# The Hidden Cost of Investment: The Impact of Adjustment Costs on Firm Performance Measurement and Regulation


## AUTHORS

**Sebastian Nick (EWI)**

**Heike Wetzel (Department of Economics, University of Cologne, and EWI)**



EWI Working Paper, No 14/03

February 2014

Institute of Energy Economics at the University of Cologne (EWI)
www.ewi.uni-koeln.de

Institute of Energy Economics
at the University of Cologne (EWI)

Alte Wagenfabrik
Vogelsanger Straße 321
50827 Köln
Germany

Tel.: +49 (0)221 277 29-100
Fax: +49 (0)221 277 29-400
www.ewi.uni-koeln.de

## CORRESPONDING AUTHOR

**Sebastian Nick**
Institute of Energy Economics at the University of Cologne (EWI)
Tel: +49 (0)221 277 29-303
Fax: +49 (0)221 277 29-400
Sebastian.nick@ewi.uni-koeln.de

ISSN: 1862-3808

# The Hidden Cost of Investment: The Impact of Adjustment Costs on Firm Performance Measurement and Regulation

Sebastian Nick[a,*], Heike Wetzel[b]

[a] *Institute of Energy Economics, University of Cologne, Vogelsanger Straße 321, 50827 Cologne, Germany.*
[b] *Department of Economics and Institute of Energy Economics, University of Cologne, Vogelsanger Straße 321, 50827 Cologne, Germany.*

---

**Abstract**

In this study, we address a major problem in the measurement of firm performance and the regulation of natural monopolies, namely the intertemporal character of long-term investment decisions. In specific, we focus on the impact of adjustment costs of investments on estimates of firms' technical and cost inefficiency. We apply nonparametric dynamic data envelopment analysis to investigate the dynamic inefficiency of electricity distribution and transmission companies in the US during the years 2004 to 2011 and compare our results with their static counterparts. Our empirical findings reveal that ignoring long-term investments and their corresponding adjustment costs significantly distorts both firm-specific and industrial inefficiency estimates and may thus create misleading incentives for the regulated firms to cut investments.

*Keywords:* dynamic inefficiency, dynamic directional distance function, dynamic data envelopment analysis, electricity transmission and distribution

JEL classification: D22, D24, D61, D92, L51.

---

☆The authors would like to thank Christian Growitsch, Felix Höffler, Alfons Oude Lansink and Spiro Stefanou for helpful comments and suggestions as well as Julia Bellenbaum for excellent research assistance.

*Corresponding author

*Email address:* `Sebastian.Nick@ewi.uni-koeln.de, +49 22127729303` (Sebastian Nick)

## 1. Introduction

Allocating the costs and benefits of economic decisions to certain time periods represents an important element in everyday economic life. In specific, the effects of an investment in capital assets have to be distributed over time by accountants in order to allow stakeholders to gain an assessment of the firm's performance within a certain period. However, an adequate allocation of the true economic costs and benefits of an investment over time is hindered by the fact that the measurable costs and benefits considered in the bookkeeping may diverge from the actual economic costs and benefits. This phenomena is referred to as the allocation problem of financial accounting (Thomas, 1969).

For an illustrative example of this accounting problem, consider a firm investing into a new, more efficient software system. In the initial period, the implementation of the new system will cause significant adjustment costs for installation, training and reorganization that are reflected in the firm's operational expenditures. In contrast, the measurable economic benefits of the new system will unfold only later in the following periods. As a consequence, the firm will appear less profitable for investors, regulators and other stakeholders during the installation period although it is implementing an investment decision that increases the performance of the company in the long run.

This work addresses a specific version of such an allocation problem in accounting, namely the mismatch between the benchmarking methods used in the context of incentive-based regulation schemes and the multi-period optimization behavior of the regulated firms. Current benchmarking practice usually ignores the intertemporal linkage of investments outlined above by relying solely on static inefficiency measures. These inefficiency measures focus on input and output data (costs or quantities) for a certain period and do not control for adjustment costs of investments that affect the observable combination of variable inputs and output in the respective benchmarking period. Thus, the regulator ignores the fact that the measured inefficiency may reflect short-term adjustment costs from investments necessary for long-run cost minimization rather than the 'actual' inefficiency. As a result, firms with high investments in the benchmarking period may be worse off when compared to peers with lower investments. In contrast, firms with low investments may operate far from the dynamic optimum but may be deemed as fully efficient from a static perspective. This distortion in the outcome of static benchmarking exercises may not even be reversed in the benchmarking process for the subsequent regulatory period since the economic lifetime of capital assets in network assets is expected to heavily exceed the duration of one regulatory period.

