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Keyword Dynamic efficiency, innovation, investment incentives, benchmarking, electricity

JEL Classification L43, L51, L94, D21, D23, D24

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Dynamic Efficiency and Incentive Regulation:
An Application to Electricity Distribution Networks

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Abstract

Efficiency and productivity analysis is a central concept in incentive-based regulation of network utilities. However, the efficiency measures obtained from benchmarking predominantly reflect short term performance and hence, provide only a snapshot of the firm's path towards its long run equilibrium. On the other hand, the factors affecting the short run behaviour of firms may not be adjusted instantaneously when firms undertake investment. In these instances, short run inefficiency caused by investments will be transmitted to subsequent periods. This effect, which arises from costs associated with the adjustment of capital stock or production capacity, is problematic under incentive regulation with ex-post regulatory treatment of capital expenditure. This is because it adversely affects the firms' short term efficiency and, consequently, regulated revenue. This paper analyses the dynamic behaviour of inefficiency for a balanced panel of 128 Norwegian electricity distribution companies from 2004 to 2010. We show that, in a given period, inefficiency is a combination of period-specific effects (shocks) plus a carry-over component from previous periods due to adjustment costs. Also, we estimate these two components of inefficiency along with the rate of inefficiency transmission between periods.

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1. Introduction

The pursuit of efficiency improvement is the main motivation for reform and incentive-based regulation of infrastructure and network industries such as electricity, gas, water, and telecommunications. The expectation is that incentive regulation mechanisms would provide more powerful incentives for regulated firms to deliver the objectives of regulators (Joskow, 2005).

In theory, regulators would be expected to pursue three forms of efficiency of the regulated firms (Coelli et al., 2003). Firstly, the operation of regulated firms should take into consideration the opportunity cost of scarce resources to the society and hence, move as close as possible to the production frontier – i.e. regulated firms need to be technically efficient. Secondly, where feasible, regulated firms are required to use optimum mix of inputs (or outputs) to produce a given level and quality of output with minimum cost (or maximise revenue) – i.e. regulated activities should be "allocative efficient"[1]. Thirdly, regulation should incentivise firms to undertake innovation, make sufficient investment, promote their technical level and improve their management practices to smoothly address future challenges. In other words, regulators need to ensure that the firms are also "dynamically efficient".

Investment and innovation are the key factors in addressing the future challenges of industries. This is particularly the case in a capital intensive sector such as the electricity networks. Thus an important challenge for the sector regulators is to ensure sufficient and efficient investments and innovation in the natural monopoly utilities. In other words, regulators need to promote the dynamic efficiency in regulated firms. However, until recently the dynamic aspect of efficiency analysis was absent from the efficiency and productivity literature and, in particular, in the context of the regulated industries (Serra et al., 2011).

This paper introduces the concept of dynamic efficiency under incentive regulation with ex-post regulatory treatment of investments using the case of electricity distribution networks in Norway. We show that incentive regulatory models based on the total cost benchmarking are problematic for investment and optimal inter-temporal accumulation of capital of regulated firms. This is because it induces an autoregressive process in the level of technical efficiency and exposes the firms to financial loss following investment and capital stock adjustment. The paper demonstrates that, in a given period, technical inefficiency of regulated utilities is a combination of period-specific effects

[1] This condition requires a behavioural assumption of profit maximisation (or cost minimisation) which might not be valid in regulated industries. As Coelli et al (2003) states, in practice, regulators often disregard allocative efficiency in their efficiency analysis because it is difficult to achieve in regulated utilities. Input mix allocative efficiency is ignored because capital intensity of network companies is determined by population density. Output mix allocative efficiency is not considered because regulated companies rarely have the ability to change their output mix (e.g., mix of different customer categories).

(shocks) and a carry-over component from previous periods. The latter component is due to the sluggish adjustment of outputs in the presence of investment and the associated adjustment costs. Additionally, we estimate these two components of inefficiency along with the rate of inefficiency transmission across periods (adjustment towards the long run equilibrium).

The next section provides a theoretical framework for the effect of adjustment cost and incentive regulation of electricity distribution networks on the dynamics of inefficiency. Section 3 discusses the empirical model adopted to estimate the two components of inefficiency (i.e., period specific shock and carry-over). The empirical results are presented and discussed in Section 4. Section 5 provides the conclusions.

2. Theoretical framework

In this section we develop a simple framework to describe the process of capital stock adjustment of a firm and its effect on evolution of inefficiency under incentive regulation with ex-post regulatory treatment of investment such as (1).

$$RE_t = C_t + \lambda(C_t^* - C_t) \qquad (1)$$

The relation in (1) presents a generic form of incentive regulation model with ex-post regulatory treatment of investments where t indexes time periods, RE_t is regulated revenue, C_t is the actual costs and C_t^* is the efficient cost obtained from efficiency analysis of regulated firms (i.e., $C_t^* = e_t C_t$ where e_t is the technical efficiency of the firm)[2]. The actual cost includes capital expenditures and other costs (operation and maintenance, etc.). With incentive regulation we refer to those regulatory regimes in which the revenue of the firm is partially (or totally) decoupled from its actual (own) cost depending on the magnitude of power of incentive λ in (1)[3]. This amounts to a non-zero value for λ within its feasible boundary ($0 \leq \lambda \leq 1$).

As the revenue of firm is linked to the technical efficiency hence, the incentive regulatory model in (1) promotes an indirect competition among regulated firms to reduce their inputs for given levels of outputs or maximise the outputs for a given input set (Müller et al. 2010).

[2] The aim of this regulatory model is to incentivise efficiency improvement in regulated utilities. In theory, a higher than optimum level of cost (C_t^*) means revenue loss to the firm. Thus, the regulated firms have incentive to move as closely as possible to the production frontier (Poudineh and Jamasb, 2013a).

[3] Depending on the value of λ, the model in (1) represents an spectrum of incentive regulations ranges from a high powered incentive regulation (i.e. $\lambda = 1$) where the firm's cost is fully decoupled from the revenue of firm to a low powered incentive regulation (i.e., $\lambda = 0$) where the firm revenue is the same as the actual cost (i.e., rate of return regulation).

Under the ex-post regulatory model of investment treatment the regulator does not interfere directly with the investment level of regulated firms. The regulator, however, evaluates the companies' performance, ex-post, using benchmarking techniques and sets their allowed revenues based on their deviation from the sector best practice. In this approach, the effect of investment behaviour of regulated firms will be reflected in their efficiency with the consequence for their revenue.

