOs to an identical range of initial efficiency in order to achieve the best possible comparability regarding the potential to improve efficiency in contrast to the aforementioned targets of cost reduction (see Section 5.2 on robustness analysis).

[10] The second wave of shifts to the r regime was partly caused by a more favorable value of x, from 87.5% to 96.14%. Demanding less cost reduction reinforces the cost inflation incentive. (Recall that x applies independently of the DSO's actual efficiency level.)

[11] The pre-set homogeneous efficiency score is, in fact, the most decisive factor. In combination with different degrees of risk inclination it can explain why more DSOs have opted for the r regime in the second period than in the first one. Furthermore, as the score was known before the base year (as well as the other bureaucratic facilitations) and since eligibility is strictly determined by the number of consumers, assuming that unobserved temporary individual-specific shocks do not influence the participation decision seems warranted.

[12] While our final sample is only subject to data availability we presume that this selection is not biased. Although compliance is not universal (though increasing every year), one could conjecture that the early compliers are more efficient. Assuming that this early-complier selection does not bias the comparison between the two regimes, this would also not adversely affect our results as we explicitly focus on the more efficient firms.

[13] We also have to disregard very small DSOs with the legal status of a small corporation (Section 267 German Commercial Code), which exempts them from reporting detailed cost data in their annual statements.

[14] This classification stems from the second regulatory period as expenditures in the base year 2011 affect revenue caps in the second period 2014–2018.

Table 1
Summary statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max	Description
Population	522	51,975	71,405	3512	545,124	Population in area served at low voltage level
Exit points	524	31.08	46.78	1.80	327.72	Total number of exit points at all voltage levels in 1000
Energy delivered	524	394.99	867.35	22.70	7021.60	Annual energy delivered to end users in GWh
Area served	517	25.01	31.33	2.00	257.00	Area served at low voltage level in km^2
Network length	524	883.59	1464.07	65.00	14190.50	Total length of underground and overhead lines at all voltage levels in km
Growth solar cap.	524	166.54	234.07	9.20	4083.63	Growth rate of installed capacity for solar power electricity generation in %
Cap. renewable	524	16.63	29.06	0.07	253.58	Installed capacity for renewable electricity generation in MW
Network acquisition	524	0.04	0.19	0	1	Dummy indicating network acquisitions
Price of labor	524	17.47	1.44	16.03	20.72	Official wage in energy sector in euro/h (mean at federal state level)
Totex	524	8.72	13.64	0.32	109.85	Effective network-operation costs in m euro
Opex	524	6.51	11.67	0.22	95.07	(= capex + opex)
Capex	524	2.21	2.74	0.07	28.09	Standardized operational expenditures in m euro

Notes: Summary statistics for data of 131 DSOs for years 2010–2013. Accounting data in 2010 euro.
Sources: DSOs' annual statements with separate accounting information for network operation as demanded by Section 6b German Energy Act; DSOs' network data published on their websites complying with Section 27 Network Charges Ordinance; data on renewable energy production published by transmission system operators complying with Section 73 Renewable Energy Sources Act.

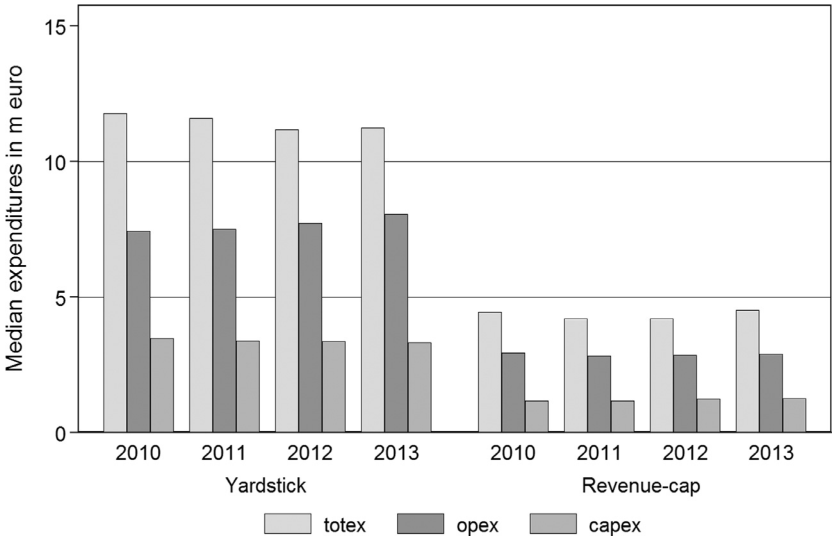

Fig. 1. Evolution of expenditures by type and by regulatory regime.

Our cost data is derived from the DSOs' annual statements.[15] We follow the IRO method to compute effective network-operation costs (*totex*): we subtract non-controllable cost components from total costs on the DSO's balance sheet. Non-controllable costs comprise costs such as concession fees, charges for the use of upstream network levels, or feed-in remuneration for decentralized renewable electricity generation.[16] We divide total network operation costs (*totex*) into their operational and capital components (*opex* and *capex*).

Our data is complemented by a series of controls which we are able to obtain thanks to a variety of data disclosure requirements the DSOs are subject to. A first set of controls can be obtained from the DSOs' websites. It includes (among others) data on the number of exit points, the length of underground and overhead lines, energy delivered, area served, and population.[17] Second, transmission system operators release data on the extension of renewable electricity generation. This information also allows us to retrace different speeds of extension and, thus, different demands for expenditures. Finally, by consulting annual statements and publications of municipalities, we identify whether concessions have been awarded, i.e., whether a DSO has acquired new networks.

Table 1 displays summary statistics and Fig. 1 depicts the development of expenditures distinguished by regime.[18]

[15] We deflate data from the annual statements by the domestic producer price index for industrial products and an index for earnings in the energy supply sector, respectively.

[16] See Appendix A.3 for details. Even though we do not possess detailed cost data necessary for the official standardization, we are able to account for the crucial cost blocks which are within the DSOs' control and those which are not.

[17] This information has to be published on the DSOs' websites on a yearly basis and is collected by the service provider *ene't* whose database we consult and replenish. Data gaps with respect to these variables also restrict our final sample.

[18] Table A.4 provides summary statistics for the non-restricted sample comprising all 150 DSOs, i.e. including DSOs with official efficiency sores outside the range of 82.5–92.5%.

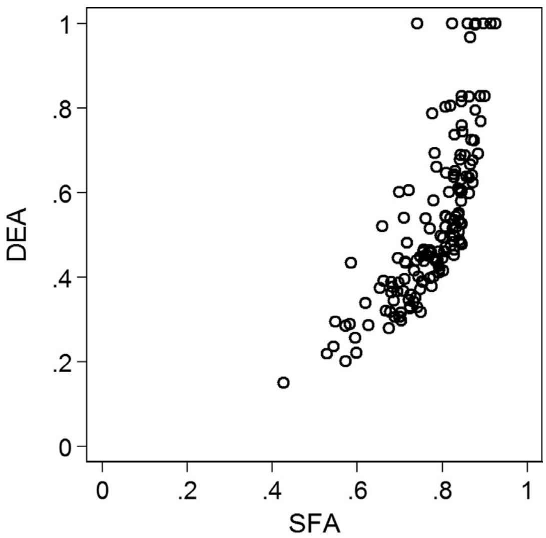

Fig. 2. Efficiency scores Notes: Efficiency scores of year 2010 for all 150 DOs. Means: 0.77 (SFA), 0.53 (DEA). Standard deviations: 0.09 (SFA), 0.19 (DEA). Pearson's correlation coefficient: 0.75.

4.3. Efficiency analysis

Our efficiency analysis aims to replicate the German incentive regulation and thus follows the guidelines laid down by the IRO to obtain efficiency scores comparable to the official ones. The IRO stipulates an input-oriented efficiency analysis: DSOs operating a given network with lowest costs establish a frontier; and the remaining DSOs are rated in relation to that benchmark. Specifically, each DSO is assigned an efficiency level determined by the better of two values: one resulting from Data Envelopment Analysis (DEA), one from Stochastic Frontier Analysis (SFA). The DEA method is non-parametric and relies on linear optimization. According to this method, deviations from the efficiency frontier are deemed deterministic (Charnes et al., 1978). By contrast, the SFA method is based on regression analysis and allows for noise (Aigner et al., 1977; Meeusen and van den Broeck, 1977). As the resulting efficiency scores only serve as inputs for our main investigation, we do not dwell on technical details and refer the interested reader to Coelli et al. (2005) or Bogetoft and Otto (2011).

In addition to the previously-mentioned input *totex*, we use the following outputs measures: total number of exit points; annual energy delivered; length of underground lines; length of overhead lines; and total installed capacity for renewable electricity.[19]

Despite the unavailability of data as disaggregated as in the official analyses conducted by Agrell et al. (2008, 2014), our dataset allows us to perform comparable efficiency analyses.[20] These analyses are based on 2010 data, the year preceding the base year. This is important since (as per our theoretical analysis) we expect 2011 cost data to be biased by "strategic" wasteful expenditures (recall that 2011 is the base year for the subsequent regulatory period).[21]

The resulting cost efficiency scores are depicted in Fig. 2. The SFA scores are more compressed around a higher mean, but both methods generally produce strongly correlated scores. In addition to the continuous-variable scores, we also define an "efficient DSO" dummy corresponding to DSOs with an above-median SFA score.[22]

4.4. Estimation

We implement the DiD approach by means of a log-linear fixed-effects OLS regression:

$$totex_{it} = \gamma\,(\text{revenue cap}_i \times \text{base year}_t) + x_{it}\beta + \delta_t + \alpha_i + u_{it}$$

where $totex_{it}$ denotes the log level of total network operation costs of DSO i in year t; "revenue cap" and "base year" denote dummy variables with the obvious interpretation (revenue cap=1 iff the DSO is under regime r; base year = 1 iff $t = 2011$); and x_{it} represents various (logged) covariates (more on these below).

[19] These were selected by a regression of *totex* on a set of potential cost determinants; see Appendix A.3 for details.

[20] We use the R packages "Benchmarking" by Bogetoft and Otto (2015) for DEA (assuming non-decreasing returns to scale) and "frontier" by Coelli and Henningsen (2013) for SFA (assuming a Cobb-Douglas cost function with a half-normally distributed inefficiency term). See Appendix A.3 for details. We employ the unrestricted sample.

[21] It is possible that 2011 expenditures are higher simply because DSO shift expenditures from 2010 to 2011. However, the potential of cost shifting is rather as assessed by the national regulator (Bundesnetzagentur, 2014, pp. 218f.). Moreover, if all firms were to engage in such investment withholding activities we would still identify DSO efficiency based on 2010 data. If only more efficient firms shift costs, we would underestimate the effect.

[22] As robustness checks we consider the upper quartile as well as the DEA-based efficiency scores.

Table 2
Differences among regulatory regimes.

Variable	"Yardstick" (1)	"Revenue Cap" (2)	Diff. (t-stat) (3): (1), (2)
Population	132,601	28,253	8.30***
Exit points	80.43	15.59	8.15***
Energy delivered	1147.86	177.74	5.85***
Area served	45.12	17.73	4.85***
Network length	2171.68	473.28	6.28***
Cap. renewable	31.87	7.40	4.65***
Growth cap. solar	283.11	210.38	0.94
DSOs	31	100	

Notes: Data from year 2010; *,**,***: significant differences at 10%, 5% and 1%, respectively (two-sided t-test).