Following this line of argumentation, the need for dynamic benchmarking approaches in order to explicitly address the intertemporal character of long-term input decisions made by firms has been widely acknowledged. However, there is only limited empirical research on the application of dynamic inefficiency estimation in the presence of adjustment costs. Moreover, the regulatory implications of applying dynamic rather than static inefficiency measures have yet to be addressed.

This paper seeks to fill this research gap. Using a data set of US electricity transmission and distribution firms for the period 2004 to 2011, we assess the firms' dynamic technical inefficiency explicitly accounting for changes in the capital stock and their implied adjustment costs. Drawing upon dynamic data envelopment analysis (DEA), we compute a dynamic directional distance function that enables us to analyze the dynamic technical inefficiency of our sample firms. Nonparametric DEA is applied rather than parametric estimation techniques in order to avoid imposing a restrictive functional form on our heterogeneous sample of firms. We use the established duality between the dynamic directional distance function and the current value of the optimal value function of the intertemporal cost minimization problem in order to compute the dynamic cost inefficiency and the dynamic allocative inefficiency in an adjustment cost framework. We compare our derived dynamic inefficiency estimates to their static counterparts, i.e., the inefficiency estimates obtained by ignoring the adjustment costs of changes in the capital stock. This allows us to assess the impact of applying dynamic inefficiency measures on the outcome of benchmarking exercises, both on a firm-specific and industrial level.

This study provides two main contributions to empirical research in the field of inefficiency measurement: First, our paper illustrates the impact of the important methodological choice of static vs. dynamic inefficiency measures on the outcomes of benchmarking exercises frequently carried out in regulatory practice. In doing so, we discuss the incentives implied in both methodologies with regard to long-term investments for the firms under regulation. Second, we provide previously unknown insights into the dynamic inefficiency of the US electricity transmission and distribution industry, explicitly controlling for the adjustment costs of investments.

Overall, our empirical findings suggest that investments in capital assets and their implicit adjustment costs should be accounted for by the regulator in order to avoid biased firm-specific cost saving targets and misleading incentives to cut investments. We find that the average dynamic technical inefficiency of the US electricity transmission and distribution industry is around 26% during the sample period. The dynamic approach yields on average lower technical inefficiency scores than the corresponding static inefficiency estimates focusing exclusively on variable input contraction (40%). Dynamic cost inefficiency of the industry amounts on average to 37% and is 3 percentage points lower than the corresponding static measure. On a firm-specific level, the application of dynamic inefficiency measures has even stronger implications on the inefficiency estimates. Thus, the economic impact of biased inefficiency factors derived from static benchmarking procedures for the firms under regulation are expected to be severe.

The paper is structured as follows: Section 2 provides the theoretical background and Section 3 discusses relevant previous research. The methodology is outlined in Section 4. Section 5 presents the data, while empirical results are discussed in Section 6. Section 7 concludes.

## 2. Theoretical Background

The need for regulation of natural monopolies in network industries such as telecommunication, railway or energy distribution and transmission has been extensively discussed (see, e.g., Leland, 1974; Joskow, 2011). As emphasized by Jamasb and Pollitt (2007), regulatory measures applied to these industries aim to provide incentives for an efficient operation of the regulated firms and to ensure a sharing of productivity gains between firms and customers. Historically, 'cost-of-service' (rate of return) regulation has been used by regulators. Under rate of return of regulation, the regulator sets the price which the utility can charge in such a way that the utility can cover its operating costs and additionally is allowed to earn a specified rate of return on its capital. Although the rate of return regulation is effective in terms of 'rent extraction' (Joskow, 2008), it lacks cost reduction incentives and provides incentives to overinvest in capital. The latter shortfall is widely known as the Averch-Johnson effect (Averch and Johnson, 1962).

In order to avoid the aforementioned economic inefficiencies, the seminal work of Shleifer (1985) proposes an alternative regulatory approach that promises a more efficient outcome based on cost comparisons among comparable firms, the so-called 'yardstick competition'. Incentive-based regulatory regimes reflecting the idea of yardstick competition are nowadays common practice in the regulation of natural monopolies, usually implemented via a price- or revenue-cap mechanism.[1] As the price or revenue cap is fixed for a certain period, any cost reductions translate into additional profit for the firms, thereby providing a strong incentive for cost-efficient behavior of the regulated firms.