Poudineh and Jamasb (2013a) show that, under the incentive regulation model in (1), firms need to achieve a certain level of technical efficiency, following investment, in order to avoid cost disallowance in the benchmarking exercise. This level of efficiency, termed "no impact efficiency", depends on the investment level (In), cost and technical efficiency of the firm before investment (i.e. C_1 and e_1 respectively) and can be presented as in (2) (see Poudineh and Jamasb, 2013a).

$$e^* = \frac{C_1 e_1 + In}{C_1 + In} \qquad (2)$$

Alternatively, it can be shown that there is an optimal level of investment (In^*), for a given level of no impact efficiency (e^*), which can be obtained by solving (2) with respect to In as in (3).

$$In^* = \frac{c_1(e^* - e_1)}{1 - e^*} \qquad e^* \neq 1 \qquad (3)$$

As seen from (3), as no impact efficiency moves towards unity (though never equals one), the optimum level of investment for the firm will be higher. In practice, the regulated firm neither observes nor can choose the level of no impact efficiency whereas it only adjusts the investment level (and other costs). However, the firm knows that high level of investment involves the risk of cost disallowance because it requires a higher level of efficiency achievement following investment. Moreover, as shown in Poudineh and Jamasb (2013a), in a static setting, the lower than optimum level of investment can increase other costs of the firm and hence, reduces efficiency in the benchmarking process which consequently will be reflected in its revenue.

Therefore, the firm conjectures the optimum level of investment, given its current level of efficiency. The capital accumulation process follows the following relation:

$$K^*_{t+1} = (1 - \varphi)K^*_t + In^*_t \qquad (4)$$

where K is the stock of capital of the firm, φ is the depreciation rate of capital and the star superscript indicates optimally. In theory, deviation from the optimum investment level (i.e., under- or over-investment), under the incentive model in (1), will be translated into a cost to the firm in the form of efficiency loss. Thus, the regulated firm has an incentive to adjust the level of capital stock employed in the production process.

However, there are two barriers to the full and fast adjustment of capital stock towards the optimum level. First, the firm needs to take into consideration the revenue effect of investments and possible cost disallowance in the benchmarking practice. This is because the firm carries out investment based upon an ex-ante prediction of optimum level of investment. However, the firm's actual investment can turn out to be lower or higher than the optimum level following the ex-post efficiency benchmarking (for a detailed discussion see Poudineh and Jamasb, 2013a). Second, the adjustment costs as a result of changing capital stock (e.g., cost of installation, disturbing production process, and personnel training, etc.) manifest themselves as reduced output or resource cost and lead to sluggish capital stock adjustment.[4]. Adjustment costs are often modelled as either explicit resource cost or as output-reducing cost incurred by firms as a result of diversion of resources from production to investment support activities (Silva and Stefanou, 2007).

Therefore, in any regulatory period, the firm's objective (with regard to investment) is to minimise the cost of deviation from the optimum capital stock, as well as, the cost of adjustment. In the context of incentive regulated firms, it is reasonable to assume that adjustment cost appears as a resource cost to the firm rather than an output-reducing cost. This is because output is determined by demand which is exogenous and hence, the utilities adjust their input to deliver a given level of output and service quality.

Following Pereira (2001) we adopt a loss function to represent the regulated firm's decision for investment and capital level. Within this framework, the firm minimises the expected sum of future adjustment cost and the cost of deviation from the optimal path of capital stock, which are discounted appropriately, subject to a capital accumulation process as follows:

$$Min\ E_t \sum_{i=0}^{\infty} \eta^i \left[(K_{t+i} - K^*_{t+i})^2 + b(In_{t+i})^2\right]$$

$$s.t \qquad K_{t+i+1} - K_{t+i} = I_{t+i} - \varphi K_{t+i} \qquad (5)$$

where $0 < \eta < 1$ is the discount factor and $b(In_{t+i})^2$ is a quadratic function representing the adjustment cost with b denoting the importance of adjustment cost in disequilibrium cost. E_t is the expectation operator conditional on available information set to the firm at time t.

Using discrete time calculus of variations, the first order condition for the dynamic optimisation problem in (5) will lead to the Euler equation in (6), which shows the optimal path for capital stock (Pereira, 2001).

[4] In this analysis we do not consider external adjustment costs which are related to market for capital goods (i.e., monopsony in the market for supply of capital goods).

$$E_tK_{t+1} - \frac{\left[(1-\varphi)^2 + b^{-1} + \eta^{-1}\right]}{(1-\varphi)} K_t + \frac{1}{\eta} K_{t-1} = -\frac{b^{-1}}{(1-\varphi)} K_t^* \qquad (6)$$

Using a simplifying assumption of zero depreciation rate ($\varphi = 0$) and the conditional expectation operator converts (7) into the following:

$$\left(B^2 + \zeta B^{-1} + \frac{1}{\eta}\right) E_t K_{t-1} = -b^{-1} E_t K_t^* \qquad (7)$$

where $\zeta = -[1 + b^{-1} + \eta^{-1}] < 0$ and B represents an operator defined as $B^{-j} E_t x_t = E_t x_{t+j}$.

The equation (7) can be further decomposed into its factors as follows:

$$(\theta_1 - B^{-1})(\theta_2 - B^{-1}) E_t K_{t-1} = -b^{-1} E_t K_t^* \qquad (8)$$

where $\theta_1 + \theta_2 = -\zeta$ and $\theta_1 \theta_2 = \frac{1}{\eta}$. As the summation and multiplication of roots are positive we can conclude that the roots θ_1 and θ_2 are both positive. Furthermore, Pereira (2001) shows that one of these roots is smaller than unity and the other is beyond the unit root circle. The solution of (8) with respect to the unstable root, say θ_2, will lead to the equation of motion for capital stock in (9):

$$K_t = \theta_1 K_{t-1} + \theta_1 \eta b^{-1} \sum_{i=0}^{\infty} (\theta_1 \eta)^i E_t\, K_{t+i}^* \qquad (9)$$

If we multiply both sides of (9) with $(B^{-1} - 1)$ a similar equation of motion for investment can be obtained as follows:

$$I_t = \theta_1 I_{t-1} + \theta_1 \eta b^{-1} \sum_{i=0}^{\infty} (\theta_1 \eta)^i E_t\, I_{t+i}^* \qquad (10)$$

where $I_t = K_{t+1} - K_t$ and $I_t^* = {K_{t+1}}^* - {K_t}^*$.[5]

Therefore, the level of capital (or investment), in the current period, is directly influenced by its value in the previous period and also with the current and expected future levels of optimum capital (investment). In other words, the equation of motion, for capital (investment) of the regulated firm, follows an autoregressive process.

The presence of an autoregressive process in capital (or investment) evolution induces a similar relationship in the technical inefficiency of the firm. Figure 1 presents schematically, the technical, allocative and economic efficiency of a firm. It assumes that the firm uses two inputs (capital (K) and other input (L)) to produce a single output.

[5] Recall that depreciation has been assumed to be zero for simplicity in governing the equations.

The isoquant SS' represents the production frontier. The line CC', on the other hand, shows the minimum cost mix of inputs.