The regression coefficient γ measures whether DSOs in the revenue-cap (r) regime had higher effective network-operation costs in the base year 2011 compared to the year 2013 and compared to the DSOs in the yardstick (y) regime. We further interact this variable with a dummy indicating the efficiency of DSOs in the revenue-cap regime. (To check robustness we also employ an interaction with the continuous efficiency variable.)

The regression coefficient δ_t captures time-specific effects, α_i depicts (unobserved) DSO-specific effects, and u_{it} is an idiosyncratic error term. The above regression is based on a cluster-robust estimate of the variance-covariance matrix, where we cluster at the DSO level.[23]

Several conditions must be met in order for a DiD approach to be valid.[24] First, Table 2 reveals that DSO characteristics differ across regimes. In order to account for differences, we include various (logged) covariates x_{it} in the regression: number of exit points, annual energy delivered, network length, and installed capacity for renewable electricity generation.[25]

Second, the common trend assumption must not be violated. Our setting assumes that decreasing costs paths only differ as a result of different efficiency levels, duly controlling for other dimensions of DSO heterogeneity.[26] As previously stated, we only consider DSOs in the yardstick regime having official cost reduction targets that are comparable to the homogenous one in the revenue-cap regime, i.e., in the range from 82.5 to 92.5%. In addition, besides accounting for an unequal expansion of renewable-energy power plants we account for different prices of labor (measured by the official wage in energy sector at the federal state level) and include a dummy for network acquisitions. Such acquisitions are subject to an official tendering for municipal grid concessions. Their availability follows a 20-year cycle so that the year of acquisition cannot be controlled by the DSOs and the corresponding increases in capital expenditures have to be accounted for. Moreover, we also conduct a placebo test. We do not find any bias, which supports the validity of the common trend assumption.[27]

Third, the covariates must be exogenous, in particular not influenced by the treatment. This assumption seems reasonable in the present case: the number of exit points, network length and annual energy delivered are demand-driven (which is close to inelastic), network acquisitions follow a 20-year municipal concession-awarding cycle, and official wages are negotiated at a higher administrative level. While the capacity for renewable electricity generation is determined by local producers, a violation of the exogeneity assumption might be possible: Given a high expansion in the previous year, additional network-stabilizing expenditures might become necessary if a shock occurs in the form of, e.g., extraordinarily high solar radiation. To account for this possibility, we include the lagged installed capacity as an additional control variable.

Fourth, we have to consider anticipation effects. As mentioned earlier, higher 2011 costs could simply result from shifting 2010 or 2012 expenditures. Although, as shown earlier, the scope for such shifting is rather small, we account for this possibility by estimating a log-linear panel with firm fixed effects. Employing this "within estimator" helps to account for shifting in any direction as we compare deviations from the mean which comprises costs of any year of the observation period.

Finally, we again acknowledge that our approach does not preclude the possibility of a selection bias arising from the non-random assignment of treatment. However, a DiD regression with fixed effects enables us to recover the average treatment effect on the treated, namely the additionally wasteful expenditures incurred by DSOs in the low-powered revenue-cap regime in the base year; and that is the primary focus of our analysis.

[23] Although treatment only varies at the group level, inference of the DiD coefficient is not affected by clustering issues as mentioned by Bertrand et al. (2004) or Donald and Lang (2007). As we only focus on one jurisdiction and both groups have common dynamic incentives, we can safely assume away any group effects in the composite error, which in turn guarantees consistent estimators. In our setting, another source of uncertainty over time is absent as treatment status is not serially correlated but only arises in the base year.

[24] We refer to the assumptions outlined by Lechner (2011): common trend, exogeneity of covariates (i.e. they are not influenced by the treatment), no anticipation (i.e. the treatment does neither affect the control nor the treatment group in the pre-treatment period).

[25] We disregard population due to high correlation with exit points (Pearson's correlation coefficient: 0.96).

[26] Due to a lack of data we cannot show the development of expenditure measures before 2010. However, as German regulation bases revenues on costs and since revenues are derived from network access charges, we can provide an indirect picture showing the development of network access charges. Fig. A.2 hints at a common trend — especially when considering the period before the IRO was active in 2009.

[27] See Table A.5 where the interaction of the treated group with the year 2010 preceding the treatment year shows no significant coefficients

Table 3
Difference-in-differences results - total expenditures.

Dependent variable:	ln(totex)		
	No efficiency distinction (1)	Efficiency distinction: median (2)	Efficiency distinction: upper quartile (3)
"Revenue Cap" × base year	0.022		
	(1.31)		
Efficient × "Revenue Cap" × base year		0.037**	0.043**
		(2.14)	(2.34)
Non-efficient × "Revenue Cap" × base year		0.006	0.015
		(0.32)	(0.83)
ln(exit points)	0.024	0.022	0.023
	(0.54)	(0.51)	(0.53)
ln(energy delivered)	0.068	0.067	0.069
	(1.48)	(1.45)	(1.50)
ln(network length)	0.371***	0.367***	0.365***
	(3.55)	(3.55)	(3.50)
ln(cap. renewable)	0.015	0.014	0.015
	(0.75)	(0.69)	(0.72)
ln(lagged cap. renewable)	0.013	0.012	0.012
	(1.03)	(0.93)	(0.97)
Grid acquisition	0.034	0.034*	0.035*
	(1.65)	(1.68)	(1.71)
ln(price of labor)	0.392	0.307	0.417
	(0.58)	(0.45)	(0.61)
2011	−0.030	−0.028	−0.030
	(−1.48)	(−1.34)	(−1.48)
2012	−0.045	−0.039	−0.045
	(−1.21)	(−1.04)	(−1.22)
2013	−0.045	−0.036	−0.045
	(−0.86)	(−0.68)	(−0.87)
Constant	10.745***	11.057***	10.711***
	(5.11)	(5.26)	(5.12)
DSOs	131	131	131
R^2 within	0.16	0.17	0.17
F	3.40***	3.38***	3.67***

Notes: OLS estimation with DSO-fixed effects and time-fixed effects. Standard errors clustered at DSO level. t statistic in parentheses. Distinction between non- and efficient DSOs using SFA efficiency scores. Years 2010–2013. *,**,***: significant at 10%, 5% and 1%, respectively.

5. Results

5.1. Difference-in-differences results

We start with the general comparison between DSOs in the revenue-cap and the yardstick regime. Column (1) of Table 3 reveals no significant higher total network operation costs (*totex*) among the DSOs in the low-powered revenue-cap regime in the base year compared to DSOs in the high-powered yardstick regime. Besides network length we neither find any effect for the covariates included to control for differences among DSOs, which suggests these characteristics do not affect expenditures in a significant way. Notably, the time dummies indicate that costs decrease over the regulatory period. At this level we find no direct empirical support for our first hypothesis. In other words, ignoring firm heterogeneity (in terms of efficiency level) DSOs under the revenue-cap regime do not seem to inflate their base-year's costs more than those under the yardstick regime.

We next turn to our second hypothesis, where we consider spending behavior according to DSO efficiency level. In column (2) we define efficient DSOs in the revenue-cap regime as those with above-median efficiency score; whereas in column (3) we define efficient DSOs as those in the upper quartile.[28]

Column (2) reveals a positive and statistically significant DiD coefficient on *totex*, indicating that, in the base year, efficient DSOs under the revenue-cap regime had about 3.7% higher total expenditures than those under the (high-powered) yardstick regime. The difference in the rate of *totex* change is about 9 percentage points.[29] Column (3) shows that the effect is even stronger when focusing on upper quartile in terms of DSO efficiency level: the coefficient is now about 4.3 percentage points (higher than DSOs under the yardstick regime).

[28] In both cases the efficiency score is estimated with the SFA approach.

[29] The statistically significant coefficient for grid acquisition implies that this variable captures a factor that seemingly confounds spending.

Table 4
Difference-in-differences results - expenditure measures.

Dependent variable:	ln (opex)			ln(capex)		
	No efficiency distinction (4)	Efficiency distinction: median (5)	Efficiency distinction: upper quartile (6)	No efficiency distinction (7)	Efficiency distinction: median (8)	Efficiency distinction: upper quartile (9)
"Revenue Cap" × base year	0.029			−0.010		
	(1.40)			(−0.75)		
Efficient × "Revenue Cap" × base year		0.048**	0.054**		−0.003	−0.005
		(2.15)	(2.25)		(−0.23)	(−0.28)
Non-efficient × "Revenue Cap" × base year		0.011	0.021		−0.017	−0.012
		(0.44)	(0.95)		(−1.17)	(−0.86)
ln(exit points)	−0.028	−0.030	−0.029	0.121	0.120	0.121
	(−0.91)	(−1.06)	(−1.00)	(1.36)	(1.36)	(1.36)
ln(energy delivered)	0.057	0.057	0.059	0.064	0.064	0.064
	(1.14)	(1.12)	(1.17)	(0.97)	(0.96)	(0.97)
ln(network length)	0.318***	0.313***	0.311***	0.566***	0.564***	0.564***
	(2.76)	(2.73)	(2.69)	(3.66)	(3.66)	(3.66)
ln(cap. renewable)	0.012	0.010	0.011	0.012	0.011	0.012
	(0.46)	(0.41)	(0.44)	(0.64)	(0.62)	(0.64)
ln(lagged cap. renewable)	0.026*	0.024	0.025*	−0.019	-0.020	-0.019
	(1.81)	(1.66)	(1.72)	(−0.95)	(−0.98)	(−0.96)
Grid acquisition	0.027	0.028	0.029	0.045	0.045	0.045
	(1.06)	(1.07)	(1.11)	(1.59)	(1.60)	(1.60)
ln(price of labor)	0.893	0.791	0.921	−0.359	−0.395	−0.353
	(0.94)	(0.83)	(0.97)	(−0.49)	(−0.54)	(−0.48)
2011	−0.053*	−0.049*	−0.052*	0.034	0.035*	0.034
	(−1.89)	(−1.76)	(−1.89)	(1.63)	(1.67)	(1.62)
2012	−0.090*	−0.083	−0.091*	0.047	0.049	0.047
	(−1.77)	(−1.63)	(−1.79)	(1.10)	(1.15)	(1.09)
2013	−0.100	−0.089	−0.100	0.055	0.059	0.055
	(−1.35)	(−1.20)	(−1.36)	(0.92)	(0.98)	(0.92)
Constant	9.860***	10.231***	9.822***	9.734***	9.865***	9.725***
	(3.58)	(3.71)	(3.57)	(3.69)	(3.74)	(3.69)
DSOs	131	131	131	131	131	131
R^2 within	0.09	0.10	0.10	0.28	0.28	0.28
F	3.78***	3.92***	4.35***	3.92***	3.70***	3.68***

Notes: OLS estimation with DSO-fixed effects and time-fixed effects. Standard errors clustered at DSO level. t statistic in parentheses. Distinction between non- and efficient DSOs using SFA efficiency scores. Years 2010–2013. *,**,***: significant at 10%, 5% and 1%, respectively.

Together, these results provide partial evidence for Proposition 1 (high-powered-incentive regulation leads to greater efficiency); and strong evidence for Proposition 2 (the effect of incentives is greater for more efficient firms).[30]

In Table 4 we focus on the sub-component *opex* and *capex*. As before, we do not find evidence for Proposition 1 but for Proposition 2 with respect for opex (columns (2) and (3)). The magnitude is even reinforced: efficient DSOs have about 5 percentage points higher rates of change. By contrast, we find no statistically significant effects regarding the rates of *capex* change (columns (5) and (6)). Together, these results provide support for Proposition 3: the effect of regulation incentives is greater for operating expenditures than for capital expenditures.