In order to determine the socially-optimal price or revenue cap, empirical benchmarking techniques such as data envelopment analysis (DEA) or stochastic frontier analysis (SFA) are frequently applied. These techniques measure a firm's inefficiency relative to its peers. Firm-specific cost saving targets, the so-called 'X-factors', are then derived from the benchmarking outcome. The X-factor specifies the inefficiency decrease for a certain firm within a regulatory period required by the regulator in order to force the firm back to the efficient frontier. It is then incorporated into the adaption of the price or revenue cap for the next regulatory period (Joskow, 2008):

$$P_{1,i} = P_{0,i}(1 + RPI - X_i) \tag{1}$$

In Equation (1), $RPI$ denotes the inflation of input prices (rate of input price increase), $X_i$ denotes the firm-specific rate of inefficiency decrease, and $P_{0,i}$ and $P_{1,i}$ are the initial and the adjusted firm-specific price or revenue caps, respectively (Joskow, 2008).

Changes in the capital stock and the corresponding costs can cause various problems when static benchmarking models are applied to derive the X-factors within incentive-based regulation schemes. Increases in capital costs directly transfer into measured inefficiency if total costs enter the static benchmarking model as input data. That way, firms with high investments are penalized by significant X-factors. To avoid misleading incentives to reduce investments, capital costs are frequently excluded from the benchmarking model (Joskow, 2008). However, even if only operational costs are subject to benchmarking, adjustment costs such as expenditures for reorganization,

[1] See, e.g., Joskow (2008) for a review on incentive-based regulation in electricity networks.

investment support or staff training may distort the validity of static benchmarking outcomes since these costs are reflected in the operational expenditures.

The regulatory problem arising from adjustment costs can be illustrated using a simple example. Consider two homogeneous firms $i$ and $j$ subject to incentive-based regulation where static benchmarking on operational costs is carried out at the beginning of the regulatory period. For the upcoming regulatory period, both firms have the option to either minimize their long-run costs by choosing a combination of contracting the variable input usage and expanding the capital stock via investments or to focus exclusively on contracting their variable input usage, i.e., solely minimize their short-run costs. If, in the presence of adjustment costs, firm $i$ decides to stick to long-run cost minimizing behavior and therefore invests in its capital stock, it will be unable to contract the usage of variable inputs to the same extent as firm $j$ that exclusively focuses on contracting variable input usage. As a consequence, firm $j$ will be deemed as fully efficient by the static benchmarking outcome. In contrast, firm $i$ is classified as inefficient due to the adjustment costs implied in the investments and reflected in the operational costs, although it sticks to the socially-optimal minimization of long-run costs. Even if the benefits from the changes in the capital stock of firm $i$ unfold later on, the relative disadvantage of firm $i$ against firm $j$ in terms of the assigned X-factor may not be (fully) mitigated in the subsequent benchmarking since the economic lifetime of capital assets usually heavily exceeds the duration of one regulatory period.[2]

The example places emphasis on two interesting effects: First, firms that carry out investments consistent with long-run cost minimization may be classified as inefficient by static benchmarking methods since they suffer from adjustment costs that translate into higher operational costs. In contrast, firms that deviate from the long-run cost minimizing behavior by cutting investments may be deemed as fully efficient in the static benchmarking process. Second, firms may have an incentive to cut investments. The second effect results from the first since firms try to avoid being classified as inefficient although they minimize their long-run costs.[3]

[2] CEPA et al. (2010) estimate the economic lifetime of capital assets in the electricity transmission and distribution industry to vary between 10 and 140 years. The weighted average is calculated to be around 50 years for electricity transmission and around 70 years for electricity distribution. In contrast, a typical regulatory period within incentive-based regulation schemes comprises three to eight years (Ernst & Young, 2013).

[3] Beside cutting investments, firms may also have an incentive to defer investments into other periods than the

To sum up, the X-factors derived from static benchmarking measures are inconsistent with long-run cost minimization in the presence of adjustment costs and may thus encourage firms to deviate from the optimal input decision path by cutting investments. The source of this problem is that the static benchmarking models used by regulators are based on a 'snapshot' combination of input and output without taking into account the intertemporal effect of investments on inefficiency. The usage of this 'snapshot' without controlling for adjustment costs in static benchmarking models makes it impossible to distinguish between 'true' operational inefficiency and transitory inefficiency caused by changes in capital assets. Thus, regulators that rely on static benchmarking models ignore the fact that the measured inefficiency may be partly caused by investments that are necessary for the minimization of long-run costs. The regulatory problem is illustrated in Figure 1 using the example outlined above.

