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BY

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Abstract

Norwegian distribution companies have been subjected to an incentive regulation scheme from 1997, and the efficiency incentives were further strengthened with the introduction of yardstick regulation in 2007. We examine the productivity development for these companies in the period from 2004 to 2013. Using three benchmarking methods, DEA, SFA, and StoNED, we examine productivity change, with the usual decompositions into efficiency change, technical change, and scale efficiency change. Increasing investments and use of accounting-based capital costs in our analysis may lead to a negative bias in the productivity change estimates, and we therefore perform our analysis with and without capital costs. Our results indicate a negative productivity development for the whole period from 2004 to 2013, and we do not observe a positive effect of the change in regulation regime from 2007.

1 Introduction

With electricity sector reforms in the 1990s, the structure, organization, and operating environment for the electricity sector in many countries experienced great change. The central objectives of the reforms were to implement market competition in electricity generation and supply sectors, and to improve the efficiency or productivity of the natural monopoly activities of distribution and transmission through suitable regulatory schemes. In this paper we focus on the electricity distribution companies.

The aim of the regulatory reforms is to provide the distribution companies with incentives to improve their investment and operating efficiency and to ensure that consumers benefit from the efficiency gains. Regulators have therefore adopted a variety of approaches to incentive regulation, including rate-of-return (ROR), cost-of-service (COS) regulation, and so on. The most widely used incentive schemes are based on price cap, revenue cap, and yardstick regulation. In practice, many regulators implement these incentive regimes with different benchmarking methods. Within this context, the standard definition of benchmarking is a comparison of some measure of actual performance against a reference performance. The common way of obtaining a comprehensive benchmarking is to establish production or cost frontiers for the companies, and then to estimate the performance of individual companies based on the corresponding frontier.

In Norway, the Energy Act of 1990, in force from 1991, introduced a regulatory reform of the Norwegian electricity market. The reform laid the ground rules for competition in the supply sector and regulation in transmission and distribution sectors. In 1997, the Norwegian Water Resources and Energy Directorate (NVE) implemented an incentive regulation scheme with revenue caps that were updated every 5 years based on Data Envelopment Analysis (DEA). From 2007, the incentives were strengthened in a yardstick regulation scheme with annual updates of the revenue caps. See Bjørndal et al. (2010) for a more detailed discussion of the various regulation schemes that have been used. Amundsveen and Kvile (2014) discusses the present yardstick regulation.

There are several different approaches to measure the relative efficiency and productivity of companies in relation to a sample's efficient frontier (Jamasb and Pollit, 2001). These approaches are generally placed into two broad categories: non-parametric and parametric techniques. DEA (Charnes et al., 1978; Farrell, 1957) is a non-parametric method that is capable of handling multiple inputs and multiple outputs, while stochastic frontier analysis (SFA) (Aigner et al., 1977) and corrected ordinary least squares (COLS) (Richmond, 1974) are parametric methods. Lately, a semi-nonparametric approach has been proposed, i.e. stochastic semi-parametric envelopment of data, or StoNED (Kuosmanen and Kortelainen, 2012), and this method has been used for regulation of Finnish distribution companies (Kuosmanen, 2012). We use the StoNED method to examine the productivity performance for Norwegian electricity distribution companies, and we compare the StoNED results to estimates based on DEA and SFA. Our analysis is based on a sample of 123 distribution companies for the period 2004-2013. We also decompose the respective productivity indices, and we discuss efficiency change, technical change and scale efficiency change for the companies.

The rest of the paper is organized as follows: First we review previous productivity studies of electricity distribution in Norway and other countries in Section 2. The necessary methodology, i.e. Malmquist, DEA, SFA, and StoNED, is introduced in Section 3. The data and the empirical results are described in Sections 4 and 5, respectively, and we conclude in Section 6.

2 Previous studies

Hjalmarsson and Veiderplass (1992) applied DEA to investigate productivity development of electricity distribution in Sweden between 1970 and 1986. They found a high rate (5%) of productivity growth, due to economies of density, over a period 17 years. Giannakis et al. (2003) studied technical efficiency and productivity change for electricity distribution companies in the United Kingdom for the period 1991/92 to 1998/99 using the DEA approach. Their analysis indicated significant productivity growth, and the gains could be attributed to reduced efficiency gap among the companies, frontier shift, and improved quality of service. Pombo and Taborda (2006) did a DEA-based Malmquist productivity study of Colombia’s electricity distribution companies for the period 1985 to 2001, and they found that the largest companies experienced increasing productivity, due to frontier shift after the reform in 1994. Nakano and Managi (2008) estimated the Luenberger productivity indicator using DEA and dynamic generalized method of moments (GMM) for Japanese electricity distribution companies over the period 1978–2003. They found a positive productivity effect of the regulatory reforms, mainly due to technological change. Pérez-Reyes and Tovar (2009) applied DEA to study productivity development of electricity distribution companies in Peru over the period 1996-2006. They found an annual average productivity growth of 4.3%, and most of this growth was due to technological change. Ramos-Real et al. (2009), using DEA, found an annual productivity growth of 1.3% for Brazilian electricity distribution companies from 1998 to 2005, and they concluded that technological change was the main cause of growth.

Førsund and Kittelsen (1998) used DEA to study productivity development of Norwegian distribution companies between the two years 1983 and 1989. They found positive growth of almost 2% per year on average, and the growth was mostly due to technological change. Edvardsen et al. (2006) used DEA to study productivity change of Norwegian electricity distribution companies over the period 1996-2003. They found an annual productivity increase of 1.1%, which was driven by both efficiency change and technological change. Migueís et al. (2011) used DEA to examine productivity change for Norwegian electricity distribution companies between 2004 and 2007, and they included environmental factors as output variables with restricted virtual weights. Their study found almost 0.3% annual productivity growth, mostly due to technological change. They also identified innovator firms, i.e., firms that contributed to positive frontier shifts.