5.2. Robustness checks

To check the robustness of our results, we change our regressions in various ways. First of all, we test the robustness of our results with respect to the selection of the two treatment groups and the control group. In our main analysis, we split our treatment group into two different subgroups, efficient and inefficient DSOs, whereas our control group is a single group comprising DSOs of all actual efficiency levels. (All groups, however, have comparable cost reduction targets due to comparable official efficiency scores in the range from 82.5 to 92.5%.) This might lead to the measurement of a rather mechanical effect: Efficient firms in the revenue cap regime are on average more efficient than the average of the entire yardstick regulated control group. Efficient DSOs in the revenue cap regime would therefore be less likely to reduce costs (they are on a "flatter" cost path) than the average over all yardstick regulated DSOs, some of which also have lower efficiency values. This

[30] Note that this result can also be partly driven by the possibility that the uniform exogenous rate x in the revenue-cap regime might require too strong cost reductions from the more efficient firms. However, we do not expect a stronger incentive scheme than under the yardstick regime and assume that the revenue cap of all small DSOs is always less binding than the yardstick model because the IRO also attributes quite high allowances to the firms in the revenue-cap regime. That is, the amount of costs that are deemed permanently non-controllable by the regulator is much higher than in reality which is why a later revision of the IRO greatly reduced the respective allowances in the third regulatory period (see Appendix A.2).

control group effect is independent of the otherwise very similar distributions of DSO' efficiencies in the respective revenue and yardstick regulation regimes.[31] Instead of the cost inflation effect induced by revenue cap regulation that we intend to measure, we would rather address the mechanical effect of cost reduction potential. Thus, to clearly identify the revenue cap regulation effect, we narrow down the range of revenue cap regulated DSOs to official efficiency scores of 85 to 90% for yardstick regulated DSOs and only employ revenue-cap regulated DSOs that are in the same range of actual efficiency scores as spanned by these yardstick regulated DSOs. This makes DSOs of both regimes as comparable as they can get: The initial potential to save costs is then more similar due to this pre-selection of DSOs. This assures measuring the revenue regulation induced effect and excludes the possibility of measuring a possibly mechanical effect. Our empirical results are confirmed as can be seen from Table A.7. The coefficients on the base-year effect remain statistically significant and their magnitude is only slightly lower than in our main results.

Second, we employ DEA efficiency scores instead of SFA scores.[32] The results, shown in Table A.8, confirm our basic results. Table A.9 contains the DEA results for the reduced efficiency range from the first check. Third, we interact the DiD-variable with a continuous efficiency score variable instead of a dummy indicating more and less efficient DSOs. Table A.10 reassures our previous results and shows that *totex* and *opex* of DSOs in the revenue-cap regime significantly increase with each additional efficiency-score percentage point. In addition, we test whether there is a non-linear relationship by including the efficiency score squared. The coefficient of the squared term is positive for *totex*, while the coefficient of the linear term is insignificant. This confirms our previous result that the effect of incentive regulation is especially significant for higher efficiency firms.

Fourth, we narrow our sample to DSOs serving less than 100,000 connected consumers in order to consider only firms with more comparable supply obligations. Table A.11 reveals that our results also hold for the reduced sample.[33] Fourth, Table A.12 shows that the results are robust to considering alternative output measures in the efficiency analyses.

Finally, as an alternative to DiD we estimate the differential effect of revenue-cap regulation vis-Ã -vis yardstick regulation by means of a matched regression. Specifically, we match on exit points, energy delivered, network length, and (lagged) installed capacity for renewable electricity generation, while disregarding any DSOs with grid acquisitions, which could otherwise not be sufficiently accounted for. We also employ rates of cost changes (defined as% change over the previous year) to account for differences in size. The results, included in Table A.13, show that, for firms in the upper efficiency quartile, the rates of change in *totex* and *opex* are greater for DSOs under the low-powered incentive regime, thus providing additional credence to our DiD results.

5.3. Welfare analysis and discussion

As a final exercise, we put the consequences of the piling up of inefficient expenditures in perspective. As the inflated costs in the base year translate into higher revenue caps that have to be borne by consumers paying the (increased) network access charges, we can evaluate the loss in consumer welfare. The loss is depicted by the excess expenditures of more efficient DSOs in the revenue-cap regime compared to their counterparts in the yardstick regime.[34] However, we abstain from calculating the welfare effects directly using our DiD coefficients.[35] Doing so would imply to assume that DSOs in the revenue-cap regime would face the same cost-reduction targets as before. However, this is not the case. If they were in the yardstick regime, they would receive cost-reduction targets based on their individual efficiency.

Therefore, we instead perform an alternative back-of-the-envelope calculation and assume that their cost-reduction targets would be updated. In particular, we conduct a nearest-neighbor matching to estimate excess expenditures. In contrast to our previous analysis, we now employ the full dataset of 150 DSOs which also comprises DSOs in the yardstick regime that, in the first regulatory period, have received official efficiency scores that are not comparable to the homogeneous one in the revenue-cap regime. We thus have an increased number of potential matching partners for the more efficient firms.

We match DSOs of both regimes on the SFA efficiency score of 2010. We also match on exit points, energy delivered, network length, and (lagged) installed capacity for renewable electricity generation while disregarding any DSOs with grid acquisitions in the base year. Table 5 provides the matching results with respect to the rates of *totex* change, which we use to account for size effects. We focus on *totex* because it is eventually providing the basis for revenue and thus network access charges.[36] Obviously, the more efficient DSOs in the revenue-cap regime have higher rates of *totex* change than

[31] See distributions of efficiencies in Table A.6. Minimum, maximum, mean and percentiles are close to identical.

[32] Even though the altered distinction does not affect the number of DSOs classified as efficient, their composition is changed. Regarding the median distinction only 46 of 50 DSOs in the simplified procedure are characterized as efficient by both methods. Regarding the upper-quartile distinction only 18 of 25 DSOs are deemed efficient by both methods.

[33] This also applies to a sample containing only firms with less than 75,000 consumers.

[34] In other words, even if cost inflation is a general industry practice, the additional increase we estimate represents the excess burden of suboptimal regulation.

[35] Taking the DiD coefficient from column (3) of Table 3, the excessive *totex* for the upper quartile efficient DSOs in the revenue-cap regime would amount to 4.3% which corresponds to about 3.2 million euros in absolute terms only for those DSOs in our sample.

[36] Table A.14 contains the matching results for the remaining expenditure measures as well as for DEA scores. We find significant effects regarding *opex* with the upper quartile distinction using SFA scores. Whereas the analysis using DEA scores does not yield significant results, the effects point in a similar direction with half of the magnitude.

Table 5
Matching results for welfare analysis.

Dependent variable:	rate of totex change		
	"Revenue Cap" vs. "Yardstick" (1)	median efficient in "Revenue Cap" vs. "Yardstick" (2)	upper quartile efficient in "Revenue Cap" vs. "Yardstick" (3)
	Number of nearest neighbors: 4		
Average treatment effect on the treated	0.939 (3.085)	6.781* (3.833)	10.534** (4.807)
	Number of nearest neighbors: 5		
Average treatment effect on the treated	1.128 (2.884)	7.374** (3.493)	10.747** (4.429)
	Number of nearest neighbors: 6		
Average treatment effect on the treated	1.269 (2.770)	7.032** (3.331)	10.993*** (4.217)
DSOs	132	86	63

Notes: Treatment-effects estimation using nearest-neighbor matching (Mahalanobis distance metric). AI robust standard errors in parentheses. Efficiency distinction based on SFA efficiency scores. Matching on SFA efficiency score, exit points, energy delivered, network length, cap. renewable, and lagged cap. renewable. DSOs that encountered network acquisitions were disregarded. Year 2011. *,**,***: significant at 10%, 5% and 1%, respectively.

their matching partners in the yardstick regime. This is statistically significant regarding the median and upper quartile distinction. We focus on the latter in the following.

Based on these estimates of inflated rates of *totex* change we subsequently calculate the absolute *totex* values for each of the upper quartile efficient DSOs in the revenue-cap regime if their actual rates had not been inflated by 10.534 to 10.993% (column (3)). Comparing these hypothetical *totex* values to the realized ones then allows to quantify the excessive spending. Using the respective values for the upper quartile efficient DSOs we find that the excessive *totex* range between 9.9 and 10.3% of the realized *totex* in the base year (or in absolute numbers: 6.8-7.1 million euros for this subsample of DSOs).[37]

Admittedly, this is not the end of the story: one advantage of the revenue-cap regime is that it saves on regulatory costs (e.g., estimating each DSO's efficiency level). That said, a difference of about 10%, once extrapolated to the hundreds of DSOs subject to revenue-cap regulation, adds up to about 70 million euros.[38] Seen from another angle, hypothetically assuming that all (bigger) 184 DSOs under the yardstick regime were instead regulated by the revenue-cap regime; and considering that these firms are close to efficient (their average (official) efficiency is of about 95%); this would entail a damage of more than 800 million euros (based on their total effective network-operation costs in 2011[39]). Looking at it from a positive perspective, the fact that these 184 firms have been under yardstick regulation has generated a benefit of 800 million euros.

6. Conclusion

We set out to compare two alternative regulatory regimes currently in place in the German electricity distribution sector. Conceptually, the revenue-cap regime, closer to cost-based regulation, provides lower incentives for cost reduction than the yardstick regime (which is also cost-based with respect to the initial base costs in our setting), especially for firms that are more efficient to begin with. The results from our difference-in-differences analysis are broadly consistent with theoretical prediction: We find that relatively more efficient operators achieve lower costs when under a higher-powered regulation regime. We also find that this pattern is particularly noticeable when it comes to flexible operational expenditures, as opposed to capital costs.

Although we focus on a very specific setting (Germany electric utilities during the 2010s), we believe our results are of wider interest. In essence, our results confirm that, when it comes to utility regulation, incentives work: A higher-powered regulatory regime leads firms to be more efficient in cost cutting.

There are a number of additional questions which can be addressed with a more structural approach, including: how to treat bi-directional flows in a distribution network, how to internalize external cost effects of different network usage by producing consumers, or, more generally, how to set prices for network transmission dynamically using multi-part tariffs to avoid unnecessary investments. In all of these cases, the issue of incentives to inflate the cost base — the central focus of our chapter — is of primary importance.

[37] Regarding DEA scores (see Table A.14) the excessive *totex* range would be 3.9-4.8% (3.0–3.7 million euros).

[38] The value of excess expenditure in our sample is about 10 million euros for 23 more efficient DSOs. Extrapolating to the efficient upper quartile of 650 DSOs under the revenue-cap regime we get a value of 70 million euros.

[39] See Bundesnetzagentur (2014, p. 122).