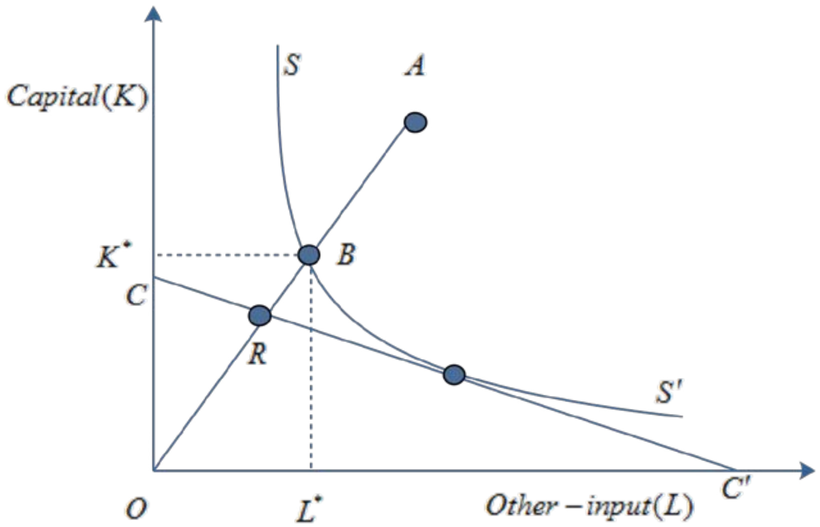

Figure 1: Technical, allocative and economic efficiency

Source: Authors

Given that point A is the observed performance of a firm, the technical efficiency can be defined as $TE = \frac{OB}{OA}$ and allocative efficiency is $AE = \frac{OR}{OB}$.

Economic efficiency, on the other hand, is the product of technical and allocative efficiency as follows:

$$EE = TE \times AE = \frac{OR}{OA} \qquad (11)$$

As stated previously an autoregressive process in capital will lead to a similar process in state of firm's technical inefficiency.

It is clear from figure (1) that $OB = \sqrt{{K^*}^2 + {L^*}^2}$ where K^* and L^* shows efficient levels of capital and other input. Similarly, $OA = \sqrt{K^2 + L^2}$ where K follows the process in (9).

By defining technical efficiency as $TE = \exp(-z_t)$, where z_t is the inefficiency level, we obtain:

$$z_t = -\log(TE) = -\log\left(\frac{OB}{OA}\right) = -\log\left(\frac{\sqrt{{K^*}^2+{L^*}^2}}{\sqrt{K^2+L^2}}\right) = \frac{1}{2}\log\left(\frac{K^2+L^2}{{K^*}^2+{L^*}^2}\right) \qquad (12)$$

which can be further simplified to:

$$z_t = \frac{1}{2}\log[(\frac{K}{K^*})^2 \times \text{KS} + \text{LS}] \qquad (13)$$

where $KS = \frac{1}{1+\frac{L^{*2}}{K^{*2}}}$ and $LS = \frac{L^2}{K^{*2}+L^{*2}}$.

If we substitute from (9) into (13) we will have:

$$z_t = \frac{1}{2}\log[(\frac{\theta_1 K_{t-1} + \theta_1 \eta b^{-1} \sum_{i=0}^{\infty}(\theta_1\eta)^i E_t K_{t+i}^*}{K^*})^2 \times \text{KS} + \text{LS}] \qquad (14)$$

which can be rearranged as in (15).

$$z_t = \frac{1}{2}\log\{\left(\frac{\theta_1 K_{t-1}}{K^*}\right)^2 \text{KS} + \text{LS} + \frac{(\theta_1\eta b^{-1}\sum_{i=0}^{\infty}(\theta_1\eta)^i E_t K_{t+i}^*)^2 + 2(\theta_1 K_{t-1})(\theta_1 \eta b^{-1} \sum_{i=0}^{\infty}(\theta_1\eta)^i E_t K_{t+i}^*)}{K^{*2}}\text{KS}\} \qquad (15)$$

As, $z_{t-1} = \frac{1}{2}\log[(\frac{K_{t-1}}{K^*})^2\text{KS} + \text{LS}]$, the relation in (15) clearly shows that inefficiency in the current period is correlated with inefficiency in the previous period. The econometric version of this relation for z_{t-1} is:

$$z_t = \alpha + (1-\psi)z_{t-1} + \varepsilon_t \qquad (16)$$

where α is a constant, ε_t is a random shock to the level of the current period inefficiency and $1-\psi$ shows persistence of inefficiency[6] (i.e., ψ is the speed of adjustment of inefficiency).

The term $\alpha + (1-\psi)z_{t-1}$ in (16) is the expected value of z_t given z_{t-1}. In other words, given the previous level of inefficiency and presence of an autoregressive process, firm inefficiency is expected to be composed of a constant term (α), and its inefficiency in the previous period (z_{t-1}) which is partially adjusted ($-\psi z_{t-1}$). However, in practice, the observed level of inefficiency can be higher or lower than the expected value due to period specific shocks (i.e. ε_t). These shocks have a zero expectation and cause the firm inefficiency to deviate from its expected path. Ann and Sickles (2000) attribute these shocks to emergence of new technologies, regulation or deregulation and changes in behaviour of competitors. Investment also is an important factor that creates period specific shock to the current level of inefficiency which persists over subsequent periods.

It is evident from (16) that inefficiency transmission across periods exists only when $\psi \neq 1$. A value between zero and unity ($0 < \psi < 1$) means that the rate of inefficiency

[6] The value of ψ can be different for every observation. The empirical model in the next section is setup to enable an observation specific estimation of ψ.

transmission is diminishing as time passes. Under this condition, a higher ψ (or a lower $1-\psi$) implies a faster adjustment towards the long run equilibrium and a lower level of inefficiency persistence. On the contrary, a lower ψ implies prolonged persistence of inefficiency and hence; inability of producers to optimise their cost quickly. A value of $\psi = 0$, on the other hand, implies that there is no tendency for inefficiency to revert back to an equilibrium point.

Although, in the short run, inefficiency of firm depends on the past value, in the long run it only depends on the value of α and ψ. If $0 < \psi < 1$ and ε_t is a white noise process, the expected long run inefficiency would be $\frac{\alpha}{\psi}$ [7].

Therefore, in any given period, technical inefficiency has two components. One element is related to period-specific effects (ε_t) and the other is the inefficiency carried over from previous periods ($\alpha + (1-\psi)z_{t-1}$). This implies that inefficiencies which are related to sluggish adjustment of capital and the associated adjustment costs persist over time, without firms having much control over them in the short run. At the same time, the incentive regulation model in (1) penalises and rewards firms based on their observed levels of efficiency which, in effect, includes an uncontrollable component due to investment cycles. This is problematic for optimising investment and capital as it exposes the regulated firm to revenue loss.