3 Methodology

3.1 The Malmquist productivity index and its decompositions

The concept of the Malmquist productivity index originated from Caves et al. (1982a). In order to define it we need to specify the production technology as

$$P^t(\boldsymbol{y}^t) = \{\boldsymbol{x}^t : \boldsymbol{x}^t \text{ can produce } \boldsymbol{y}^t\}, \tag{1}$$

where $\boldsymbol{x}^t$ and $\boldsymbol{y}^t$ represent the input vector and output vector at each time period $t, t = 1, \cdots, T$, respectively. The set $P^t(\boldsymbol{y}^t)$ is assumed to be non-empty, closed, convex and bounded. It satisfies strong disposability of inputs and outputs, and also contains all input vectors that can produce output $\boldsymbol{y}^t$. A functional representation of the technology is constructed by Shephard's (1970) input distance function

$$D^t(\boldsymbol{y}^t, \boldsymbol{x}^t) = \sup\{\varphi : (\boldsymbol{x}^t/\varphi) \in P^t(\boldsymbol{y}^t), \varphi > 0\}. \tag{2}$$

The function $D^t(\boldsymbol{y}^t, \boldsymbol{x}^t)$ represents the maximum proportional contraction of inputs given outputs at each period t. $D^t(\boldsymbol{y}^t, \boldsymbol{x}^t)$ is defined in terms of period t dataset and technology, and adjacent-period input distances using period t or $t+1$ data and period $t+1$ or t technology are defined as

$$D^{t+1}(\boldsymbol{y}^t, \boldsymbol{x}^t) = \sup\{\varphi: (\boldsymbol{x}^t/\varphi) \in P^{t+1}(\boldsymbol{y}^t), \varphi > 0\} \tag{3}$$

and

$$D^{t}(\boldsymbol{y}^{t+1}, \boldsymbol{x}^{t+1}) = \sup\{\varphi: (\boldsymbol{x}^{t+1}/\varphi) \in P^{t}(\boldsymbol{y}^{t+1}), \varphi > 0\}, \tag{4}$$

respectively (Grifell-Tatje and Lovell, 1995).

Following Färe and Primont (1995), the input distance function $D^t(\boldsymbol{y}^t, \boldsymbol{x}^t)$ is reciprocal to Farrell's input oriented measure of efficiency, which is

$$E^t(\boldsymbol{y}^t, \boldsymbol{x}^t) = \min\{\theta: (\theta\boldsymbol{x}^t) \in P^t(\boldsymbol{y}^t), \theta > 0\}. \tag{5}$$

The efficiencies for the adjacent-period input distance functions can be obtained as

$$E^{t+1}(\boldsymbol{y}^t, \boldsymbol{x}^t) = \min\{\theta: (\theta\boldsymbol{x}^t) \in P^{t+1}(\boldsymbol{y}^t), \theta > 0\} \tag{6}$$

and

$$E^{t}(\boldsymbol{y}^{t+1}, \boldsymbol{x}^{t+1}) = \min\{\theta: (\theta\boldsymbol{x}^{t+1}) \in P^{t}(\boldsymbol{y}^{t+1}), \theta > 0\}. \tag{7}$$

The Malmquist productivity index between period t and $t+1$ can be expressed as

$$MPI(\boldsymbol{y}^t, \boldsymbol{x}^t, \boldsymbol{y}^{t+1}, \boldsymbol{x}^{t+1}) = \left[\frac{E^t_{crs}(y^{t+1},x^{t+1})}{E^t_{crs}(y^t,x^t)} \frac{E^{t+1}_{crs}(y^{t+1},x^{t+1})}{E^{t+1}_{crs}(y^t,x^t)}\right]^{\frac{1}{2}} = EC \cdot TC \cdot SEC, \tag{8}$$

where E^t_{crs} is the efficiency under constant returns to scale (CRS). Equation (8) also shows that the productivity index can be decomposed into efficiency change (EC), technical change (TC) and scale efficiency change (SEC) (Ray and Desli, 1997). We define E^t_{vrs} as efficiency under variable returns to scale (VRS), as well as

$$EC = \frac{E^{t+1}_{vrs}(y^{t+1},x^{t+1})}{E^t_{vrs}(y^t,x^t)}, \tag{9}$$

$$TC = \left[\frac{E^t_{vrs}(y^{t+1},x^{t+1})}{E^{t+1}_{vrs}(y^{t+1},x^{t+1})} \frac{E^t_{vrs}(y^t,x^t)}{E^{t+1}_{vrs}(y^t,x^t)}\right]^{\frac{1}{2}}, \text{ and} \tag{10}$$

$$SEC = \left[\frac{\frac{E^t_{crs}(y^{t+1},x^{t+1})}{E^t_{vrs}(y^{t+1},x^{t+1})}}{\frac{E^t_{crs}(y^t,x^t)}{E^t_{vrs}(y^t,x^t)}} \frac{\frac{E^{t+1}_{crs}(y^{t+1},x^{t+1})}{E^{t+1}_{vrs}(y^{t+1},x^{t+1})}}{\frac{E^{t+1}_{crs}(y^t,x^t)}{E^{t+1}_{vrs}(y^t,x^t)}}\right]^{\frac{1}{2}}. \tag{11}$$

3.2 Impact of environmental factors

The performance of electricity distribution companies are typically affected by environmental factors that are beyond the companies' control, such as differences in weather conditions or topology. In order to account for the environmental impact in a comparable manner under our three methodological approaches, as described in Sections 3.3-3.5 below, we follow the procedure suggested by Barnum and Gleason (2008). In an output-oriented benchmarking model, they suggest accounting for the effect of the environment on output via a regression where output is regressed on both inputs and environmental variables. Then the effect of environmental variables is removed from the observed output and the new adjusted value of output is obtained, and the benchmarking exercise can be done with the new adjusted data. In our input-oriented application we use the following model to regress the endogenous input (total cost) on the outputs and the environmental variables:

$$\log(\boldsymbol{x}_i) = \omega_i + \boldsymbol{\rho}_i \log(\boldsymbol{y}_i) + \boldsymbol{\delta_i z}_i + \epsilon_i, \quad i = 1, \cdots, n \tag{12}$$

In this equation, x_i is the single input, $\boldsymbol{y_i}$ is the output vector, and $\boldsymbol{z}_i$ is the vector of environmental factors, of company i. The vector $\boldsymbol{\delta_i}$ contains the coefficients representing the environmental impact on the total cost of company i. Also, $\boldsymbol{\rho}_i$ is the vector of output coefficients, ω_i is the intercept, and ϵ_i is the statistical error term, for company i. We then adjust the total cost by removing the estimated environmental impact as follows

$$x_i^{adjust} = x_i \cdot \exp(-\boldsymbol{\delta_i z}_i), \tag{13}$$

and the adjusted cost x_i^{adjust} is used as input variable in the benchmarking models described in the next three subsections.