Appendix A

A.1. Proofs

Proof of Proposition 1. The first-order condition under regulatory system y is given by

$$e(\theta)f'(w) - 1 = 0 \tag{16}$$

leading to

$$w^y = g\left(\frac{1}{e(\theta)}\right) \tag{17}$$

where $g(\cdot)$ is the inverse of $f'(w)$. By contrast, under regulatory system r the f.o.c. is given by

$$e(\theta)f'(w)(2-x) - 1 = 0 \tag{18}$$

leading to

$$w^y = g\left(\frac{1}{(2-x)\,e(\theta)}\right). \tag{19}$$

Taking differences,

$$\Delta = g\left(\frac{1}{(2-x)\,e(\theta)}\right) - g\left(\frac{1}{e(\theta)}\right) \tag{20}$$

Note that, given our assumptions on $f(w)$, it follows that $f'(w)$ is a strictly positive and strictly decreasing function in $\mathbb{R}^+$; and so $g(\cdot)$ is also a strictly positive and strictly decreasing function in $\mathbb{R}^+$. Together with our assumption that $x \in (0, 1)$, the result follows. □

Proof of Proposition 2. If $f(x) = \log(x),\ g(x) = 1/x$. Eq. (20) then becomes

$$\Delta = (2-x)\,e(\theta) - e(\theta) = (1-x)\,e(\theta) \tag{21}$$

The result then follows from the assumption that $e(\theta)$ is strictly decreasing. □

Proof of Proposition 3. The first-order conditions under regulatory system y is given by

$$e(\theta)f'(w_o) - 1 = 0 \tag{22}$$

$$e(\theta)f'(w_k) - 2 = 0 \tag{23}$$

leading to

$$w_o^y = g\left(\frac{1}{e(\theta)}\right) \tag{24}$$

$$w_k^y = g\left(\frac{2}{e(\theta)}\right) \tag{25}$$

where $g(\cdot)$ is the inverse of $f'(w)$. By contrast, under regulatory system r the first-order conditions are given by

$$e(\theta)f'(w_o)\,(2-x) - 1 = 0 \tag{26}$$

$$e(\theta)f'(w_k)\,(2-x) - 2 = 0 \tag{27}$$

leading to

$$w_o^y = g\left(\frac{1}{(2-x)\,e(\theta)}\right) \tag{28}$$

$$w_k^y = g\left(\frac{2}{(2-x)\,e(\theta)}\right). \tag{29}$$

Taking differences,

$$\Delta_o = g\left(\frac{1}{(2-x)\,e(\theta)}\right) - g\left(\frac{1}{e(\theta)}\right) \tag{30}$$

$$\Delta_k = g\left(\frac{2}{(2-x)\,e(\theta)}\right) - g\left(\frac{2}{e(\theta)}\right). \tag{31}$$

If $f(\cdot) = \log(\cdot),$ then

$$\Delta_o = (2-x)e(\theta) - e(\theta) = (1-x)\,e(\theta) \tag{32}$$

$$\Delta_k = (2-x)e(\theta) - e(\theta) = (1-x)\,e(\theta) \tag{33}$$

It follows that $\Delta_o > \Delta_k$. □

A.2. Incentive regulation in Germany

In 2009, Germany's previous cost-based regulation of electricity network access charges was replaced by the Incentive Regulation Ordinance (IRO). DSOs are given individual revenue caps that linearly decrease within the regulatory periods of five years thereby demanding a reduction of inefficient costs. In the default (high-powered incentive) regime, this amount is determined by an efficiency analysis conducted among DSOs prior to the respective regulatory period. By means of Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), the German regulator identifies DSOs being able to produce a given output (measured by exit points, network length, annual peak load and area served amongst others) with fewest costs. These DSOs serve as a benchmark to which less cost efficient DSOs have to converge.

Only controllable costs are considered for this comparison. That is, any costs that DSOs cannot influence (like concession fees, charges for the use of upstream network levels or feed-in remuneration for decentralized electricity generation) are identified in a cost audit three years before the start of the regulatory period. These non-controllable costs are subtracted from the overall network-operation costs consisting of (standardized) capital and operational expenditures (see next section).[40]

Revenue caps limiting the scope of access charges are then calculated using the following regulatory formula:

$$RC_t = C_{pnc,t} + (C_{tnc,0} + (1-V_t) \times C_{c,0}) \times \left(\frac{CPI_t}{CPI_0} - PF_t\right) \times EF_t + Q_t. \tag{34}$$

The revenue cap, RC_t, in year t mainly consists of three parts: (i) the 'permanently non-controllable' costs ($C_{pnc,t}$, '*pnc* costs' henceforth), (ii) the effective costs of network operation, which are further decomposed in a part that is 'temporarily non-controllable' ($C_{tnc,0}$, i.e. the costs of an efficient network operation derived by multiplying the effective costs of network operation with the efficiency score), and in a part of 'controllable' costs ($C_{c,0}$, i.e. inefficient costs), and (iii) an additional quality element preventing cost reductions at the expense of supply quality (Q_t).[41] $(1-V_t)$ is a factor linearly distributing the required reduction of inefficient costs over the regulatory period.[42] The effective costs of network operation are deflated by the development of the consumer price index (*CPI*) as these costs are retrieved in the base year 0, in which the cost audit is conducted. This development is further corrected for the industry's productivity growth (PF_t). Finally, changes in supply obligations are respected by the expansion factor (EF_t) correcting the effective costs of network operation.

Fig. A.1 depicts the path of cost reduction for an exemplary DSO. All revenue caps in the regulatory period are based on the overall costs of network operation occurring in the base year. In this example, 30% of these costs are deemed permanently non-controllable (and do not change over the period). Only the remaining costs are considered in the official efficiency analysis. Here, the DSO has obtained an efficiency score of 80%. This implies that its effective network-operation costs have to be reduced by 20% by the end of the regulatory period. The DSO receives revenue caps that — starting from the cost level in the base year (solid line) — are lowered by a certain percentage every year within the regulatory period.

The just described regulation generally applies to all DSOs. However, smaller DSOs with less than 30,000 connected consumers can opt out of this default "standard procedure" for the whole regulatory period. In an alternative "simplified procedure" small DSOs face lower reporting requirements and better planning reliability as they are exempted from the efficiency analysis and are instead given a pre-set, homogeneous efficiency score. In the first regulatory period 2009–2013 this score was fixed at 87.5% (second period (2014–2018): 96.14%).

Moreover, 45% of overall network-operation costs are deemed *pnc* costs without any exhaustive identification.[43] Revenue caps are also calculated using the regulatory formula but disregarding the quality element.[44] However, whereas in the standard procedure any changes in *pnc* costs lead to an adjustment of revenue caps, only concession fees and charges for the use of upstream network levels are accounted for. Small DSOs further lack the possibility to deduct additional investment expenses caused by a high extension of renewable electricity generation that is not captured by the expansion factor.

A.3. Efficiency analysis and cost approximation

The IRO prescribes in detail which costs serve as input for the efficiency analysis. In general, total expenditures (*totex*) are composed of operational and capital expenditures (*capex* and *opex*), but both are subject to standardization. *capex* comprises

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[40] The German regulatory authority, in fact, conducts four efficiency analyses: SFA and DEA with standardized and non-standardized costs, respectively. DSOs then receive the highest respective score (best-of-four).

[41] The official regulatory formula further comprises an element accounting for the volatility of fuel costs and a balancing element accounting for the administrative delay when *pnc* costs, for instance, suddenly increase justifying a raised revenue cap but the official adjustment is only carried out in the subsequent year.

[42] That is, for a 5-year period: $V_1 = 0.2$, $V_2 = 0.4$, $\ldots$, $V_5 = 1$.

[43] A major revision of the IRO in 2016 reduced this allowance to 5%. This, however, leaves our analysis unaffected.

[44] This would otherwise necessitate the (bureaucratic) reporting of detailed data like SAIDI.

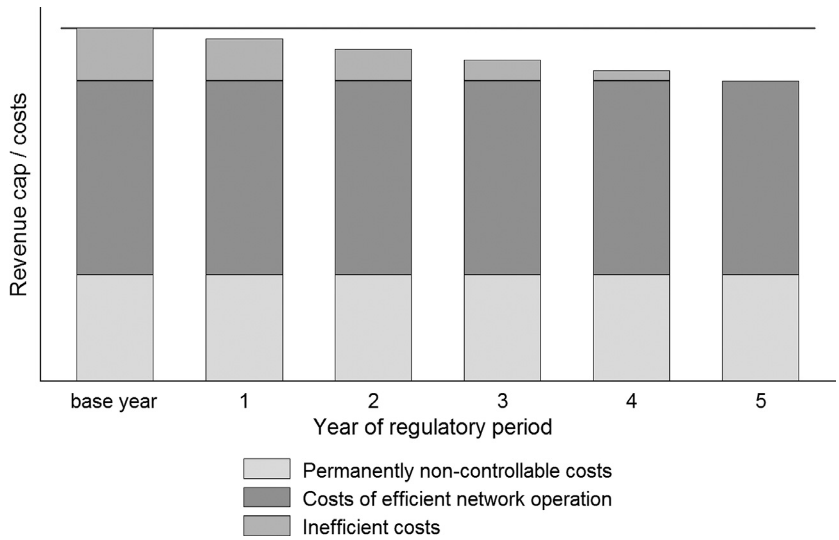

Fig. A.1. Composition and development of revenue caps.

the imputed equity yield rate and imputed depreciation. Imputation is carried out at the plant level and, depending on activation dates, evaluated at costs or at current costs. The equity yield rate is then calculated by adding up imputed net book values of fixed assets and the book values of financial and current assets necessary for operation, and by multiplying this sum by official interest rates.

As we do not possess cost data at the plant level and cannot determine whether all financial and current assets are necessary for operation, we approximate *capex* in the following manner: We model the equity yield rate as fixed assets (at costs) times the official multiplier for 'new' assets (9.05% before corporation tax) and we employ the respective balance sheet item for depreciation (at book value).

opex consists of material, personnel and sundry costs (at book values), which we model by their respective profit-and-loss-account items. *opex* is further supplemented by the interest on borrowed capital but at most at equity market levels. We account for this by adding up liabilities and liability provisions and multiply this by the official value (3.98%).

Costs that are officially deemed permanently non-controllable ('*pnc* costs') are deducted from these overall network-operation costs. Again, we cannot reproduce the full standardization required by Section 11.2 IRO due to a lack of detailed cost data. However, we are able to consider the three major blocks comprising concession fees, charges for the use of upstream network levels, and feed-in remuneration for decentralized renewable electricity generation. We possess explicit data on the latter, but have to approximate the former two. This works well for the concession fees (described in the next paragraph) but seems, in our opinion, rather problematic for the charges for the use of upstream network levels. Their calculation depends on annual energy delivered and annual peak load. We, unfortunately, do not have consistent data on the latter. In order to prevent any bias in our pivotal cost variable, we abstain from any approximation attempts. We rather make use of a more promising approach. The material costs item of the profit and loss account is subdivided into cost of raw materials and supplies, and cost of purchased services. Charges for the use of upstream network levels and feed-in remuneration for decentralized renewable electricity generation are filed into the former and depict the majority of this item (the rest basically comprises fuel costs, which are also separately accounted for in the official regulatory formula). We thus simply deduct this sub-item and only keep the cost of purchased services of the material costs item still promising to account for any autonomous cost inflation.

Concession fees, which are claimed by local municipalities, are filed into the sundry costs item. Being non-controllable by the DSOs they have to be approximated and deducted. Their scope is legally limited and depends on the municipalities' population. As they contribute to the municipalities' revenues and as municipalities are rather poor, we assume the highest possible charges. We, thus, approximate the DSOs' concession fees by apportioning annual energy delivered into a part delivered to end users and into a part delivered to firms.[45] We multiply the respective parts by the respective charges depending on the municipalities' population.[46] Some DSOs have reported their actual expenditures for concession fees enabling us to test the quality of our approximation. Regressing the actual values on our approximations yields a considerable R-squared of 0.91.

[45] We determine the amount of energy delivered to end users by assuming inhabitants living in two-person household consuming 3000 kWh per year. The remaining energy delivered is assumed to be transmitted to firms.

[46] The respective figures are laid down in Section 2.2 Concession Levy Ordinance.