3. Empirical model

This section presents a parametric method to estimate the two components of inefficiency and the rate of inefficiency transmission, across periods, as described in Section 3. Application of parametric methods to address the dynamic aspect of inefficiency is relatively new. Ahn and Sickles (2000) were the first to use a dynamic model to provide a structural explanation for variations in the efficiency levels of a firm. They assume that technical inefficiency evolves over time in an autoregressive manner due to the firm's inability to adjust its efficiency in a timely manner. This model is reduced to a normal dynamic panel data model if the speed of inefficiency adjustment is assumed to be the same for all firms. Emvalomatis et al. (2011) use a similar dynamic efficiency model based on the standard stochastic distance function model, but allow the efficiency scores of the firms to be correlated through time. The autocorrelated inefficiency model is developed in a state-space framework and nonlinear Kalman

[7] ***Proof***: a recursive substitution of (16) gives $z_t = (1-\psi)^n z_{t-n} + \alpha[\sum_{i=0}^{n}(1-\psi)^i] + [\sum_{i=0}^{n}(1-\psi)^i \varepsilon_{t-i}]$. On the other hand $E(z_t)= (1-\psi)^n E(z_{t-n})+ \alpha[\sum_{i=1}^{n-1}(1-\psi)^i]$ because ε_t is assumed to be a white noise process, and $E(\varepsilon_t) = 0$. Thus the cumulative effect when $n \to \infty$ is: $E(z_t) = \frac{\alpha}{1-(1-\psi)} = \frac{\alpha}{\psi}$.

filtering is used to evaluate the likelihood function and obtain the technical efficiency scores.

Tsionas (2006) proposes a stochastic frontier model that allows for technical inefficiency effects and dynamic technical inefficiency by adopting Bayesian inference procedures based on Markov chain Monte Carlo (MCMC) techniques. Emvalomatis (2012) considers the implications of stochastic frontier models with autocorrelated inefficiency in the presence of unobserved heterogeneity. The study specifies random- and correlated random-effects models and proposes a Bayesian estimation approach to measure dynamic efficiency.

3.1 Model development

Following the approach in Coelli and Perelman (1996) we define an input distance function as follows:

$$D^I(x, y, t) = max\left\{\gamma: \left(\frac{x}{\gamma}\right) \in L(y)\right\} \quad (17)$$

where $L(y)$ represents the set of input vectors $x \in R^Q$ that can produce the output vector $y \in R^M$ in period t and γ indicates the proportional reduction in a given input vector. If $x \in L(y)$ then $D^I \geq 1$ however, $D^I = 1$ if x is on the frontier of the input requirements set. Technical efficiency is defined as $TE_{it} = 1/D^I(x, y, t)$. Taking the logarithm of both sides and imposing homogeneity of degree one in inputs by normalizing the $Q - 1$ inputs with respect to Qth. input leads to an econometric version of this relationship as in (18):

$$-logx_{Qit} = logD_{it}^I\left[\left(\frac{x_{qit}}{x_{Qit}}\right), y_{mit}, t\right] + v_{it} + \log(TE_{it}) \quad (18)$$

where v_{it} is a normally distributed idiosyncratic error term and $\log(TE_{it})$ is the one sided inefficiency term which enters the equation as the logarithm of technical efficiency. It can be seen that the logarithm of the distance function can be written in terms of an estimable linear function of $\boldsymbol{x}_{it}$ and a vector of coefficients $\boldsymbol{\beta}$ as in (19).

$$y_{it} = \boldsymbol{x}_{it}'\boldsymbol{\beta} + v_{it} + \log(TE_{it}) \quad (19)$$

Following Emvalomatis et al. (2011), we assume an autoregressive process for the efficiency by making non-linear transformation of inefficiency as in (20)-(22)[8].

[8] This transformation is for estimation purpose and allows us to have observation specific inefficiency transmission. Thus, equation (21) is comparable to equation (16) in Section 3 in the following way (subscript i is removed for simplicity):

$$\frac{dz}{dz_{t-1}} = 1 - \psi = \frac{dz}{ds_t} \times \frac{ds_t}{ds_{t-1}} \times \frac{ds_{t-1}}{dz_{t-1}} = \frac{exp(s_t)}{(1+exp(s_t))^2} \times \rho \times \frac{1}{z_{t-1}(1-z_{t-1})}.$$

$$s_{it} = \log(\frac{TE_{it}}{1-TE_{it}}) \quad (20)$$

$$s_{it} = \delta + \rho s_{it-1} + u_{it} \qquad u_{it} \sim N(0, \sigma_u^2) \quad (21)$$

$$s_{i1} = \mu_1 + u_{i1} \qquad u_{i1} \sim N(0, \sigma_{u1}^2) \quad (22)$$

where s_{it} is the logarithm of ratio of efficiency to inefficiency and ρ is an elasticity that measures the percentage change in the ratio of efficiency to inefficiency that is transferred from one period to the next. Equation (22) initialises the stochastic process and assumes stationarity. Stationarity also implies that, in the long run, the expected value of s_{it}, unconditional on $s_{i,t-1}$, is the same for all firms and the possible observed differences are due to shocks or the difference in the stage of the path towards long run equilibrium. Under this condition (stationarity), the two additional parameters can be obtained by (23) and (24).

$$\mu_1 = \frac{\delta}{1-\rho} \quad (23)$$

$$\sigma_{u1}^2 = \frac{\sigma_u^2}{1-\rho^2} \quad (24)$$

If the process is not stationary the expected value of the firms' efficiency, over time, tends towards unity or zero. Similarly, the expected value of s_{it} can incline towards positive or negative infinity. As suggested in Tsionas (2006), it is unlikely that data is generated by a process with unit root, especially when efficiency approaches zero. This is because we normally expect inefficient firms to fall out of a competitive market or, in the case of regulated firms, suffer from financial losses as their revenue is directly linked with their efficiency level. Thus, the number of very inefficient firms will be small. Given stationarity, the long run efficiency can be obtained by (25)[9].

$$Long\ run\ TE = 1/[1 + exp(-\frac{\delta}{1-\rho})] \quad (25)$$

Following Emvalomatis (2012), we add a firm specific term ω_i to (18) in order to account for unobserved heterogeneity among the firms, assuming $\omega_i \sim N(0, \sigma_i^2)$. We

For the above relationship we have used $z_t = 1 - TE_t$ which is the same as $z_t = -\log(TE_t)$ for low values of inefficiency. This is because based on the Taylor series of e^{-z_t} we have:

$$e^{-z_t} = \sum_{n=0}^{\infty} \frac{(-z_t)^n}{n!} = 1 - z_t + \frac{{z_t}^2}{2!} - \frac{{z_t}^3}{3!} + \cdots$$

and hence, $Lim\,\{e^{-z_t}\}$=$1 - z_t$ because all the higher order terms will approach towards zero quickly as $z_t \to 0$.

[9] ***Proof:*** We know s_{it} has the following process: $s_{it} = \delta + \rho s_{it-1} + u_{it}$ Thus, the long run value of s_{it} is $\frac{\delta}{1-\rho}$ (the proof of this is exactly similar to the footnote 7) On the other hand we know that s_{it} is defined as:$s_{it} = log(\frac{TE_{it}}{1-TE_{it}})$ Thus we can obtain the long run efficiency by: $log\left(\frac{TE_{it}}{1-TE_{it}}\right) = \frac{\delta}{1-\rho}$ hence, $\frac{TE_{it}}{1-TE_{it}} = exp(\frac{\delta}{1-\rho})$ and therefore: $Long\ run\ TE = 1/[1 + exp(-\frac{\delta}{1-\rho})]$.

estimate the parameters of the hidden state model (21)[10] and measurement equation (18) simultaneously using only the observed data in (18).