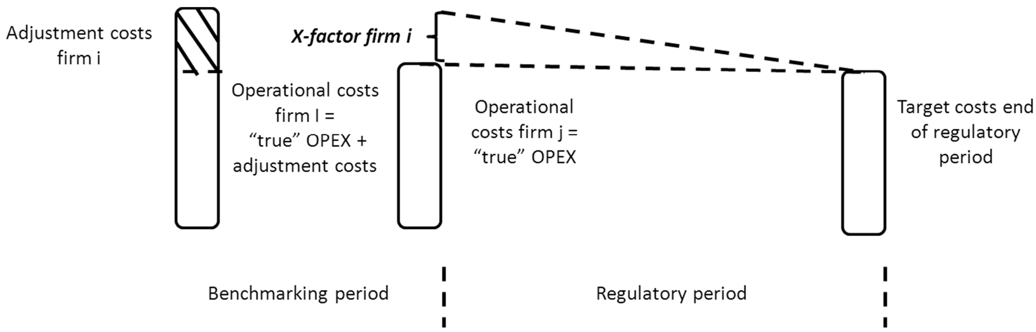


Figure 1: Bias in X-factors derived from static benchmarking in the presence of adjustment costs

Overcoming the bias in X-factors derived from static benchmarking results requires accounting for the adjustment costs induced by investments in capital assets. In Section 4, we discuss a dynamic approach to inefficiency measurement that is able to do so. Prior to that, Section 3 shortly reviews relevant previous research concerning the impact of incentive-based regulation on the investment activity of the regulated firms as well as the application of benchmarking within this context.

benchmarking period. However, the effectiveness of this approach depends on the persistence of the adjustment costs induced by the respective investment.

## 3. Previous Research

The relationship between investment and incentive-based regulation has been intensively discussed in the literature (see, e.g., Guthrie, 2006; Kwoka, 2009). While economic theory initially suggested that incentive-based regulation is generally associated with underinvestment, some recent theoretical and empirical studies draw a more comprehensive picture. In particular, they indicate that investment decisions within an incentive-based regulatory regime highly depend on the way in which regulation is handled in practice (Vogelsang, 2010). In a study from 2009, Roques and Savva show that a relatively high price-cap can speed up investment, while a low price cap can be a disincentive for investment. Nagel and Rammerstorfer (2009) obtain similar results. They find that a stringent price cap encourages firms to lower investments. Furthermore, in an empirical application to a sample of EU energy utilities from 1997 to 2007, Cambini and Rondi (2010) show that the investment behavior of incentive-regulated firms is negatively related to the level of the X-factor set by the regulatory authority.

With regard to benchmarking, a number of studies deal with nonparametric approaches to dynamic inefficiency measurement. One strand of this literature uses dynamic network DEA (Färe and Grosskopf, 1997; Nemoto and Goto, 1999, 2003). An interesting application of this methodological approach on the inefficiency of European electricity transmission system operators are the studies of Burger and Geymüller (2007) and Geymüller (2007). Within this methodological framework, intertemporal behavior is modeled by allowing outputs from the initial period to be used as inputs in the following periods (Fallah-Fini et al., 2013).

Within another strand of the literature, introduced by Sengupta (1994, 1999) and Silva and Stefanou (2003, 2007), intertemporal behavior among subsequent periods is captured via model constraints within a dynamic formulation of the conventional DEA framework (Fallah-Fini et al., 2013). In particular, Silva and Stefanou (2003, 2007) define an intertemporal cost minimizing problem in which the decision making unit in every time period is required to minimize its discounted flow of costs over time.

Building on this theoretical framework, Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013) measure dynamic inefficiency in the presence of adjustment costs via a directional distance function approach. Moreover, they establish duality between the primal representation of the adjustment cost production technology, the dynamic directional distance function, and the current value of the optimal value function of the intertemporal cost minimization problem.

In this paper, we follow the approach developed by Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013) and apply dynamic DEA to a sample of US electricity distribution and transmission companies. Furthermore, we compare the derived dynamic inefficiency measures to their static counterparts in order to assess how the consideration of economic costs and benefits induced by investments affects the outcome of empirical benchmarking approaches. To our knowledge, this is the first paper that applies this concept of dynamic inefficiency measurement to a sample of firms within the electricity distribution and transmission sector. Moreover, our study is innovative in the sense that it relates an empirical application of dynamic inefficiency measures to existing benchmarking practice in the context of incentive-based regulation schemes.

## 4. The Model

In this section, we present and discuss the dynamic inefficiency measurement model formulated by Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013). We review the main elements of the model using Oude Lansink and Silva's notation and provide some additional explanations and economic interpretation, also with a graphical illustration.