The resulting block of effective network-operation costs is used as input for the efficiency analysis. The official efficiency analyses conducted by Agrell et al. (2008, 2014) consider the following outputs: the total number of exit points (at all voltage levels), area served, the length of underground and/or overhead lines at HV and MV level respectively, the total length of both underground and overhead lines at LV level, annual peak load (at HV/MV and MV/LV level respectively), the number of substations,[47] and the total installed capacity for decentralized electricity generation (at all voltage levels). These outputs were, however, identified as cost drivers regarding large DSOs and building on the detailed but confidential official database. As we consider rather smaller DSOs and also lack data on annual peak load, disaggregated decentralized electricity generation, and substations, we conduct an own identification of cost drivers drawing on Agrell et al. (2008, 2014). Table A.1 presents the respective regression results with an increasing degree of aggregation regarding lines.

We prefer specification (7) implying the lowest BIC and promising to account for DSOs servicing more expensive overhead lines. The IRO requires conducting efficiency analyses using both SFA and DEA. The only methodological prerequisite concerns DEA to assume non-decreasing returns to scale, which we accordingly do.[48] For SFA, we assume a Cobb-Douglas cost function with a half-normally distributed inefficiency term.[49] Choosing specification (7), however, complicates SFA. As some DSOs do not have any overhead lines, taking logs is precluded. We, therefore, draw on Battese (1997) and add a dummy variable to indicate non-use. The SFA regression results for are presented in Table A.2. We further conduct an efficiency analysis using specification (8) which has the highest degree of aggregation and also disregards the output 'area served' which is prescribed by IRO but shows no statistical significance in our analysis. This specification allows taking logs of all variables. Output is presented in Table A.3. Although the classification of DSOs within the revenue-cap regime is changed, our DiD results remain robust (see Table A.12).

A.4. Tables

Table A.1
Cost drivers.

	Dependent variable: effective network-operation costs (in euro)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exit points	199563***	187006***	195759***	99183**	201753***	188965***	196861***	100631**
	(3.58)	(3.05)	(4.07)	(2.28)	(3.57)	(3.06)	(4.01)	(2.28)
Cap. renewable	−140998***	−139703***	−144285***	−90744**	−131848***	−133637***	−135719***	−87741**
	(−3.59)	(−3.47)	(−4.23)	(−2.05)	(−3.07)	(−3.03)	(−3.73)	(−1.98)
Area served	28,989	18,986	30,743	12,560				
	(0.88)	(0.61)	(0.91)	(0.41)				
Energy delivered (sum)	−1561	373	−1706	3096	−1555	302	−1743	3031
	(−0.51)	(0.15)	(−0.56)	(1.20)	(−0.49)	(0.12)	(−0.55)	(1.14)
Lines underground (LV)	5544**				6351***			
	(2.42)				(2.74)			
Lines overhead (LV)	14737**				15001**			
	(2.18)				(2.23)			
Network length (LV)		8088***				8527***		
		(2.90)				(3.30)		
Lines underground (> LV)	2011	−4615			1723	−4546		
	(0.20)	(−0.53)			(0.17)	(−0.51)		
Lines overhead (> LV)	15157***	17870***			15469***	17971***		
	(3.11)	(4.41)			(3.13)	(4.32)		
Lines underground (all levels)			4817**				5445***	
			(2.38)				(2.91)	
Lines overhead (all levels)			15121***				15494***	
			(4.65)				(4.78)	
Network length (sum)				7130***				7367***
				(3.24)				(3.31)
Constant	−454823	−312186	−483313	−533322	−325005	−231017	−351717	−478249
	(−0.88)	(−0.66)	(−0.94)	(−0.97)	(−0.67)	(−0.50)	(−0.72)	(−0.96)
DSOs	148	148	148	148	148	148	148	148
R^2	0.94	0.93	0.94	0.92	0.94	0.93	0.94	0.91
BIC	4994	5000	4985	5022	4991	4995	4982	5018

Notes: We employ the full data set for the year 2010. OLS estimation using standard errors clustered at DSO level. t statistic reported in parentheses. *,**,***: significant at 10%, 5% and 1%, respectively.

[47] In the second official efficiency analysis, this variable has been replaced by the number of meters.

[48] The IRO does not prescribe any particular functional form for SFA, it only specifies that the choice of output variables (next to some prescribed ones) has to be guided by statistical means in order to capture the DSOs supply obligations.

[49] We do not consider a translog functional form as this implies estimating many more parameters producing poor results for our dataset.

Table A.2
SFA regression results (model with lowest BIC).

Soc. frontier normal/half-normal model				Number of obs: 150 Log likelihood: -57.05713
ln(totex)	Coef.	Std. Err.	z	$P > \|z\|$
ln(exit points)	0.403	0.077	5.226	0.000
ln(cap. renewable)	0.002	0.032	0.073	0.942
ln(energy delivered)	0.162	0.067	2.425	0.015
ln(lines underground (all levels))	0.359	0.093	3.845	0.000
ln(lines overhead (all levels))	0.043	0.019	2.212	0.027
I(lines overhead (all levels) = 0)	−0.022	0.103	−0.212	0.832
Constant	10.836	0.344	31.532	0.000
sigma_sq	0.203	0.061	3.326	0.001
gamma	0.596	0.252	2.366	0.018

Notes: I(lines overhead (all levels) = 0) is a dummy indicating whether a DSO does not have any overhead lines at any voltage level. The DSO's according value for ln(lines overhead (all levels)) is then set to zero. This approach follows Battese (1997) and renders the use of the Cobb−Douglas functional form possible, even under the presence of non-used outputs. gamma is the share of the inefficiency term's variation on the composite error term's variation (sigma_sq). Its relatively high value indicates the presence of inefficiency (and not just noise).

Table A.3
SFA regression results (model with highest degree of aggregation).

Stoc. frontier normal/half-normal model				Number of obs: 150 Log likelihood: −58.21459
ln(totex)	Coef.	Std. Err.	z	$P > \|z\|$
ln(exit points)	0.400	0.076	5.298	0.000
ln(cap. renewable)	0.005	0.033	0.150	0.881
ln(energy delivered)	0.140	0.068	2.042	0.041
ln(network length (sum))	0.427	0.092	4.652	0.000
Constant	10.604	0.334	31.724	0.000
sigma_sq	0.212	0.063	3.391	0.001
gamma	0.621	0.238	2.606	0.009

Notes: gamma is the share of the inefficiency term's variation on the composite error term's variation (sigma_sq). Its relatively high value indicates the presence of inefficiency (and not just noise).

Table A.4
Summary statistics (non-restricted sample).

Variable	Obs.	Mean	Std. dev.	Min	Max	Description
Population	598	71,020	99,000	3512	689,582	Population in area served at low voltage level
Exit points	600	42.60	62.10	1.80	429.26	Total number of exit points at all voltage levels in 1000
Energy delivered	600	502.15	956.53	22.70	7021.60	Annual energy delivered to end users in GWh
Area served	593	34.93	56.36	2.00	420.00	Area served at low voltage level in km^2
Network length	600	1283.70	2207.14	65.00	15163.00	Total length of underground and overhead lines at all voltage levels in km
Growth solar cap.	600	165.64	220.99	9.20	4083.63	Growth rate of installed capacity for solar power electricity generation in %
Cap. renewable	600	28.97	77.13	0.07	902.99	Installed capacity for renewable electricity generation in MW
Network acquisition	600	0.04	0.19	0	1	Dummy indicating network acquisitions
Price of labor	600	17.41	1.39	16.03	20.72	Official wage in energy sector in euro/h (mean at federal state level)
Totex	600	12.31	18.90	0.32	109.85	Effective network-operation costs in m euro
Opex	600	9.47	16.06	0.22	95.32	(= capex + opex)
Capex	600	2.84	4.09	0.07	39.03	Standardized operational expenditures in m euro

Notes: Summary statistics for data of 150 DSOs for years 2010–2013. Accounting data in 2010 euro.
Sources: DSOs' annual statements with separate accounting information for network operation as demanded by Section 6b German Energy Act; DSOs' network data published on their websites complying with Section 27 Network Charges Ordinance; data on renewable energy production published by transmission system operators complying with Section 73 Renewable Energy Sources Act.

Table A.5
Test of common trend assumption.

Dependent variable:	ln(totex) (1)	ln(opex) (2)	ln(capex) (3)
ln(exit points)	0.023	−0.025	0.120
	(0.52)	(−0.79)	(1.34)
ln(energy delivered)	0.063	0.055	0.066
	(1.41)	(1.10)	(0.97)
ln(network length)	0.377***	0.318***	0.565***
	(3.65)	(2.80)	(3.67)
ln(cap. renewable)	0.015	0.012	0.010
	(0.76)	(0.49)	(0.57)
ln(lagged cap. renewable)	0.016	0.030**	−0.019
	(1.32)	(2.02)	(−0.96)
Grid acquisition	0.037*	0.031	0.045
	(1.85)	(1.21)	(1.61)
ln(price of labor)	0.525	1.004	−0.297
	(0.80)	(1.04)	(−0.41)
2010	0.029	0.080	−0.048
	(0.54)	(1.07)	(−0.74)
2011	0.003	0.049	−0.022
	(0.07)	(0.88)	(−0.48)
2012	−0.029	−0.008	−0.021
	(−1.40)	(−0.31)	(−1.01)
2010 × “Revenue Cap”	0.039	0.043	−0.003
	(1.31)	(1.22)	(−0.09)
2011 × “Revenue Cap”	0.050*	0.040	−0.005
	(1.84)	(1.24)	(−0.19)
2012 × “Revenue Cap”	0.043**	0.028	0.018
	(2.32)	(1.29)	(1.07)
Constant	10.308***	9.407***	9.607***
	(4.86)	(3.24)	(3.59)
DSOs	131	131	131
R^2 within	0.17	0.10	0.28
F	3.12***	3.14***	3.80***

Table A.6
Distribution of efficiency scores by regulatory regime.

Variable:	SFA efficiency scores		DEA efficiency scores	
	“Yardstick” (1)	“Revenue Cap” (2)	“Yardstick” (3)	“Revenue Cap” (4)
min	0.598	0.427	0.221	0.150
p25	0.748	0.724	0.439	0.388
mean	0.786	0.774	0.519	0.523
p50	0.797	0.801	0.498	0.482
p75	0.840	0.844	0.604	0.640
max	0.900	0.915	1.000	1.000

Table A.7
Difference−in−differences results - expenditure measures (alternative efficiency score range; SFA efficiency scores).