In order to estimate the vector of all parameters, $\boldsymbol{\theta} = [\boldsymbol{\beta},\ \sigma_v, \delta, \rho, \sigma_u,\ \sigma_\omega]'$ we set up the likelihood function by letting s_i denote the $T \times 1$ vector of the latent state variable for the firm i as in (26).

$$
\begin{aligned}
&p(\boldsymbol{y}, \{\omega_i\}, \{s_i\} | \boldsymbol{\theta}, \boldsymbol{X}) = \ p(\boldsymbol{y} | \{\omega_i\}, \{s_i\}, \beta, \sigma_v, \boldsymbol{X}) \times p(\{s_i\} |, \delta, \rho, \sigma_u\ ) \\
&= \frac{1}{(2\pi\sigma_v{}^2)^{\frac{NT}{2}}} exp\left\{-\frac{\sum_{i=1}^{N}\sum_{t=0}^{T-1}(y_{it} - \omega_i - \boldsymbol{X}_{it}'\beta - logTE_{it})^2}{2\sigma_u^2}\right\} \\
&\times \frac{1}{(2\pi\sigma_{u1}{}^2)^{\frac{N}{2}}} exp\left\{-\frac{\sum_{i=1}^{N}(s_{i1} - \delta_1)^2}{2\sigma_{u1}^2}\right\} \\
&\times \frac{1}{(2\pi\sigma_u{}^2)^{\frac{N(T-1)}{2}}} exp\left\{-\frac{\sum_{i=1}^{N}\sum_{t=1}^{T-1}\left(s_{it} - \delta - \rho s_{i,t-1}\right)^2}{2\sigma_u^2}\right\} \qquad (26) \\
&\times \frac{1}{(2\pi\sigma_\omega{}^2)^{\frac{N}{2}}} exp\left\{-\frac{\sum_{i=1}^{N}\omega_i^2}{2\sigma_\omega^2}\right\}
\end{aligned}
$$

where $\boldsymbol{y}$ and $\boldsymbol{X}$ represent the vector and matrix of dependent and independent variables respectively and δ_1 and σ_{u1}^2 are the mean and variance of s_{i1} in equation (22). The last term in likelihood function captures the heterogeneity effects. This likelihood function enables a simultaneous estimation of equations (18) and (21).

The estimation is carried out in a Bayesian framework. For $\boldsymbol{\beta}$ and δ, normal priors are selected. For the variance parameters the inverted Gamma has been chosen because it is conjugate. Moreover, for ρ a Beta prior has been used to restrict it in unit interval. In order to estimate the posterior moments of the model's parameters a posterior simulation based on Markov chain Monte Carlo (MCMC) is employed.

3.2 Data and model specification

The dataset used for the application is a balanced panel of 128 Norwegian electricity distribution networks observed from 2004 to 2010. All financial data are in real terms which are adjusted based on 2010 prices. The Norwegian distribution companies are working under incentive regulation with ex-post regulatory treatment of investment based on the formula (1). The power of incentive (λ) in Norwegian regulatory model is currently 60% in order to motivate companies to move as close as possible to the efficient frontier.

[10] Equation (21) is called hidden (latent) state because we do not observe the data in this equation.

Following the Norwegian energy regulator, we construct the regulatory asset base (RAB) using the book value of capital stock plus 1% as working capital. The return on regulatory asset base is computed using the regulator rate of return[11]. Other variables include operational cost of network companies, number of customers and distributed energy. Number of customers reflects the total number of connected consumers to the grid including the holiday homes[12]. The summary of descriptive statistics of model variables is presented in Table 1.

Table 1: Descriptive statistics

Variable Description	Variable	Min.	Max.	Mean	Std. Dev.
Operational cost (000'NOK)	$Opex$	878	854646	43244.95	88270.88
Return on RAB (000'NOK)	$Capex$	0.113	263071	15366.9	31772.38
Distributed energy (MWh)	DE	6915	1.68e+07	561877	1575379
Number of customers (#)	CU	18	544925	21115	55979.07

The model specification for the application is a distance function that allows estimation in a multi-input multi-output context. The outputs in our model are energy distributed (DE) and total number of customers (CUS) connected to the grid. Operational expenditures ($Opex$) and return on regulatory asset base ($Capex$) are the two inputs. These variables are commonly used in efficiency analysis of electricity networks (e.g., Growitsch et al., 2012; Miguéis et al., 2011). Substituting the inputs and outputs into equation (18) and using operating costs as the normalising input leads to[13]:

$$\begin{aligned} -\log(Opex) = {} & \beta_0 + \beta_1 \log(DE) + \beta_2 \log(CUS) + \beta_3 \log(Capex^*) + \frac{1}{2}\beta_4 log^2(DE) \\ & + \frac{1}{2}\beta_5 log^2(CUS) + \frac{1}{2}\beta_6 \log^2(Capex^*) + \beta_7 \log(DE)\log(CUS) \\ & + \beta_8 \log(DE)\log(Capex^*) + \beta_9 \log(CUS)\log(Capex^*) + \omega_i + \xi_1 t + \frac{1}{2}\xi_2 t^2 \\ & + v_{it} + logTE_{it} \end{aligned} \qquad (27)$$

where $Capex^*$ is the normalised $Capex$, t is time trend and ω is used to capture the unobserved heterogeneity in the operating environment of the firms. Given the possibility of the presence of correlation between firm effect (ω) and technical efficiency, two models are estimated based on the method proposed by Emvalomatis (2012). In the first model we assume that the firm specific effect is uncorrelated with technical efficiency (simple random effects). For the second model we take into account

[11] The regulator rate of return, currently, is 5.62% in Norway.

[12] The Norwegian regulator has separated holiday cottages from other customers as they have a different load profile compared with conventional consumers.

[13] We used an input rather an output orientation when measuring efficiency to comply with consensus that in regulated utilities demand is exogenous.

the possibility of correlation between the firm specific effects with the independent variables using the technique in Mundlak (1978). For ease of interpretation of the first order terms, all data are divided by their sample mean prior to estimation.

4. Results and discussion

4.1 Empirical results

Table 2 presents the results, of the models estimated, based on the posterior means of the parameters and their standard deviation. The estimations include simple random effects (no correlation between firm specific effect and technical efficiency) and correlated random effects. All first order terms show consistent signs for the simple random effect model whereas only the coefficient of distributed energy has an unexpected sign for the correlated random effects model. Moreover, the parameters of the correlated random effects model are, on average, smaller compared with the simple random effects model. The first order parameters, in both models, can be interpreted as the elasticity of input with respect to outputs at the sample mean.