3.3 DEA frontier

DEA is an axiomatic, non-parametric approach to calculate the efficient or best-practice frontier of a sample (Farrell, 1957; Charnes et al., 1978). It employs a piecewise linear frontier production (cost) function to estimate performance of the sample companies. The frontier envelops the data as tightly as possible, and observed companies, termed best practice, will form the benchmarking technology. DEA models can be input-oriented or output-oriented, and they can be specified with constant returns to scale (CRS) or variable returns to scale (VRS). We use the input-oriented model to examine the performance of electricity distribution companies, since the objective of a distribution company is, typically, to produce exogenously given output quantities at minimum cost.

Under the CRS assumption, the efficiency score $E_i^t\left(\boldsymbol{x}_i^{t+1}, \boldsymbol{y}_i^{t+1}\right)$ for company i in period $t+1$ relative to the technology in period t is the optimal value of

$$
\begin{aligned}
&\min_{\theta,\boldsymbol{\lambda}} \theta \\
&\text{s.t.} \\
&-\boldsymbol{y}_i^{t+1} + \boldsymbol{Y}^t\boldsymbol{\lambda} \geq 0 \qquad\qquad i = 1,\cdots,n; t = 1,\cdots,T \\
&\theta\boldsymbol{x}_i^{t+1} - \boldsymbol{X}^t\boldsymbol{\lambda} \geq 0 \qquad\qquad i = 1,\cdots,n; t = 1,\cdots, \\
&\qquad\qquad \boldsymbol{\lambda} \geq 0.
\end{aligned} \tag{14}
$$

Here, θ represents the efficiency score, $\boldsymbol{\lambda}$ is a non-negative $n \times 1$ vector of reference weights, and $\boldsymbol{x}_i^t$ and $\boldsymbol{y}_i^t$ represent the input and output column vectors, respectively, of company i in period t. The $m \times n$ matrix $\boldsymbol{X}^t$ and the $r \times n$ matrix $\boldsymbol{Y}^t$ represent m inputs and r outputs, respectively, for n companies in period t. Similarly, we obtain $E_i^{t+1}(\boldsymbol{x}_i^t, \boldsymbol{y}_i^t)$ as the optimal value of (14), when $\boldsymbol{X}^t$ and $\boldsymbol{Y}^t$ is replaced by $\boldsymbol{X}^{t+1}$ and $\boldsymbol{Y}^{t+1}$, respectively, and $\boldsymbol{x}_i^{t+1}$ and $\boldsymbol{y}_i^{t+1}$ is replaced by $\boldsymbol{x}_i^t$ and $\boldsymbol{y}_i^t$, respectively. To obtain efficiency scores under the VRS assumption, the convexity constraint $\sum \boldsymbol{\lambda} = 1$ has to be added. Combining variations of Model (14) with Equations (8)-(11), we obtain the productivity index and its decompositions, i.e., $MPI_i^{dea}, EC_i^{dea}, TC_i^{dea}, SEC_i^{dea}$.

3.4 SFA frontier

In this study, the SFA approach by Pantzios et al. (2011) is used to implement the input-oriented Malmquist productivity index. Based on Section 3.1, the input-oriented Malmquist productivity index based on the SFA approach is defined as[1]

$$MPI_i^{sfa}(\boldsymbol{y}_i^t, \boldsymbol{y}_i^{t+1}, x_i^t, x_i^{t+1}) = EC_i^{sfa} \cdot TC_i^{sfa} \cdot SEC_i^{sfa}. \tag{15}$$

The estimation of this parametric Malmquist productivity index requires specification and estimation of the input distance function (IDF), D. This IDF can be specified and estimated in several ways (see, e.g., Kumbhakar et al., 2015). Since we use panel data, a panel data estimator is a natural choice. Here we use the state-of-the art stochastic frontier panel data model by Colombi et al. (2014) and Kumbhakar et al. (2014). In this model the error term (of the regression equation) is split into four components. The first component captures firms' latent heterogeneity, which is disentangled from long-

[1] The decomposition of Pantzios et al. (2011) included also an additional component, the input-mix effect. That component dropped out in this study, since the data set only includes one input.

run (persistent) inefficiency, and the second component captures short-run (time-varying) inefficiency. The third component captures long-run (persistent) inefficiency, while the last component captures random shocks. With panel data and a translog function within an input distance function framework the estimation equation looks like[2]

$$-\ln x_i^t = \ln D(\boldsymbol{y}_i^t) + \mu_i - u_i + v_i^t - \tau_i^t$$

$$= \alpha_0 + \sum_{l=1}^{r} \beta_l \ln y_{li}^t + \frac{1}{2}\sum_{l=1}^{r}\sum_{q=1}^{r} \beta_{lq} \ln y_{li}^t \ln y_{qi}^t + \alpha_t t + \frac{1}{2}\alpha_{tt} t^2 +$$

$$\sum_{l=1}^{r} \beta_{lt} \ln y_{li}^t t + \mu_i - u_i + v_i^t - \tau_i^t,$$

$$i = 1, \cdots\cdots, n; l = 1, \cdots\cdots, r; q = 1, \cdots\cdots, r, \tag{16}$$

where $\ln x_i^t = \ln(\text{Total cost})$ (see the data section below) for company i in period t, y_{li}^t is output l for company i in period t and α and β are unknown parameters to be estimated. The symmetry restrictions imply that $\beta_{lq} = \beta_{ql}$. In this model, v_i^t is the idiosyncratic noise component capturing random shocks, τ_i^t is the time-varying stochastic inefficiency capturing short-run inefficiency effects, u_i is the time-invariant (long-run) inefficiency and μ_i is unconstrained and treated as firm effects.