Dependent variable:	ln(totex)			ln(opex)			ln(capex)		
	No efficiency distinction (1)	Efficiency distinction: median (2)	Efficiency distinction: upper quartile (3)	No efficiency distinction (4)	Efficiency distinction: median (5)	Efficiency distinction: upper quartile (6)	No efficiency distinction (7)	Efficiency distinction: median (8)	Efficiency distinction: upper quartile (9)
“Revenue Cap”	0.024			0.028			0.004		
× base year	(1.14)			(1.05)			(0.25)		
Efficient × “Revenue Cap”		0.040*	0.041*		0.053*	0.049*		−0.002	0.001
× base year		(1.84)	(1.77)		(1.93)	(1.66)		(−0.11)	(0.06)
Non-efficient × “Revenue Cap”		0.008	0.018		0.002	0.020		0.010	0.005
× base year		(0.36)	(0.82)		(0.06)	(0.71)		(0.59)	(0.31)
ln(exit points)	−0.010	−0.009	−0.010	−0.036	−0.034	−0.036	0.039	0.039	0.039
	(−0.37)	(−0.31)	(−0.38)	(−1.31)	(−1.27)	(−1.37)	(0.73)	(0.72)	(0.73)
ln(energy delivered)	0.018	0.020	0.020	0.024	0.027	0.027	0.005	0.004	0.005
	(0.46)	(0.50)	(0.51)	(0.54)	(0.60)	(0.60)	(0.08)	(0.07)	(0.07)
ln(network length)	0.348**	0.335**	0.344**	0.311*	0.290*	0.306*	0.503***	0.508***	0.504***
	(2.60)	(2.48)	(2.56)	(1.83)	(1.69)	(1.79)	(3.62)	(3.64)	(3.62)
ln(cap. renewable)	−0.007	−0.008	−0.007	−0.013	−0.014	−0.013	−0.001	−0.001	−0.001
	(−0.42)	(−0.44)	(−0.42)	(−0.55)	(−0.58)	(−0.56)	(−0.10)	(−0.08)	(−0.10)
ln(lagged cap. renewable)	0.017	0.016	0.016	0.020	0.018	0.019	0.006	0.006	0.006
	(1.43)	(1.25)	(1.33)	(1.27)	(1.06)	(1.17)	(0.59)	(0.65)	(0.60)
Grid acquisition	0.048*	0.048*	0.048*	0.035	0.035	0.035	0.050**	0.050**	0.050**
	(1.86)	(1.85)	(1.85)	(1.01)	(1.00)	(1.01)	(2.08)	(2.07)	(2.07)
ln(price of labor)	0.638	0.685	0.709	0.903	0.979	0.995	0.259	0.241	0.246
	(1.09)	(1.19)	(1.21)	(1.15)	(1.32)	(1.27)	(0.31)	(0.29)	(0.30)
Constant	11.208***	11.138***	11.018***	10.504***	10.391***	10.254***	9.787***	9.813***	9.823***
	(5.53)	(5.53)	(5.46)	(3.84)	(3.93)	(3.76)	(3.98)	(4.02)	(4.01)
DSOs	99	99	99	99	99	99	99	99	99
R^2 within	0.15	0.16	0.15	0.08	0.10	0.09	0.23	0.24	0.23
F	4.09***	4.40***	4.47***	3.24***	3.84***	3.66***	3.41***	3.29***	3.14***

Notes: OLS estimation with DSO-fixed effects and time-fixed effects (omitted for better presentation). Standard errors clustered at DSO level. *t* statistic in parentheses. Distinction between non- and efficient DSOs using SFA efficiency scores. Years 2010–2013. *,**,***: significant at 10%, 5% and 1%, respectively.

Table A.8
Difference-in-differences results - expenditure measures (DEA efficiency scores).

Dependent variable:	ln(totex)			ln(opex)			ln(capex)		
	No efficiency distinction	Efficiency distinction: median	Efficiency distinction: upper quartile	No efficiency distinction	Efficiency distinction: median	Efficiency distinction: upper quartile	No efficiency distinction	Efficiency distinction: median	Efficiency distinction: upper quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
“Revenue Cap” × base year	0.022			0.029			−0.010		
	(1.31)			(1.40)			(−0.75)		
Efficient × “Revenue Cap” × base year		0.037**	0.042**		0.047**	0.054**		−0.003	−0.010
		(2.07)	(2.16)		(2.10)	(2.23)		(−0.20)	(−0.52)
Non-efficient × “Revenue Cap” × base year		0.007	0.015		0.011	0.021		−0.017	−0.010
		(0.35)	(0.87)		(0.48)	(0.95)		(−1.21)	(−0.76)
ln(exit points)	0.024	0.022	0.021	−0.028	−0.030	−0.032	0.121	0.120	0.121
	(0.54)	(0.51)	(0.47)	(−0.91)	(−1.06)	(−1.08)	(1.36)	(1.36)	(1.36)
ln(energy delivered)	0.068	0.070	0.068	0.057	0.060	0.057	0.064	0.065	0.064
	(1.48)	(1.50)	(1.47)	(1.14)	(1.18)	(1.13)	(0.97)	(0.98)	(0.96)
ln(network length)	0.371***	0.370***	0.368***	0.318***	0.316***	0.314***	0.566***	0.565***	0.566***
	(3.55)	(3.59)	(3.52)	(2.76)	(2.76)	(2.72)	(3.66)	(3.67)	(3.66)
ln(cap. renewable)	0.015	0.014	0.015	0.012	0.010	0.011	0.012	0.011	0.012
	(0.75)	(0.68)	(0.73)	(0.46)	(0.40)	(0.44)	(0.64)	(0.62)	(0.64)
ln(lagged cap. renewable)	0.013	0.012	0.012	0.026*	0.025*	0.025*	−0.019	−0.020	−0.019
	(1.03)	(0.95)	(0.97)	(1.81)	(1.67)	(1.72)	(−0.95)	(−0.98)	(−0.95)
Grid acquisition	0.034	0.034*	0.034*	0.027	0.028	0.028	0.045	0.045	0.045
	(1.65)	(1.69)	(1.67)	(1.06)	(1.08)	(1.08)	(1.59)	(1.60)	(1.59)
ln(price of labor)	0.392	0.261	0.320	0.893	0.740	0.802	−0.359	−0.419	−0.360
	(0.58)	(0.39)	(0.47)	(0.94)	(0.78)	(0.84)	(−0.49)	(−0.58)	(−0.50)
Constant	10.745***	11.137***	11.010***	9.860***	10.318***	10.193***	9.734***	9.913***	9.737***
	(5.11)	(5.36)	(5.25)	(3.58)	(3.74)	(3.68)	(3.69)	(3.82)	(3.74)
DSOs	131	131	131	131	131	131	131	131	131
R^2 within	0.16	0.17	0.17	0.09	0.10	0.10	0.28	0.28	0.28
F	3.40***	3.50***	3.58***	3.78***	4.05***	4.30***	3.92***	3.64***	3.59***

Notes: OLS estimation with DSO-fixed effects and time-fixed effects. Standard errors clustered at DSO level. t statistic in parentheses. Distinction between non- and efficient DSOs using DEA efficiency scores. Years 2010–2013. *,**,***: significant at 10%, 5% and 1%, respectively.

Table A.9
Difference-in-differences results - expenditure measures (alternative efficiency score range; DEA efficiency scores).

Dependent variable:	ln (totex)			ln(opex)			ln(capex)		
	No efficiency distinction (1)	Efficiency distinction: median (2)	Efficiency distinction: upper quartile (3)	No efficiency distinction (4)	Efficiency distinction: median (5)	Efficiency distinction: upper quartile (6)	No efficiency distinction (7)	Efficiency distinction: median (8)	Efficiency distinction: upper quartile (9)
"Revenue Cap" × base year	0.024			0.027			0.005		
	(1.08)			(0.96)			(0.33)		
Efficient × "Revenue Cap" × base year		0.034	0.027		0.040	0.036		0.009	0.001
		(1.47)	(1.11)		(1.39)	(1.19)		(0.50)	(0.04)
Non-efficient × "Revenue Cap" × base year		0.014	0.023		0.012	0.025		0.002	0.006
		(0.57)	(1.02)		(0.41)	(0.87)		(0.13)	(0.38)
ln (exit points)	−0.017	−0.017	−0.018	−0.059**	−0.058**	−0.059**	0.079	0.079	0.079
	(−0.49)	(−0.48)	(−0.49)	(−1.99)	(−2.01)	(−2.00)	(0.96)	(0.96)	(0.96)
ln (energy delivered)	0.005	0.007	0.005	0.017	0.019	0.016	−0.020	−0.019	−0.020
	(0.13)	(0.17)	(0.12)	(0.34)	(0.39)	(0.33)	(−0.30)	(−0.29)	(−0.30)
ln (network length)	0.347***	0.348***	0.347***	0.333**	0.335**	0.332**	0.458***	0.458***	0.458***
	(3.01)	(3.04)	(3.00)	(2.32)	(2.35)	(2.31)	(3.55)	(3.56)	(3.55)
ln (cap. renewable)	−0.014	−0.016	−0.014	−0.035	−0.038	−0.035	0.032	0.032	0.033
	(−0.48)	(−0.56)	(−0.48)	(−1.04)	(−1.13)	(−1.04)	(1.00)	(0.98)	(1.01)
ln (lagged cap. renewable)	0.011	0.011	0.011	0.030	0.030	0.030	−0.038	−0.038	−0.038
	(0.47)	(0.48)	(0.47)	(1.08)	(1.09)	(1.08)	(−1.09)	(−1.09)	(−1.09)
Grid acquisition	0.029	0.029	0.029	0.014	0.012	0.013	0.046*	0.046*	0.046*
	(1.13)	(1.11)	(1.13)	(0.40)	(0.37)	(0.40)	(1.98)	(1.97)	(1.97)
ln (price of labor)	1.086	1.018	1.070	1.711	1.615	1.669	0.021	−0.001	0.041
	(1.60)	(1.51)	(1.57)	(1.54)	(1.45)	(1.49)	(0.02)	(−0.00)	(0.04)
Constant	10.339***	10.511***	10.388***	8.572**	8.812**	8.702**	10.781***	10.835***	10.718***
	(4.74)	(4.86)	(4.72)	(2.51)	(2.57)	(2.52)	(3.77)	(3.77)	(3.68)
DSOs	95	95	95	95	95	95	95	95	95
R^2 within	0.14	0.14	0.14	0.09	0.09	0.09	0.23	0.23	0.23
F	3.15***	2.97***	2.91***	3.79***	3.83***	3.59***	3.70***	3.41***	3.38***

Notes: OLS estimation with DSO-fixed effects and time-fixed effects. Standard errors clustered at DSO level. t statistic in parentheses. Distinction between non- and efficient DSOs using DEA efficiency scores. Years 2010–2013. *,**,***: significant at 10%, 5% and 1%, respectively.

Table A.10
Difference-in-differences results - continuous efficiency score.