The estimated parameter ρ is around 92% for both the simple and correlated random effect models which are quite similar and fairly high. The value of ρ directly influences the rate if inefficiency transmission $(1-\psi)$ (discussed in Section 2) across periods. We have used their relationship, as the way shown in Footnote 8, to obtain the rate of inefficiency transmission for each observation. Unlike ρ which is constant for the whole sector inefficiency transmission rate $(1-\psi)$ is observation specific and has a mean of 88%.

However, distribution of rate of inefficiency persistence $(1-\psi)$ presented in figure 2, shows significant variation at the level of individual companies. The small value shows short duration of problematic inefficiency persistence and hence, speedy adjustment. The large value of $1-\psi$ indicates that inefficiency transmission between periods has affected the performance of firms significantly. The magnitude of inefficiency transmission rates are influenced by the scale of investment. In any regulatory period, investment appears as a shock to the current level of firms' inefficiency whose duration of inefficiency persistence depends on gestation period of the projects. In this way, firms remain under financial constraints due to inefficiency induced by investments. This effect exists until the firm reaches the long run equilibrium. The estimates of long run efficiency of the distribution networks under simple and correlated random effects are very close and, as seen from Table 2, approximately 82%.

At the same time, figure 2 shows that majority of observations have rate of inefficiency transmissions which are less than one. This means inefficiency shocks fade-off over time. However, few firms randomly show an inefficiency transmission rate higher than one however, it has not been persistent and hence, can be attributed to the observations far from point of approximation (mean). This is because a value of inefficiency transmission rate higher than one suggests that the firm becomes progressively inefficient over time something which is very unlikely under reward and penalty scheme of incentive regulation (because revenue is directly linked with efficiency as in (1)).

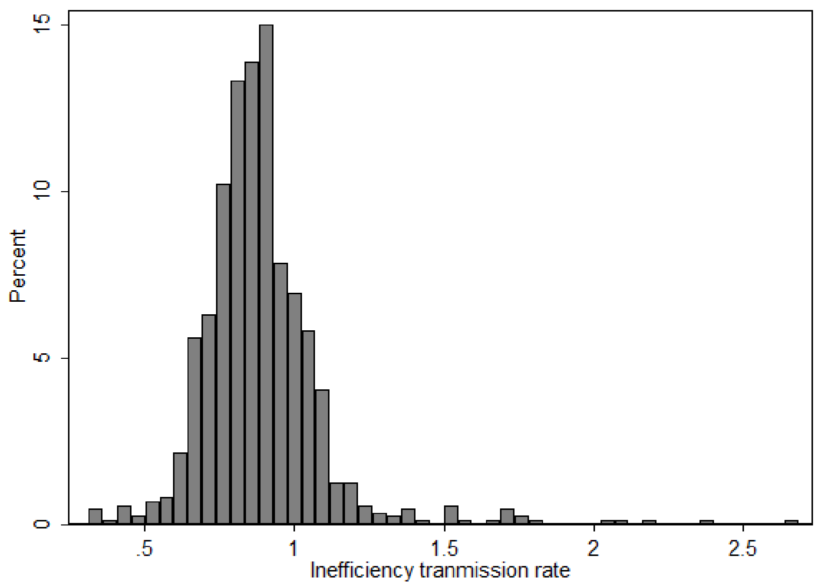

Figure 2: Distribution of inefficiency transmission rate $(1-\psi)$

Figure 3 presents the mean of decomposed inefficiencies for the whole sector and different years. Inefficiency decompositions include two terms: inefficiency carry-over from previous periods and period-specific inefficiency shocks which jointly construct the observed inefficiency of the period. It is worth noting that period-specific effects are different from uncontrollable noise that affect inefficiency, as our model controls for noise and unobserved heterogeneity[14]. As seen in Figure 3, the mean of period specific term can be positive, negative and zero in different years. For example, in 2004, the mean of observed inefficiency increased by about 2% with respect to its expected value as a result of the period-specific term. In the same way, the mean of observed inefficiency remained unchanged in 2009 and declined by around 1% in 2007. Cyclical investment is the most important factor in introducing positive period-specific shocks which persist over time. On the contrary, underinvestment, cost reducing measures, and innovative managerial practice can impact the period-specific term negatively.

[14] The noise and unobserved heterogeneity are reflected in the idiosyncratic error term (ν_{it}) and the firm specific term (ω_i), respectively, in equation 27.

Table 2: The posterior mean of parameters and their standard deviation[15]

	Simple random effects		Correlated random effects	
Coefficient	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
β_0	-6.678	(1.377)	-1.280	(30.93)
β_1	0.777	(0.423)	-0.065	(0.368)
β_2	0.652	(0.401)	0.857	(0.363)
β_3	1.594	(0.138)	1.648	(0.114)
β_4	0.035	(0.040)	0.008	(0.031)
β_5	0.181	(0.011)	0.084	(0.017)
β_6	-0.127	(0.007)	-0.131	(0.005)
β_7	-0.102	(0.024)	-0.054	(0.023)
β_8	-0.044	(0.021)	-0.003	(0.019)
β_9	0.014	(0.020)	-0.023	(0.019)
ξ_1	-0.014	(0.002)	-0.005	(0.003)
ξ_2	0.006	(0.000)	0.006	(0.000)
σ_v	0.010	(0.001)	0.010	(0.001)
δ	0.120	(0.019)	0.114	(0.023)
ρ	0.923	(0.011)	0.922	(0.014)
σ_u	0.254	(0.014)	0.229	(0.012)
σ_ω	0.252	(0.019)	0.216	(0.015)
$Long\ run\ TE$	0.828		0.811	

At the same time, there are significant variations in the components of decomposed inefficiency at the level of individual firms. Figure 4, shows the distribution of inefficiency decomposition for each year. As it is evident from the figure, the share of components of inefficiency in constructing the observed inefficiency varies across years. Some firms are affected considerably by period-specific shocks which are eventually reflected in their observed inefficiency. For instance, in 2004, a major share of observed inefficiency of the firms was related to the period-specific effects. These shocks again manifested themselves as increased share of inefficiency carry-over in 2005 and 2006. It is only from 2007 that these carry-over effects start to decline though increased again in 2010. Although under the condition of stationarity these shocks fade-off over an infinite time horizon, in practice their residual effects remain in the observed inefficiency of the firms.

[15] For the ease of interpretation the coefficients of model variables are multiplied by -1.