We compute the first component in Equation (15), efficiency change, using

$$EC_i^{sfa} = E_i^{t+1} - E_i^t, \tag{17}$$

where $\mathrm{E}\left[\exp\left(-\tau_i^t | (v_i^t - \tau_i^t)\right)\right]$ is used to estimate (technical) efficiency, E_i^t (Kumbhakar et al., 2015). Note that with the estimation approach in equation (15), short-run and long-run efficiency is disentangled, and it is only the short-run efficiency measure that influences the efficiency change measure.

Technical change is a product of the technical change magnitude index and the output bias index:

$$TC_i^{sfa} = \frac{D^{t+1}(y_i^{t+1}, x_i^{t+1})}{D^t(y_i^{t+1}, x_i^{t+1})} = \left[\frac{D^{t+1}(y_i^t, x_i^t)}{D^t(y_i^t, x_i^t)}\right] \times \left[\frac{D^{t+1}(y_i^{t+1}, x_i^{t+1})}{D^t(y_i^{t+1}, x_i^{t+1})} \times \frac{D^t(y_i^t, x_i^t)}{D^{t+1}(y_i^t, x_i^t)}\right]$$

$$= [\alpha_t + \alpha_{tt} t + \sum_{l=1}^{r} \beta_{lt} \ln y_{li}^t] \times [\sum_{l=1}^{r} \beta_{lt} (\ln y_{li}^{t+1} - \ln y_{li}^t)]. \tag{18}$$

---

[2] The estimator in this study is implemented using the maximum simulated likelihood estimator approach by Filippini and Greene (2015), as it is included in the statistical software Limdep (http://www.limdep.com/).

The scale efficiency measure in Equation (15) is calculated as

$$SEC_i^{sfa} = \exp\left\{\frac{1}{2\times\sum_{l=1}^{r}\sum_{q=1}^{r}\beta_{lq}}\left[\left(\left(\frac{1}{-\left(\sum_{l=1}^{r}\frac{\partial \ln D^t\left(y_i^{t+1},x_i^t\right)}{\partial \ln y_{li}^{t+1}}\right)^{-1}}-1\right)\right)^2-\left(\left(\frac{1}{-\left(\sum_{l=1}^{r}\frac{\partial \ln D^t\left(y_i^t,x_i^t\right)}{\partial \ln y_{li}^t}\right)^{-1}}-1\right)\right)^2\right]\right\}. \quad (19)$$

In Equation (19) the $\frac{\partial \ln D^t(y_i^{t+1},x_i^t)}{\partial \ln y_{li}^{t+1}}$ function is $\sum_{l=1}^{r}\beta_{lq}\ln y_{qi}^{t+1}+\beta_{lt}(t+1)$, and the $\frac{\partial \ln D^t(y_i^t,x_i^t)}{\partial \ln y_{li}^t}$ function is $\beta_l+\sum_{l=1}^{r}\beta_{lq}\ln y_{qi}^t+\beta_{lt}(t)$.

Note that with this SFA frontier approach we separate both firm heterogeneity and noise while estimating inefficiency. Furthermore, this approach separates persistent and transient inefficiency. It is expected that these aspects also influence the empirical results.

3.5 StoNED frontier

The StoNED combines non-parametric, piece-wise linear DEA-style frontiers with the stochastic SFA-style treatment of inefficiency and noise. Kuosmanen and Kortelainen (2012) found that both the DEA and SFA models can be obtained as constrained special cases of the more general StoNED model.

A two-step strategy is used for the StoNED model:
Step 1: Estimate the shape of the total cost function using the convex nonparametric least squares (CNLS) approach.

Step 2: Impose additional distributional assumptions on inefficiency and noise, and estimate the parameters of the assumed distributions based on the residuals obtained from Step 1.

For Step 1, as for the DEA, a cost frontier is used, and the CNLS optimization problem for period t can be presented as

$$\min_{\gamma,\beta,\varepsilon} \sum_{i=1}^{N} (\varepsilon_i^t)^2$$

s.t.

$$\begin{aligned}
& ln\, x_i^t = ln\, \gamma_i^t + \varepsilon_i^t && i = 1, \cdots, n \\
& \gamma_i^t = \alpha_i^t + (\boldsymbol{\beta}_i^t)' \boldsymbol{y}_i^t \geq \alpha_h^t + (\boldsymbol{\beta}_h^t)' \boldsymbol{y}_i^t && h = 1, \cdots, n; i = 1, \cdots, n \\
& \boldsymbol{\beta}_i^t \geq 0 && i = 1, \cdots, n
\end{aligned} \tag{20}$$

In Model (20), γ_i^t is the CNLS estimator of the total cost of producing $\boldsymbol{y}_i^t$ in period t, the intercept α_i^t of firm i in period t indicates its local returns to scale status ($\alpha_i^t > 0$ and $\alpha_i^t < 0$ represent DRS and IRS, respectively), and $\boldsymbol{\beta}_i^t$ is the marginal cost of outputs. The first constraint in (20) is the regression equation, and the second and third constraint ensures convexity and monotonicity, respectively. Model (20) has no sign restrictions on the intercept term α_i^t, which implies that we allow variable returns to scale (VRS). By imposing the constraint $\alpha_i^t = 0$ for all $i = 1, \cdots, n$, we can implement the assumption of constant returns to scale (CRS).

Under assumptions of half-normal inefficiency and normal noise we can obtain, in Step 2, the inefficiency and noise parameters using the method of moments (Aigner et al., 1997). The estimates of the standard deviation for inefficiency and noise, respectively, are

$$\hat{\sigma}_u^t = \sqrt[3]{\frac{\widehat{M}_3^t}{\left(\sqrt{\frac{2}{\pi}}\right)\left[\frac{4}{\pi} - 1\right]}}, \text{ and} \tag{21}$$

$$\hat{\sigma}_v^t = \sqrt[2]{\widehat{M}_2^t - \left[\frac{\pi - 2}{\pi}\right] (\hat{\sigma}_u^t)^2}, \tag{22}$$

where $\widehat{M}_2^t$ and $\widehat{M}_3^t$ are the second and third central moments of the composite errors from the solution of (20). They are

$$\widehat{M}_2^t = \sum_{i=1}^{n} (\hat{\varepsilon}_i^t - \bar{\varepsilon}^t)^2 / n \text{, and} \tag{23}$$

$$\widehat{M}_3^t = \sum_{i=1}^{n} (\hat{\varepsilon}_i^t - \bar{\varepsilon}^t)^3 / n. \tag{24}$$

Hence, the estimator of the best practice cost frontier for a given company i for period t is given by

$$\hat{C}_i^t(\boldsymbol{y}_i^t) = \gamma_i^t(\boldsymbol{y}_i^t) \cdot \exp\left(-\hat{\sigma}_u^t \sqrt{\frac{2}{\pi}}\right), \tag{25}$$

where $\gamma_i^t(\boldsymbol{y}_i^t)$ is the average-practice cost frontier (Kuosmanen and Kortelainen, 2012). I.e., the best practice cost frontier is given by the average practice cost frontier and the standard deviation of the inefficiency term.