Dependent variable:	using SFA scores						Using DEA scores					
	ln(totex)		ln (opex)		ln (capex)		ln(totex)		ln(opex)		ln(capex)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
"Revenue Cap" × base year	0.038*	−0.182	0.048*	−0.191	−0.006	−0.144*	0.062***	−0.000	0.075**	0.011	0.003	−0.049
× Efficiency score	(1.85)	(−1.60)	(1.88)	(−1.27)	(−0.34)	(−1.68)	(2.68)	(−0.00)	(2.55)	(0.12)	(0.13)	(−0.88)
"Revenue Cap" × base year ×		0.268**		0.290		0.168		0.078		0.080		0.065
Efficiency score squared		(2.03)		(1.65)		(1.63)		(1.15)		(0.81)		(0.94)
ln(exit points)	0.023	0.020	−0.030	−0.032	0.120	0.119	0.019	0.018	−0.034	−0.035	0.119	0.119
	(0.50)	(0.47)	(−0.99)	(−1.16)	(1.35)	(1.35)	(0.43)	(0.41)	(−1.17)	(−1.22)	(1.35)	(1.34)
ln(energy delivered)	0.068	0.068	0.057	0.058	0.064	0.064	0.068	0.069	0.058	0.059	0.064	0.064
	(1.49)	(1.46)	(1.15)	(1.12)	(0.97)	(0.97)	(1.49)	(1.49)	(1.15)	(1.15)	(0.97)	(0.97)
ln(network length)	0.370***	0.362***	0.316***	0.307***	0.567***	0.561***	0.368***	0.364***	0.313***	0.310***	0.567***	0.564***
	(3.57)	(3.52)	(2.76)	(2.69)	(3.66)	(3.66)	(3.58)	(3.52)	(2.75)	(2.69)	(3.67)	(3.68)
ln (cap. renewable)	0.015	0.014	0.012	0.011	0.012	0.011	0.015	0.014	0.011	0.011	0.012	0.012
	(0.76)	(0.70)	(0.47)	(0.42)	(0.65)	(0.63)	(0.74)	(0.71)	(0.45)	(0.43)	(0.66)	(0.63)
ln (lagged cap. renewable)	0.013	0.012	0.026*	0.025*	−0.019	−0.020	0.012	0.012	0.025*	0.024*	−0.019	−0.019
	(1.02)	(0.96)	(1.79)	(1.68)	(−0.94)	(−0.99)	(0.96)	(0.94)	(1.70)	(1.67)	(−0.94)	(−0.96)
Grid acquisition	0.034*	0.037*	0.028	0.031	0.045	0.046	0.035*	0.036*	0.029	0.030	0.045	0.045
	(1.70)	(1.78)	(1.10)	(1.19)	(1.58)	(1.64)	(1.73)	(1.75)	(1.13)	(1.15)	(1.59)	(1.60)
ln (price of labor)	0.385	0.304	0.881	0.793	−0.348	−0.399	0.338	0.316	0.823	0.800	−0.345	−0.363
	(0.57)	(0.45)	(0.93)	(0.83)	(−0.48)	(−0.55)	(0.50)	(0.47)	(0.87)	(0.84)	(−0.48)	(−0.50)
Constant	10.785***	11.108***	9.919***	10.269***	9.698***	9.901***	10.974***	11.066***	10.151***	10.247***	9.695***	9.772***
	(5.16)	(5.33)	(3.62)	(3.71)	(3.68)	(3.80)	(5.30)	(5.35)	(3.72)	(3.74)	(3.72)	(3.80)
DSOs	131	131	131	131	131	131	131	131	131	131	131	131
R^2 within	0.17	0.17	0.10	0.10	0.28	0.28	0.17	0.17	0.10	0.10	0.28	0.28
F	3.48***	3.55***	3.93***	4.10***	3.88***	3.66***	3.99***	4.39***	4.58***	4.59***	3.82***	3.49***

Notes: OLS estimation with DSO-fixed effects and time-fixed effects (omitted for better presentation). Standard errors clustered at DSO level. t statistic in parentheses. Years 2010–2013. *,**,***: significant at 10%, 5% and 1%, respectively.

Table A.11
Difference-in-differences results - expenditure measures (DSOs with less than 100,000 connected consumers).

	No efficiency distinction	Efficiency distinction: median	Efficiency distinction: upper quartile	No efficiency distinction	Efficiency distinction: median	Efficiency distinction: upper quartile	No efficiency distinction	Efficiency distinction: median	Efficiency distinction: upper quartile
	Distinction between non- and efficient DSOs using SFA efficiency scores								
Dependent variable:	ln(totex)			ln(opex)			ln(capex)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
"Revenue Cap" × base year	0.020			0.025			−0.013		
	(1.03)			(1.05)			(−0.95)		
Efficient × "Revenue Cap" × base year		0.036*	0.041**		0.044*	0.050*		−0.007	−0.008
		(1.78)	(1.99)		(1.74)	(1.86)		(−0.44)	(−0.45)
Non-efficient × "Revenue Cap" × base year		0.004	0.013		0.006	0.017		−0.020	−0.015
		(0.18)	(0.63)		(0.24)	(0.68)		(−1.33)	(−1.05)
R^2 within	*0.16*	*0.17*	*0.17*	*0.09*	*0.10*	*0.10*	*0.28*	*0.28*	*0.28*
F	*3.26****	*3.26****	*3.54****	*3.68****	*3.84****	*4.23****	*4.27****	*4.01****	*4.02****
	Distinction between non- and efficient DSOs using DEA efficiency scores								
Dependent variable:	ln(totex)			ln(opex)			ln(capex)		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
"Revenue Cap" × base year	0.020			0.025			−0.013		
	(1.03)			(1.05)			(−0.95)		
Efficient × "Revenue Cap" × base year		0.035*	0.040*		0.043*	0.051*		−0.006	−0.013
		(1.74)	(1.86)		(1.70)	(1.87)		(−0.41)	(−0.67)
Non-efficient × "Revenue Cap" × base year		0.004	0.013		0.007	0.017		−0.020	−0.013
		(0.20)	(0.65)		(0.27)	(0.67)		(−1.38)	(−0.96)
R^2 within	*0.16*	*0.17*	*0.17*	*0.09*	*0.10*	*0.10*	*0.28*	*0.28*	*0.28*
F	*3.26****	*3.40****	*3.46****	*3.68****	*3.97****	*4.18****	*4.27****	*3.96****	*3.90****
DSOs	125	125	125	125	125	125	125	125	125

Notes: OLS estimation with DSO-fixed effects and time-fixed effects. Covariates omitted for better presentation. Standard errors clustered at DSO level. t statistic in parentheses. Years 2010–2013. *,**,***: significant at 10%, 5% and 1%, respectively.

Table A.12
Difference-in-differences results - expenditure measures (alternative efficiency analysis).

	No efficiency distinction	Efficiency distinction: median	Efficiency distinction: upper quartile	No efficiency distinction	Efficiency distinction: median	Efficiency distinction: upper quartile	No efficiency distinction	Efficiency distinction: median	Efficiency distinction: upper quartile
	Distinction between non- and efficient DSOs using SFA efficiency scores								
Dependent variable:	ln (totex)			ln(opex)			ln(capex)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
“Revenue Cap” × base year	0.022			0.029			−0.010		
	(1.31)			(1.40)			(−0.75)		
0]12emEfficient × “Revenue Cap” × base year		0.037**	0.039**		0.047**	0.047*		−0.004	−0.003
		(2.13)	(2.04)		(2.15)	(1.89)		(−0.28)	(−0.17)
0]12emNon-efficient × “Revenue Cap” × base year		0.007	0.016		0.011	0.024		−0.016	−0.012
		(0.34)	(0.92)		(0.45)	(1.07)		(−1.10)	(−0.91)
R^2 *within*	*0.16*	*0.17*	*0.17*	*0.09*	*0.10*	*0.09*	*0.28*	*0.28*	*0.28*
F	*3.40****	*3.42****	*3.41****	*3.78****	*3.91****	*4.07****	*2.92***	*3.63****	*3.65****
	Distinction between non- and efficient DSOs using DEA efficiency scores								
Dependent variable:	ln (totex)			ln(opex)			ln(capex)		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
“Revenue Cap” × base year	0.022			0.029			−0.010		
	(1.31)			(1.40)			(−0.75)		
0]12emEfficient × “Revenue Cap” × base year		0.031*	0.049**		0.036*	0.063***		−0.000	−0.006
		(1.76)	(2.58)		(1.65)	(2.62)		(−0.03)	(−0.34)
0]12emNon-efficient × “Revenue Cap” × base year		0.013	0.013		0.023	0.018		−0.020	−0.011
		(0.67)	(0.73)		(0.93)	(0.82)		(−1.42)	(−0.85)
R^2 *within*	*0.16*	*0.17*	*0.17*	*0.09*	*0.09*	*0.10*	*0.28*	*0.28*	*0.28*
F	*3.40****	*3.29****	*3.77****	*3.78****	*3.72****	*4.38****	*3.92****	*3.73****	*3.59****
DSOs	131	131	131	131	131	131	131	131	131

Notes: OLS estimation with DSO-fixed effects and time-fixed effects. Covariates omitted for better presentation. Standard errors clustered at DSO level. t statistic in parentheses. Years 2010–2013. *,**,***: significant at 10%, 5% and 1%, respectively.

Table A.13
Matching results as alternative analysis.

Dependent variable:	Rate of totex change			rate of opex change			rate of capex change		
	"Revenue Cap" vs. "Yardstick" (1)	median efficient in "Revenue Cap" vs. "Yardstick" (2)	upper quartile efficient in "Revenue Cap" vs. "Yardstick" (3)	"Revenue Cap" vs. "Yardstick" (4)	median efficient in "Revenue Cap" vs. "Yardstick" (5)	upper quartile efficient in "Revenue Cap" vs. "Yardstick" (6)	"Revenue Cap" vs. "Yardstick" (7)	median efficient in "Revenue Cap" vs. "Yardstick" (8)	upper quartile efficient in "Revenue Cap" vs. "Yardstick" (9)
	Number of nearest neighbors: 4; efficiency distinction: SFA								
Average treatment effect on the treated	0.326 (4.606)	6.585 (4.902)	10.813* (5.927)	1.911 (5.123)	8.786 (5.433)	13.164** (6.000)	−5.764 (4.947)	−2.297 (6.401)	1.338 (9.603)
	Number of nearest neighbors: 5; efficiency distinction: SFA								
Average treatment effect on the treated	0.206 (4.152)	5.047 (4.547)	8.862* (5.325)	1.584 (4.664)	6.803 (5.012)	10.667** (5.356)	−5.097 (4.647)	−2.358 (6.154)	0.978 (9.014)
	Number of nearest neighbors: 6; efficiency distinction: SFA								
Average treatment effect on the treated	−0.105 (3.893)	4.974 (4.165)	8.413* (5.073)	1.013 (4.390)	6.499 (4.583)	9.886** (5.007)	−4.630 (4.410)	−1.708 (5.799)	1.336 (8.763)
	Number of nearest neighbors: 4; efficiency distinction: DEA								
Average treatment effect on the treated	0.326 (4.606)	6.227 (4.868)	9.816* (5.775)	1.911 (5.123)	8.164 (5.411)	11.606** (5.898)	−5.764 (4.947)	−1.826 (6.299)	1.787 (9.257)
	Number of nearest neighbors: 5; efficiency distinction: DEA								
Average treatment effect on the treated	0.206 (4.152)	5.186 (4.435)	8.606* (5.187)	1.584 (4.664)	6.902 (4.867)	10.043* (5.237)	−5.097 (4.647)	−1.834 (6.031)	1.931 (8.798)
	Number of nearest neighbors: 6; efficiency distinction: DEA								
Average treatment effect on the treated	−0.105 (3.893)	4.581 (4.163)	8.478* (4.981)	1.013 (4.390)	5.985 (4.554)	9.679* (4.968)	−4.630 (4.410)	−1.598 (5.774)	2.417 (8.562)
DSOs	118	72	49	118	72	49	118	72	49

Notes: Treatment-effects estimation using nearest-neighbor matching (Mahalanobis distance metric). AI robust standard errors in parentheses. Matching on exit points, energy delivered, network length, cap. renewable, and lagged cap. renewable. DSOs that encountered network acquisitions were disregarded. Distinction between non- and efficient DSOs using efficiency scores as mentioned. Year 2011. *,**,***: significant at 10%, 5% and 1%, respectively.

Table A.14
Matching results for welfare analysis.