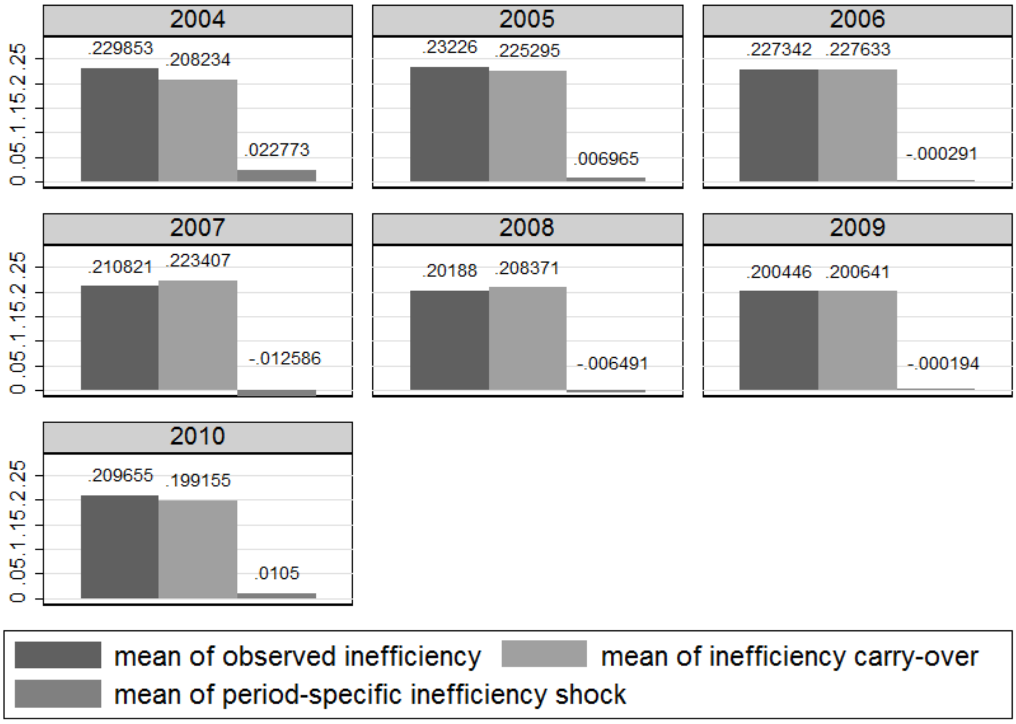

Figure 3: Inefficiency decomposition in different years

The intertemporal nature of the autoregressive process implies that one-time shocks can affect the value of evolving inefficiency far into future. In other words, the value of the current level of inefficiency is affected by past shocks because of investment or other reasons. In order to illustrate this, we have simulated the effect of period specific effects (shocks) on s_{it} using estimated parameters of autoregressive process in Equation 21. As s_{it} is related to inefficiency through Equation 20, this simulation can give an indication of the importance of period specific shocks for inefficiency.

The effect of one time shock on subsequent years and the cumulative effects over infinite time horizon have been simulated assuming different level of shocks in 2004. These are consistent with the distribution of period specific shocks that has been illustrated in Figure 3. The marginal effect can be obtained using $\frac{\partial s_{t+j}}{\partial u_t} = \rho^j$ where j denotes the length of time that separates a disturbance to input (u_{it}) and the observed value of the outputs (Hamilton, 1994). The sum of consequences for all futures values of s_{it} (cumulative effect), as result of a transitory disturbance to u_{it}, can then be computed from $\sum_{j=0}^{\infty} \frac{\partial s_{t+j}}{\partial u} = \frac{1}{1-\rho}$ (Hamilton, 1994). The results of simulation are presented in Table 3.

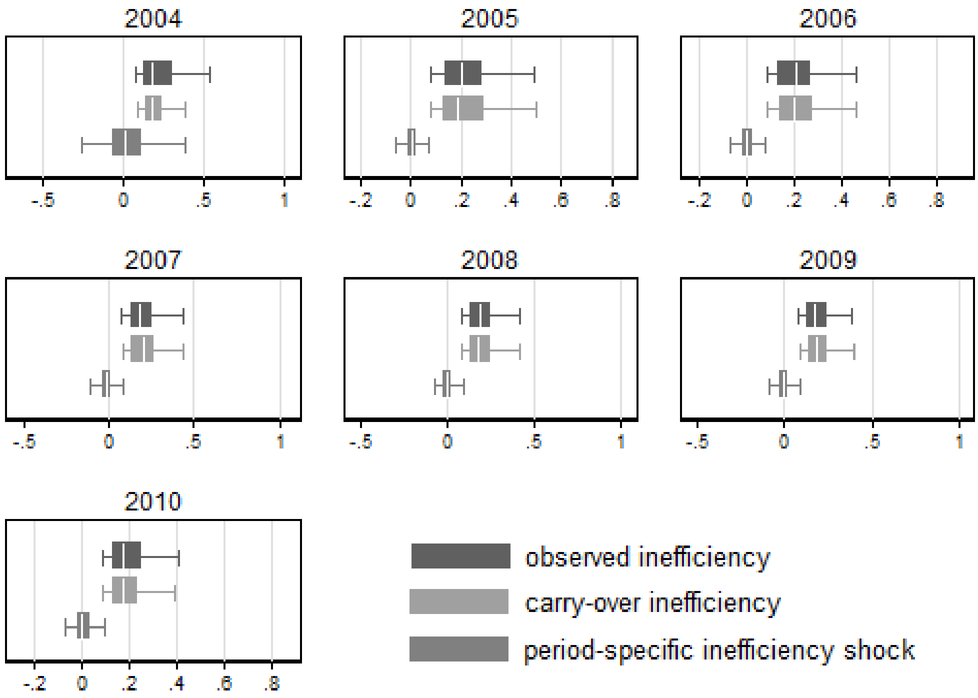

Figure 4: Distribution of inefficiency decomposition in different years

As shown in Table 3, the effect of a one-time shock carries over to subsequent years. Although, this effect diminishes over time, it takes many periods for it to decrease to less than 1% due to the high elasticity of transmission (ρ=0.92). For example, in the case of u=0.05, duration is around 20 periods and for the case of u=0.50 it takes 47 periods. Moreover, the corresponding cumulative effects of these transitory shocks are 62% and 625% respectively which are much higher than the initial perturbations.

Table 3: The effect of one time shock on s_{it}

Year / Shock	2005	2006	2007	2008	2009	2010	No. of periods needed to become <1%	Cumulative effects over infinite time
$u = 0.05$	0.046	0.042	0.038	0.035	0.032	0.030	20	0.62
$u = 0.10$	0.092	0.084	0.077	0.071	0.065	0.060	28	1.25
$u = 0.15$	0.138	0.126	0.116	0.107	0.098	0.090	33	1.87
$u = 0.20$	0.184	0.169	0.155	0.143	0.131	0.121	36	2.5
$u = 0.30$	0.276	0.253	0.233	0.214	0.197	0.181	41	3.75
$u = 0.40$	0.368	0.338	0.311	0.286	0.263	0.242	45	5
$u = 0.50$	0.46	0.423	0.389	0.358	0.329	0.303	47	6.25

The figures show that historical shocks play a major role in the current and future level of firms' productivity. Under the condition that the initial shock is due to investments, the scale and type of investment will impact the elasticity of inefficiency persistence. However, once inefficiency transmission begins, the process of adjustment is not under the control of the firm. This is against the very basic assumption of incentive regulation model in (1) which assumes that the evolution of inefficiency is entirely controllable and based upon that links the revenue of firm with the observed efficiency of firm.