According to Kuosmanen et al. (2013), the estimated cost norm can also be calculated as

$$\gamma_i^t(\boldsymbol{y}_i^t) = \max_h(\alpha_h^t + (\boldsymbol{\beta_h^t})'\boldsymbol{y}_i^t). \tag{26}$$

Adjacent-period estimated cost norms using period t or $t+1$ data and period $t+1$ or t technology are

$$\gamma_i^{t+1}(\boldsymbol{y}_i^t) = \max_h\left(\alpha_h^{t+1} + \left(\boldsymbol{\beta_h^{t+1}}\right)'\boldsymbol{y}_i^t\right), \text{ and} \tag{27}$$

$$\gamma_i^t(\boldsymbol{y}_i^{t+1}) = \max_h(\alpha_h^t + (\boldsymbol{\beta_h^t})'\boldsymbol{y}_i^{t+1}) . \tag{28}$$

The efficiency score is defined as the ratio of the minimum cost to the observed cost, i.e.

$$E_i^t(\boldsymbol{y}_i^t, x_i^t) = \frac{\hat{C}_i^t(y_i^t)}{x_i^t} \tag{29}$$

for company i in period t, and $E_i^{t+1}(\boldsymbol{y}_i^{t+1}, x_i^{t+1})$ can be obtained in an analogous manner. Based on Equations (25) and (29), we have

$$E_i^{t+1}(\boldsymbol{y}_i^t, x_i^t) = \frac{\hat{C}_i^{t+1}(y_i^t)}{x_i^t} = \frac{\gamma_i^{t+1}(y_i^t)\cdot\exp(-\hat{\sigma}_u^{t+1}\sqrt{2/\pi})}{x_i^t}, \text{ and} \tag{30}$$

$$E_i^t(\boldsymbol{y}_i^{t+1}, x_i^{t+1}) = \frac{\hat{C}_i^t(y_i^{t+1})}{x_i^{t+1}} = \frac{\gamma_i^t(y_i^{t+1})\cdot\exp(-\hat{\sigma}_u^t\sqrt{2/\pi})}{x_i^{t+1}}. \tag{31}$$

In line with Section 3.1, the Malmquist productivity index based on the StoNED approach is defined as

$$MPI_i^{stoned}(\boldsymbol{y}_i^t, \boldsymbol{y}_i^{t+1}, x_i^t, x_i^{t+1}) = EC_i^{stoned}\cdot TC_i^{stoned}\cdot SEC_i^{stoned}, \tag{32}$$

where

$$EC_i^{stoned}(\boldsymbol{y}_i^t, \boldsymbol{y}_i^{t+1}, x_i^t, x_i^{t+1}) = \frac{E_{i,vrs}^{t+1}(y_i^{t+1}, x_i^{t+1})}{E_{i,vrs}^{t,stoned}(y_i^t, x_i^t)}, \tag{33}$$

$$TC_i^{stoned}(\boldsymbol{y}_i^t, \boldsymbol{y}_i^{t+1}, x_i^t, x_i^{t+1}) = \left[\frac{E_{i,vrs}^t(y_i^{t+1}, x_i^{t+1})}{E_{i,vrs}^{t+1,stoned}(y_i^{t+1}, x_i^{t+1})}\frac{E_{i,vrs}^t(y_i^t, x_i^t)}{E_{i,vrs}^{t+1,stoned}(y_i^t, x_i^t)}\right]^{\frac{1}{2}}, \tag{34}$$

$$SEC_i^{stoned}(\boldsymbol{y}_i^t, \boldsymbol{y}_i^{t+1}, x_i^t, x_i^{t+1}) = \left[\frac{\frac{E_{i,crs}^t(y_i^{t+1}, x_i^{t+1})}{E_{i,vrs}^t(y_i^{t+1}, x_i^{t+1})}}{\frac{E_{i,crs}^t(y_i^t, x_i^t)}{E_{i,vrs}^t(y_i^t, x_i^t)}} \frac{\frac{E_{i,crs}^{t+1}(y_i^{t+1}, x_i^{t+1})}{E_{i,vrs}^{t+1}(y_i^{t+1}, x_i^{t+1})}}{\frac{E_{i,crs}^{t+1}(y_i^t, x_i^t)}{E_{i,vrs}^{t+1}(y_i^t, x_i^t)}} \right]^{\frac{1}{2}}. \tag{35}$$

4 Data

The data for the Malmquist analyses is collected by the Norwegian Water Resources and Energy Directorate (NVE). It covers 121 Norwegian distribution companies for the period 2004-2013. The variables in our data correspond to the variables used by the regulator in the benchmarking model that was implemented from 2007, i.e., it has a single input, five outputs and three environmental factors, as described in Table 1 and Table 2.

Table 1 Inputs, outputs, and environmental variables.

Variable	Type	Sub-variable	Unit
Total cost	x	Operations and maintenance cost (Opex)	1000 Norwegian kroner (NOK)
		Value of lost load (quality cost) (Voll)	1000 NOK
		Thermal power losses (Losses)	1000 NOK
		Capital depreciation (Capex)	1000 NOK
		Return on capital (Capex)	1000 NOK
High voltage lines	y		Kilometers
Network stations (transformers)	y		No. of stations
Customers	y		No. of customers
Distance to road	z		Kilometers
HV underground	z		Share of HV network (0-1)
Forest	z		Share of HV lines affected (0-1)
Geol	z	Small scale hydro	Installed capacity (MW)/cost norm[3]
		Average slope	Degrees (0-90)
		Deciduous forest	Share of HV lines affected (0-1)
Geo2	z	Wind/dist.to coast	$(m/s)^2/m$
		Islands	No. of islands /cost norm
		HV sea cables	Share of HV network (0-1)

[3] This variable is divided by the company's cost norm in order to ensure that the resulting variable is size independent. The cost norm is based on five-year average of inputs and outputs.