Dependent variable:	Rate of totex change			rate of opex change			rate of capex change		
	"Revenue Cap" vs. "Yardstick"	Median efficient in "Revenue Cap" vs. "Yardstick"	Upper quartile efficient in "Revenue Cap" vs. "Yardstick"	"Revenue Cap" vs. "Yardstick"	median efficient in "Revenue Cap" vs. "Yardstick"	upper quartile efficient in "Revenue Cap" vs. "Yardstick"	"Revenue Cap" vs. "Yardstick"	median efficient in "Revenue Cap" vs. "Yardstick"	upper quartile efficient in "Revenue Cap" vs. "Yardstick"
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Number of nearest neighbors: 4; efficiency scores and distinction: SFA								
Average treatment effect on the treated	0.939	6.781*	10.534**	2.026	7.807*	10.818**	-2.970	2.517	7.716
	(3.085)	(3.833)	(4.807)	(3.476)	(4.077)	(4.633)	(4.050)	(5.965)	(9.107)
	Number of nearest neighbors: 5; efficiency scores and distinction: SFA								
Average treatment effect on the treated	1.128	7.374**	10.747**	2.147	8.496**	11.044***	−2.320	2.964	7.790
	(2.884)	(3.493)	(4.429)	(3.217)	(3.688)	(4.249)	(3.852)	(5.646)	(8.741)
	Number of nearest neighbors: 6; efficiency scores and distinction: SFA								
Average treatment effect on the treated	1.269	7.032**	10.993***	2.146	8.141**	11.560***	−1.681	2.817	7.576
	(2.770)	(3.331)	(4.217)	(3.088)	(3.499)	(3.970)	(3.713)	(5.445)	(8.467)
	Number of nearest neighbors: 4; efficiency scores and distinction: DEA								
Average treatment effect on the treated	0.939	1.746	4.218	2.026	2.337	3.377	−2.970	−1.131	4.093
	(3.085)	(3.848)	(4.626)	(3.476)	(4.051)	(3.996)	(4.050)	(6.068)	(9.491)
	Number of nearest neighbors: 5; efficiency scores and distinction: DEA								
Average treatment effect on the treated	1.128	1.999	4.381	2.147	2.393	3.343	−2.320	−0.397	4.422
	(2.884)	(3.526)	(4.265)	(3.217)	(3.676)	(3.813)	(3.852)	(5.804)	(8.961)
	Number of nearest neighbors: 6; efficiency scores and distinction: DEA								
Average treatment effect on the treated	1.269	2.985	5.156	2.146	3.429	4.421	−1.681	0.500	4.568
	(2.770)	(3.254)	(4.125)	(3.088)	(3.383)	(3.776)	(3.713)	(5.481)	(8.737)
DSOs	132	86	63	132	86	63	132	86	63

Notes: Treatment-effects estimation using nearest-neighbor matching (Mahalanobis distance metric). AI robust standard errors in parentheses. Matching on 2010 efficiency score, exit points, energy delivered, network length, cap. renewable, and lagged cap. renewable. DSOs that encountered network acquisitions were disregarded. Distinction between non- and efficient DSOs using efficiency scores as mentioned. Year 2011. *,**,***: significant at 10%, 5% and 1%, respectively.

A.5. Figures

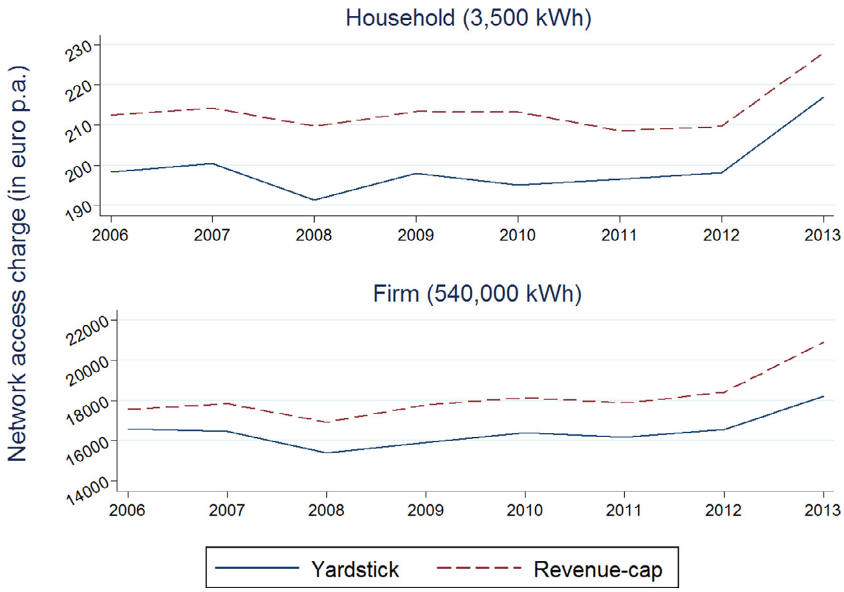

Fig. A.2. Development of network access charges for representative users by regulatory regime.

References

Agrell, P.J., Bogetoft, P., Cullmann, A., Von Hirschhausen, C., Neumann, A., Walter, M., 2008. Ergebnisdokumentation: Bestimmung der Effizienzwerte Verteilernetzbetreiber Strom. Dresden.
Agrell, P. J., Bogetoft, P., Koller, M., Trinkner, U., 2014. Effizienzvergleich für Verteilernetzbetreiber Strom 2013.
Agrell, P.J., Bogetoft, P., Tind, J., 2005. DEA And dynamic yardstick competition in scandinavian electricity distribution. J. Product. Anal. 23 (2), 173–201.
Ai, C., Sappington, D.E.M., 2002. The impact of state incentive regulation on the u.s. telecommunications industry. J. Regul. Econ. 22 (2), 133–160.
Aigner, D., Lovell, C.A.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econom. 6 (1), 21–37.
Averch, H., Johnson, L.L., 1962. Behavior of the firm under regulatory constraint. Am. Econ. Rev. 52 (5), 1052–1069.
Battese, G.E., 1997. A note on the estimation of Cobb-Douglas production functions when some explanatory variables have zero values. J. Agric. Econ. 48 (1–3), 250–252.
Beesley, M.E., Littlechild, S.C., 1989. The regulation of privatized monopolies in the united kingdom. RAND J. Econ. 20, 454–472.
Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? Q. J. Econ. 119 (1), 249–275.
Biglaiser, G., Riordan, M., 2000. Dynamics of price regulation. RAND J. Econ. J. Econ. 31 (4), 744–767.
Blundell, R., Dias, M.C., 2009. Alternative approaches to evaluation in empirical microeconomics. J. Hum. Resour. 44 (3), 565–640.
Bogetoft, P., Otto, L., 2011. Benchmarking with DEA, SFA, and R. Springer, New York, NY.
Bogetoft, P., Otto, L., 2015. Benchmarking with DEA and SFA. R package version 0.26.
Braeutigam, R.R., Panzar, J.C., 1993. Effects of the change from rate-of-return to price-cap regulation. Am. Econ. Rev. 83 (2), 191–198.
Bundesnetzagentur, 2014. Evaluierungsbericht nach §33 Anreizregulierungsverordnung. Bonn.
Cabral, L.M.B., Riordan, M.H., 1989. Incentives for cost reduction under price cap regulation. J. Regul. Econ. 1 (2), 93–102.
Cambini, C., Rondi, L., 2010. Incentive regulation and investment: evidence from european energy utilities. J. Regul. Econ. 38 (1), 1–26.
Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444.
Cicala, S., 2015. When does regulation distort costs? Lessons from fuel procurement in US electricity generation. Am. Econ. Rev. 105 (1), 411–444.
Coelli, T., Henningsen, A., 2013. frontier: Stochastic Frontier Analysis. R package version 1.10.
Coelli, T., Rao, D.S.P., O'Donnell, C.J., Battese, G.E., 2005. An Introduction to Efficiency and Productivity Analysis, 2 Springer, New York, NY.
Crew, M.A., Kleindorfer, P.R., 1996. Incentive regulation in the United Kingdom and the United States: Some lessons. J. Regul. Econ. 9 (3), 211–225.
Crew, M.A., Kleindorfer, P.R., 2002. Regulatory economics: twenty years of progress? J Regul Econ 21 (1), 5–22.
Cullmann, A., Nieswand, M., 2016. Regulation and investment incentives in electricity distribution: an empirical assessment. Energy Econ. 57, 192–203.
Davis, L.W., Wolfram, C., 2012. Deregulation, consolidation, and efficiency: evidence from US nuclear power. Am. Econ. J.: Appl. Econ. 4 (4), 194–225.
Dobbs, I.M., 2014. Intertemporal price cap regulation under uncertainty. Econ. J. 114, 421–440.
Domah, P., Pollitt, M.G., 2001. The restructuring and privatisation of electricity distribution and supply businesses in England and Wales: a Social cost–Benefit analysis. Fisc Stud 22 (1), 107–146.
Donald, S.G., Lang, K., 2007. Inference with difference-in-differences and other panel data. Rev. Econ. Stat. 89 (2), 221–233.
Evans, L., Guthrie, G., 2012. Price-cap regulation and the scale and timing of investment. RAND J. Econ. 43 (3), 537–561.
Fabrizio, K.R., Rose, N.L., Wolfram, C.D., 2007. Do markets reduce costs? assessing the impact of regulatory restructuring on US electric generation efficiency. Am. Econ. Rev. 97 (4), 1250–1277.
Finsinger, J., Kraft, K., 1984. Markup pricing and firm decisions. Zeitschrift für die gesamte Staatswissenschaft/J. Inst. Theor. Econ. 140, 500–509.
Greenstein, S., Mcmaster, S., Spiller, P.T., 1995. The effect of incentive regulation on infrastructure modernization: local exchange Companies' deployment of digital technology. J. Econ. Manag. Strat. 4 (2), 187–236.
Guthrie, G., 2006. Regulating infrastructure: the impact on risk and investment. J. Econ. Lit. 44 (4), 925–972.
Joskow, P.L., 2008. Incentive regulation and its application to electricity networks. Rev. Netw. Econ. 7 (4), 547–560.
Knittel, C.R., 2002. Alternative regulatory methods and firm efficiency: stochastic frontier evidence from the u.s. electricity industry. Rev. Econ. Stat. 84 (3), 530–540.
Kridel, D.J., Sappington, D.E.M., Weisman, D.L., 1996. The effects of incentive regulation in the telecommunications industry: a survey. J. Regul. Econ. 9 (3), 269–306.
Laffont, J.-J., Tirole, J., 1993. A Theory of Incentives in Procurement and Regulation. MIT Press, Cambridge, Mass.
Lechner, M., 2011. The estimation of causal effects by difference-in-Difference methods. Found. Trends(R) Econom. 4 (3), 165–224.

Liston, C., 1993. Price-cap versus rate-of-return regulation. J. Regul. Econ. 5 (1), 25–48.
Littlechild, S.C., 1986. Economic Regulation of Privatised Water Authorities. IWA Publishing, London.
Majumdar, S.K., 1997. Incentive regulation and productive efficiency in the u.s. telecommunications industry. J. Bus. 70 (4), 547–576.
Meeusen, W., van den Broeck, J., 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. Int. Econ. Rev. (Phila.) 18 (2), 435.
Newbery, D.M., Pollitt, M.G., 1997. The restructuring and privatisation of the CEGB – was it worth it? J. Ind. Econ. 45 (3), 269–303.
Sappington, D.E.M., Weisman, D.L., 2010. Price cap regulation: what have we learned from 25 years of experience in the telecommunications industry? J. Regul. Econ. 38 (3), 227–257.
Seo, D., Shin, J., 2011. The impact of incentive regulation on productivity in the US telecommunications industry: a stochastic frontier approach. Inf. Econ. Policy 23 (1), 3–11.
Shleifer, A., 1985. A theory of yardstick competition. RAND J. Econ. 16 (3), 319–327.
Vogelsang, I., 2002. Incentive regulation and competition in public utility markets: a 20-year perspective. J. Regul. Econ. 22 (1), 5–27.
Willems, B., Zwart, G., 2018. Optimal regulation of network expansion. RAND J. Econ. 49 (1), 23–42.