Unlike the long run efficiency which captures the dynamic aspect of firm behaviour, short run efficiency is an indicator of deviation from the static optimum frontier. Table 4 presents the summary of short term efficiency statistics for each year studied. As shown, the range of efficiency distribution is fairly significant although the magnitudes of average efficiencies are very similar and relatively high. This implies that there is little improvement in average short run efficiency. This can occur due to several reasons. One explanation could be that under the incentives regime the immediate efficiency gains are achieved from operating costs (Muller et al., 2010). On the other hand, following capital expenditures some firms become inefficient. Hence, on average, operational efficiency gain in each period offsets the inefficiency induced by capital investment and thus, the average static efficiency of sector remains relatively stable.

Table 4: Average of short run efficiencies

Year	Average Efficiency	Min.	Max.
2004	0.801	0.483	0.926
2005	0.799	0.431	0.926
2006	0.802	0.409	0.922
2007	0.815	0.356	0.928
2008	0.820	0.463	0.922
2009	0.822	0.403	0.921
2010	0.815	0.427	0.917

4.2 Regulatory challenges and the way forward

The implication of persistent inefficiency is crucial for the incentive regulation based on (1) which currently being practised in Norway and other countries. Under this model of incentives regulation, efficiency loss is equivalent to revenue loss for firms. The theory behind the short run efficiency assumes that firms are profit maximisers and the regulatory regime implies that cost minimising is valid under all conditions. However, due to the presence of dynamic aspects in the firms' decision concerning investments and innovation, static efficiency is an inadequate measure of investment behaviour and performance of utilities. Therefore, ex-post regulatory treatment of investments through benchmarking total cost distorts the long run objectives of the firms and might expose firms to financial loss. Although, this approach has been adopted to deter overcapitalisation, considering asymmetric information between the firm and the regulator, it will not necessarily lead to an efficient level of investment.

The implication of inefficiency persistence also concerns the case of innovation. Innovation is the outcome of firms' efforts to produce new or improved products and services, introduce more efficient and productive design processes and implement organisational or managerial changes. Innovation generation and adoption by the firms depends, among other factors, on the market structure and the cost of resources. The innovative behaviour entails complementary investment to the more traditional R&D concept such as investment in innovation-related training and design, investment in machinery, equipment and software. However, these types of investments can induce a prolonged inefficiency and expose the distribution companies to substantial financial losses under the penalty and reward schemes of the incentives regime.

This paper identifies the problems with ex-post regulatory treatment of investment however; the regulatory solution is not straightforward. This is because regulating the capital cost of the companies is the matter of trade-off between using information from the firm itself (i.e. project the cost) and from the peers (i.e. benchmark). An approach used by some sector regulators, to address the issue of quasi fixed input, is to exclude capital expenditures from the benchmarking models. That is to rely on firms' own information regarding capital expenditure (Capex) and benchmark only operating cost (Opex)[16]. However, this approach received several criticisms. Burn and Riechmann (2004) argue that Capex and Opex should be treated equally because benchmarking only one cost category such as Opex and different treatment of Capex creates incentive for companies to transfer costs from the 'yardstick' category to 'firm specific' category. The firm is aware that lower investment leads to lower regulatory asset base and consequently lower return, and may, therefore, engage in strategic behaviour in pursuit of gold plating capital costs.

Furthermore, as argued in Besanko and Spulber (1992), firms might choose a higher than optimal level of capital in order to persuade the regulator to allow higher operating costs and price on their product. Furthermore, Averch and Johnson (1962) showed that under this model, more capital will be employed by the regulated firm compared to a non-regulated firm, given any level of output. Additionally, from a practical point of view when the number of regulated companies are high (as in the case of Norway which are around 130 companies), scrutinising the investment plan of each individual firm might not be feasible considering the length of regulatory period.

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[16] This approach is being practised in the UK in which the companies submit their business plan to the regulator before the next regulatory period to be examined and approved if justified.

Another approach that can be considered but needs further investigation is to use directional contraction of inputs where both operating and capital costs are part of the benchmarking practice. In this case the, the inputs are contracted only in the direction of operational expenditures assuming convexity between operational and capital expenditure as two inputs. This is in contrast with the current form of radial contraction of both inputs being used in benchmarking practice. However, the convexity constraint between operating and capital expenditures might not always hold in which case this approach can be problematic. Another possibility is to develop statistical approaches that allow for controlling inefficiency persistence due to investment so the firms are only penalised for the controllable part of their inefficiency evolution. At the same times, regulators need to ensure that approaches used to ease the process of investment and innovation will not lead to overcapitalisation.

The area of dynamic efficiency under incentive regulation requires further research to address the issues of investment and innovation and also strike a balance between firms own information, sector information, investment incentives and possibility of over- and under-investment. Regulators also need to understand the long term consequences of the regulatory framework for investment and innovation and make informed decision regarding the way incentives are implemented.

5. Conclusions

The use of efficiency and productivity techniques such as total cost benchmarking, is becoming now common in incentive regulation to induce cost efficiency and prevent the firms from overcapitalisation. However, benchmarking only captures short run efficiency of network companies while they operate in a dynamic environment where technology, regulatory standards, demand and economic conditions are changing. In response to this, the utilities reorganise their production process to become more efficient in the short run.

However, the factors that affect short term efficiency of the firms (i.e. network outputs) may not be adjusted instantaneously when firms invest in new and costly technologies and practices which take time to produce result. Under this condition, in the short run, investment creates an induced inefficiency which persists for some time until the inputs and outputs are fully adjusted. On the other hand, the firms' revenues, under incentive regulation, crucially depend on the level of efficiency achieved in the benchmarking process.

The current form of incentives regulation with ex-post regulatory treatment of investment employed by many European regulators does not take this effect into account and, hence, there is a risk of financial loss for regulated companies when undertaking investment. Therefore, the simultaneous incentives for investment and static cost efficiency can send inconsistent signals to regulated firms. This potentially limits the companies' incentives for investment and innovation.

This paper analysed the concept of dynamic efficiency under incentives regulation with ex-post regulatory treatment of investment. We have shown that, in any given period, inefficiency of a firm consists of two components: the period-specific shocks and the carry-over from previous periods. The period specific inefficiency shocks can be created by investment or other factors that affect inefficiency and carry-over effect is due to inability of firms to adjust their inputs in a timely manner. Additionally, we estimated a dynamic stochastic frontier model in a Bayesian framework for a balanced panel of 128 Norwegian electricity distribution companies from 2004 to 2010.

The results show that, at the sector level, 92% of the efficiency to inefficiency ratio is transferred from one period to another. At the level of individual companies, however, the variation is significant. There are firms with very low or very high elasticity of inefficiency transmission. The high magnitude of elasticity causes the effect of the shocks to die out over a longer period. The distribution of inefficiency decomposition shows that except in 2004, the share of carry-over effects, in the observed level of firms' inefficiency, is considerable. We have simulated the effect of a one-time shock on the autoregressive process and concluded that both the cumulative effect as well as the duration of inefficiency persistence will increase by the magnitude of initial perturbation. The results also indicate that the long run efficiency of the sector is approximately 82% based on the simple and correlated random effects models.

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