Total cost is the single input, and it contains the five cost elements that are listed in Table 1. Most of the companies also own and operate part of the regional distribution network, and NVE reallocates part of this cost to the local distribution activity. This reallocation of cost is not included in our study, and our results may therefore differ slightly from the efficiency measurements published by NVE. The data for all years have been adjusted to the price level of a base year (2013). We use an industry-specific price index for adjusting operations and maintenance costs and the consumer price index for the VOLL costs. Thermal losses are valued at the average system price at Nord Pool for the base year (300 NOK/MWh). Capital depreciation is based on reported (nominal) book values, and the return on capital is calculated using the nominal rate of return set by the regulator for the base year (7.12 %). Book values and depreciation have also been adjusted for inflation. The growth in capital and depreciation values over time depends on historical inflation as well as past development in investments. Since we do not have detailed data about historical investment on company level, we have chosen to adjust capital values and depreciation by 2 % per year. This corresponds, approximately, to the average inflation since the book values was established in the beginning of the 1990s, following the deregulation of the Norwegian power market. We have made analyses to verify that our results are not very sensitive to this choice.

Table 2 Descriptive statistics of variables.

Variables	Mean	Min.	Median	Max.	Sd.dev
Total cost	108000.00	8884.00	39220.00	1771000.00	215719.80
High voltage lines	803.10	50.00	321.50	8744.00	1329.81
Network stations(transformers)	1012.00	52.00	367.00	13530.00	1888.21
Customers	22670.00	947.00	6428.00	570200.00	58710.64
Distance to road	226.00	70.37	142.90	1056.00	207.34
HV underground	0.34	0.06	0.31	0.86	0.18
Forest	0.12	0.00	0.12	0.39	0.10
Geol	0.02	-2.06	-0.43	4.72	1.49
Geo2	0.01	-0.64	-0.45	11.86	1.52

The outputs are shown in the second part of Table 1 and include high voltage lines, network stations and customers. High voltage lines and network stations represent structural and environmental conditions which may affect required network size and thereby the cost level of the companies. The last part of Table 1 shows environmental variables. The environmental variables affect the performance of the companies, but they are out of the companies' control (Coelli et al., 2005).

Figure 1 shows the development of the different cost elements over time. Total cost decreased in the period from 2004 to 2007, and thereafter it increased, except for the years 2010 and 2012. We see that the decrease from 2004 to 2007, as well as the decreases in 2010 and 2012, are due variation in the OPEX level, while the CAPEX level has increased steadily over the entire period.

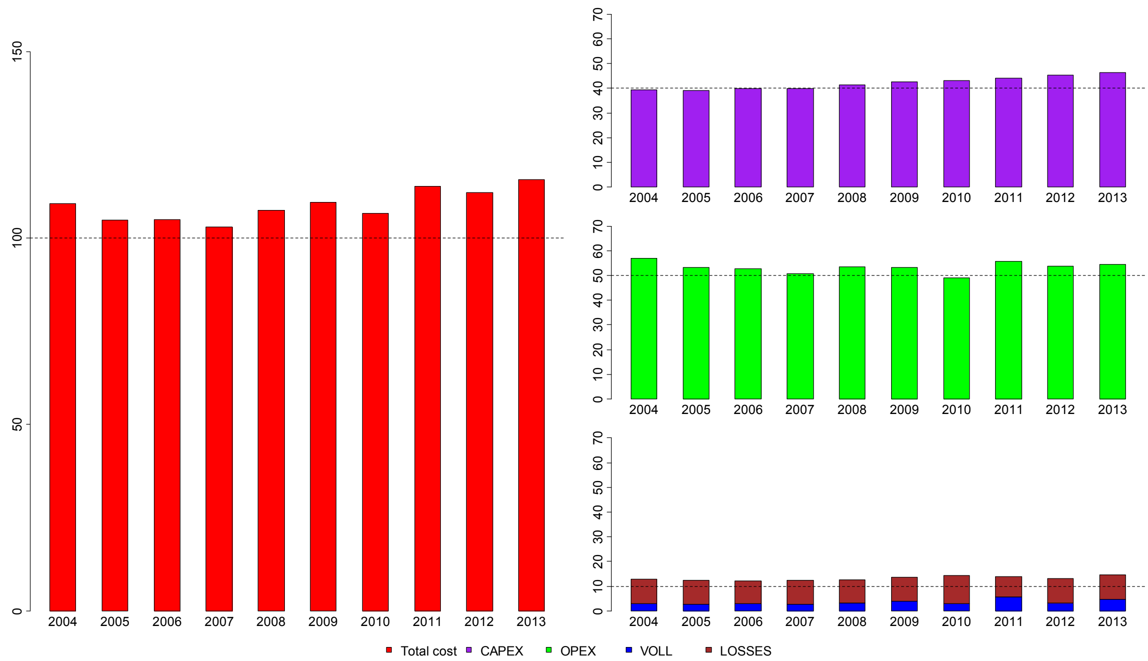

Figure 1 Development of cost elements over time (1000 000 NOK).

5 Results

5.1 Productivity change and its causes

The results of our analyses are summarized in Table 3. The table shows estimated productivity indices (MPI), efficiency change (EC), technical change (TC), and scale efficiency change (SEC) for the periods 2004/07, 2007/10, and 2010/13, as well as for 2004/13. The estimates for multi-year periods are obtained by taking geometric averages of the annual estimates. Index values greater (less) than unity indicates improvement (regress).

Table 3 Average productivity indices and their decompositions.

Periods	DEA				SFA				StoNED			
	MPI	EC	TC	SEC	MPI	EC	TC	SEC	MPI	EC	TC	SEC
2004/07	1.0146	0.9917	1.0230	1.0011	1.0034	1.0122	0.9940	0.9973	1.0147	1.0063	1.0077	1.0007
2007/10	0.9944	1.0057	0.9905	1.0003	0.9899	0.9998	0.9926	0.9974	0.9948	0.9984	0.9961	1.0002
2010/13	0.9773	1.0120	0.9665	1.0006	0.9830	0.9948	0.9910	0.9970	0.9777	1.0071	0.9700	1.0006
2004/13	0.9954	1.0031	0.9931	1.0007	0.9832	0.9971	0.9892	0.9968	0.9956	1.0039	0.9911	1.0005

Table 3 shows that the overall productivity change for the industry between 2004 and 2013 has been negative, with estimates of the decline from 0.44% to 1.68%. All three methods indicate productivity improvement for 2004/07, i.e., consistent with Migueís et al. (2010), while productivity is decreasing in the later periods. We also observe that the magnitudes of the productivity changes for the sub-periods are very similar for DEA and StoNED. The decrease in productivity in the later periods is somewhat surprising, since the efficiency incentives in the regulatory scheme should be strengthened with the introduction of yardstick regulation, with annual benchmarking to update cost norms, from 2007. We discuss this further in Section 5.2. The top part of Figure 2 shows the distribution of productivity change among the companies in the industry. We see again that the two non-parametric methods yield very similar distributions, while the distributions for SFA are narrower.

We see from Table 3 that all three methods agree that technological change for the industry has been negative between 2004 and 2013, with estimates of the average annual decline ranging from 0.69% to 1.08%. Table 3 and Figure 2 show that DEA and StoNED agree on the direction of technological change for the sub-periods, but that these methods differ somewhat with respect to the magnitude of their estimates. Both methods agree that the average technological change is positive for 2004/07, and thereafter becomes negative. Note that the TC estimates in StoNED depend on the distributional assumptions made, as shown in Cheng et al. (2015). When the observed skewness in StoNED under the VRS assumption for a given year is negative, the technical change estimates will, somewhat arbitrarily, be based on the average-practice frontier for the year in question. We see from Table 4 that this occurred for 4 of the 10 years. The SFA results indicate, on average, negative technological change for all three periods. Also, as for overall productivity change, the distributions of technological changes are narrower in the case of SFA than for the other two methods.

Table 4 Estimated skewness in StoNED under the VRS assumption.

2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
0.0002	0.0003	0.0006	0.0001	-0.0005	-0.0003	0.0002	-0.0005	-0.0006	0.0001

Figure 2 shows that the shapes of the efficiency change distributions are quite similar under DEA and StoNED, although their levels differ in some cases. We note again that some of the StoNED frontier estimates are based on the average-practice frontier, as implied by the negative skewness estimates in Table 4. As discussed in Cheng et al. (2015), using the average-practice frontier for doing efficiency change estimates will result in values close to unity. Table 3 shows, indeed, that the StoNED efficiency change estimates deviates less from unity than the corresponding DEA estimates. The efficiency change distributions for SFA in Figure 2 are, as for productivity change and technological change, narrower than the corresponding distributions for DEA and StoNED, and the levels of the industry estimates in Table 3 do not agree with those for the non-parametric methods.

As both Table 3 and Figure 2 show, the estimates of scale efficiency indices are very close to unity for all methods and sub-periods. This is not surprising, since the industry structure is constant in our data set, which consists of a balanced sample of 121 companies.

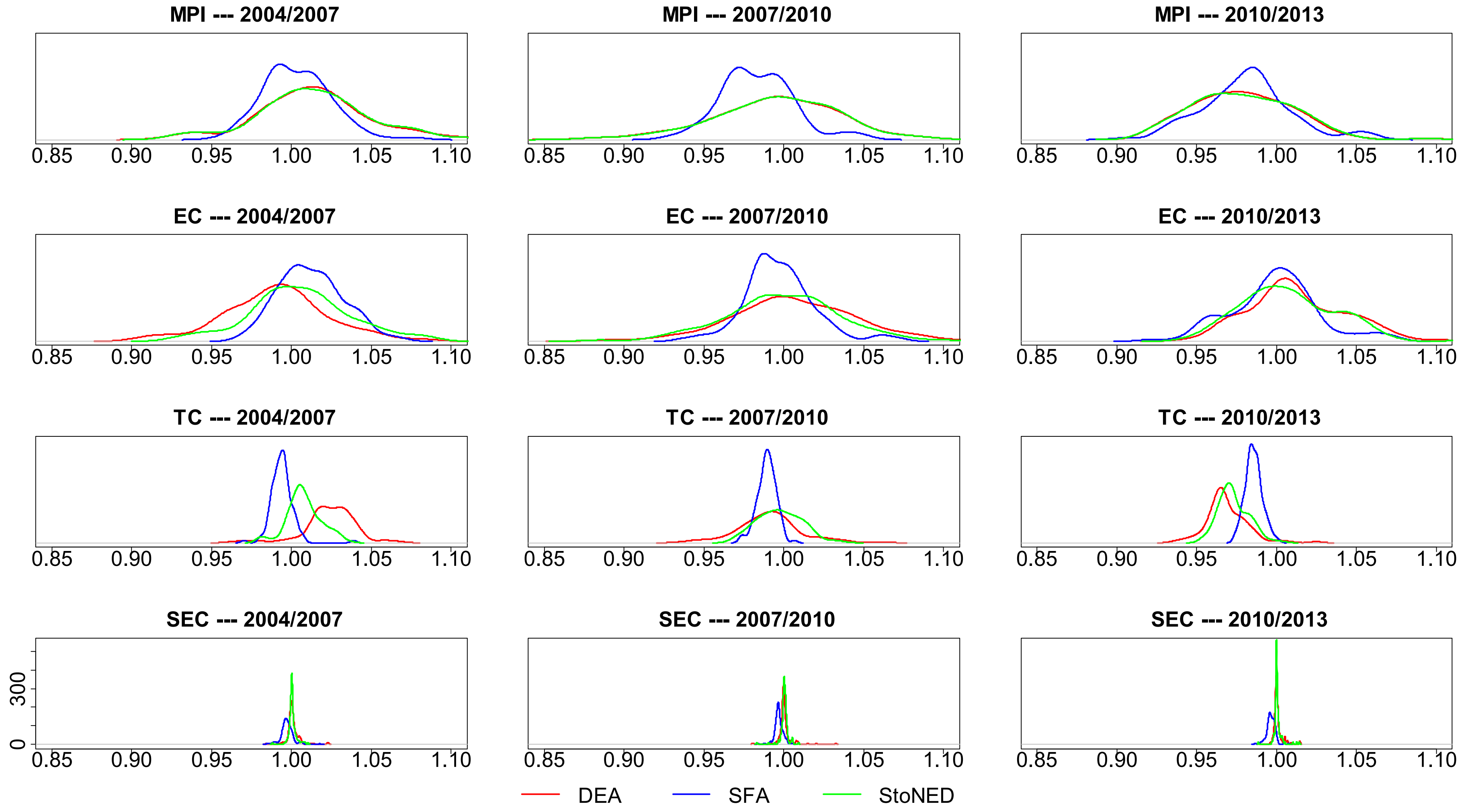

Figure 2 Distributions of MPI, EC, TC, and SEC

5.2 Effect of capital costs

In the previous section, we observed that the estimated productivity change was negative for the entire period between 2004 and 2013. A more detailed analysis showed productivity growth for 2004/07, and decline thereafter. This is surprising, since the efficiency incentives in the regulation scheme were strengthened from 2007, as mentioned above. However, there are indications that the introduction of the new regulation mechanism coincided with the start of a new investment cycle, as witnessed by the increase in capital costs shown in Figure 1. Eurelectric (2014) states that the investments in Norwegian distribution networks were quite low from about 1988 until 2006, and that the investments thereafter started to grow. The projected level of investments in 2017 is two times the level in 2010. The increase is, according to Eurelectric (2014), due to rapid growth of distributed generation, the overall network condition, increasing consumption and the roll-out of smart meters planned until 2019. Since we use accounting values based on linear depreciation, to represent capital costs in our analysis, increased investments will automatically lead to higher capital costs and lower productivity, although this may not reflect a real productivity decline.

Table 5 Average productivity indices and their decompositions when CAPEX is left out.

Periods	DEA				SFA				StoNED			
	MPI	EC	TC	SEC	MPI	EC	TC	SEC	MPI	EC	TC	SEC
2004/07	1.0256	1.0046	1.0217	1.0013	1.0023	1.0000	1.0057	0.9966	1.0253	1.0053	1.0188	1.0008
2007/10	1.0038	1.0147	1.0033	1.0008	0.9871	1.0000	0.9906	0.9965	1.0039	1.0059	0.9972	1.0005
2010/13	0.9671	1.0119	0.9577	1.0007	0.9726	1.0000	0.9760	0.9965	0.9675	1.0071	0.9592	1.0010
2004/13	0.9986	1.0104	0.9939	1.0009	0.9873	1.0000	0.9907	0.9969	0.9986	1.0061	0.9914	1.0008

Table 6 The effect of leaving out CAPEX.

Periods	DEA				SFA				StoNED			
	MPI	EC	TC	SEC	MPI	EC	TC	SEC	MPI	EC	TC	SEC
2004/07	0.0110	0.0130	-0.0013	0.0002	-0.0011	-0.0122	0.0117	-0.0006	0.0106	-0.0009	0.0111	0.0001
2007/10	0.0094	0.0090	0.0127	0.0005	0.0039	0.0002	-0.0020	-0.0009	0.0090	0.0075	0.0011	0.0003
2010/13	-0.0102	-0.0001	-0.0088	0.0001	-0.0087	0.0052	-0.0151	-0.0005	-0.0102	0.0000	-0.0108	0.0004
2004/13	0.0032	0.0073	0.0008	0.0002	0.0040	0.0029	0.0014	0.0001	0.0030	0.0022	0.0003	0.0002

Table 7 Estimated skewness in StoNED/VRS when CAPEX is left out.

2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
-0.0007	0.0008	0.0009	-0.0005	-0.0047	-0.0021	-0.0001	-0.0005	-0.0015	0.0004

Given the combination of investment cycles and the use of accounting-based capital values in our analysis, we find it natural to repeat our analysis with cost estimates that do not include capital costs, and the results are presented in Tables 5 and 6. Table 5 shows average estimates, as in Table 3, and Table 6 shows the effect of leaving out CAPEX, i.e., the difference between the values in Tables 5 and 3. For the entire period from 2004 to 2013, we observe a positive effect on overall productivity growth between 0.3 % and 0.4 % for all methods. Also, the average estimates of all the sub-indices increase when capital is excluded from the analysis. However, overall productivity change remains negative also when we exclude capital costs. After this change, DEA and StoNED agree on an average productivity decline of 0.14 % per year from 2004 to 2013, while the average productivity decline for SFA is estimated to 1.27 % per year.

As shown in Section 3.4, the efficiency change estimates under SFA are based on changes in short-run inefficiency. If the estimated short-run inefficiency scores are zero, as in our case, then the EC estimates will be equal to one. The estimated company efficiency scores will be constant over time. Interestingly, Table 7 shows that the estimated skewness values in StoNED are negative for 8 of 10 years. For pair of consecutive years where estimated skewness is negative, the StoNED estimate of efficiency change will be based on the average-practice frontier, as discussed in Section 5.1, and this also tends to give EC estimates close to unity.

6 Conclusion

We have investigated the productivity development for Norwegian electricity distribution companies for 2004-2013. Using three benchmarking methods, DEA, SFA, and StoNED, on a Malmquist productivity index framework, we examine productivity change, with the usual decompositions into efficiency change, technical change, and scale efficiency change. For the period as a whole, all three approaches agree that productivity has declined, and that there has been technological regress. However, the methods do not fully agree on the direction of efficiency change. Scale efficiency changes are very small. A priori, we would expect to see improvement in productivity following the new regulation regime from 2007, but our analysis do not support this. We have repeated the analysis with cost values excluding capital costs, to control for a suspected bias due to increasing investments/capital values. This has a positive effect on productivity change and its decompositions, but the overall impression of negative productivity change and technological regress is not altered.

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