### *4.1. Dynamic Technical Inefficiency and the Dynamic Directional Distance Function*

To model a production technology within an adjustment cost framework, assume that $y \in \Re_{++}$ denotes a vector of outputs, $x \in \Re_{+}$ denotes a vector of variable inputs, and $K \in \Re_{++}$ denotes a vector of initial capital stocks or quasi-fixed inputs that can be adjusted by a vector of gross investments $I \in \Re_{+}$. Following Silva and Stefanou (2003), the input requirement set can then be specified as:

$$V(y : K) = \{(x, I) : (x, I) \text{ can produce } y \text{ given } K\}, \tag{2}$$

where $V(y : K)$ represents all the combinations of variable inputs $x$ and gross investments $I$ that can produce the output vector $y$ given the initial capital stock vector $K$. The set $V(y : K)$ is nonempty, compact and satisfies the standard properties of no free lunch, possibility of inaction and strong disposability of variable inputs and outputs (see, e.g., Färe and Primont, 1995).

Furthermore, in order to incorporate the economic concept of adjustment costs in the production technology, Silva and Stefanou (2003) suggest three additional properties. First, we assume negative monotonicity of $V(y:K)$ in $I$. That is,

$$\text{if } (x, I) \in V(y:K) \text{ and } I' \leq I, \text{ then } (x, I') \in V(y:K). \tag{3}$$

This property explicitly accounts for the adjustment costs within the intertemporal framework. It states that an adjustment of quasi-fixed inputs through gross investments decreases the production level of the outputs given a certain level of the variable inputs. Or, in other words, an increase in the level of gross investments requires (ceteris paribus) an increase in the level of inputs to produce the same level of outputs.

Second, we assume that a higher initial capital stock increases the level of outputs given a certain level of the variable inputs. In other words, the same level of output can be achieved with lower variable input given a greater capital stock. Formally,

$$\text{if } K' \geq K, \text{ then } V(y:K) \subset V(y, K'). \tag{4}$$

Together, the properties defined in (3) and (4) reflect the trade-off within the intertemporal economic calculus of firms regarding the optimal level of gross investments: Gross investments decrease the current output levels through adjustment costs but increase future output levels via an increase in the future capital stock (Silva and Stefanou, 2003; Oude Lansink and Silva, 2013).

Finally, we assume $V(y:K)$ to be strictly convex. That is,

$$\begin{gathered} \text{if } (x, I) \in V(y:K) \text{ and } (x', I') \in V(y:K) \text{ then} \\ (\mu x + (1-\mu)x', \mu I + (1-\mu)I') \in V(y:K) \text{ for all } \mu \in [0,1]. \end{gathered} \tag{5}$$

This property implies increasing marginal adjustment costs and therefore is consistent with gradual rather than one-off investment behavior.

As shown by Silva and Oude Lansink (2009), an input requirement set that satisfies these assumptions can be represented by a dynamic directional distance function. This input-orientated dynamic directional distance function can be specified as:

$$\vec{D}(y, K, x, I; g_x, g_I) = max\{\beta \in \Re : (x - \beta g_x, I + \beta g_I) \in V(y : K)\}, \quad (6)$$

where $g = (g_x, g_I) \in \Re_{++} \times \Re_{++}$ and $\beta$ represent the direction and proportion to which the input combination $(x, I)$ is scaled, respectively, to reach the boundary or frontier of the input requirement set $V(y : K)$. The directional distance function value $\beta$ is bounded below by zero. A value of zero identifies the observed input combination as located on the frontier and, hence, as being technically efficient. Values greater than zero belong to input combinations within the frontier, indicating technical inefficiency. Thus, the dynamic directional distance function is a measure of dynamic technical inefficiency.

A graphical illustration of the relationship between dynamic technical inefficiency and the dynamic directional distance function is provided in Figure 2. The vertical axis shows the usage of variable input $x$, while the horizontal axis shows the gross investments $I$. The set $V(y : K)$ is the area of all the combinations of $x$ and $I$ that can produce the output vector $y$ given the initial capital stock vector $K$. Points $A$, $B$ and $C$ represent efficient production points located on the frontier of the input requirement set, while point $D$ above the frontier indicates an inefficient production point. Using the directional vector $g = (x, I)$, the dynamic directional distance function then measures the proportion to which the original input combination $(x, I)$ at point $D$ can be simultaneously contracted in $x$ and expanded in $I$ to reach the efficient input combination $(x - \beta\, x, I + \beta\, I)$ at point $C$.

In contrast, from a static perspective, the input requirement set V(y:K) reduces to the line segment $0D'$ on the vertical axis since investments are neglected. Within the static framework, $A'$ represents the efficient variable input level of production point $A$, and $D'$ represents the inefficient variable input level of production point $D$. Hence, the static directional distance function measures the proportion in which the original variable input level at point $D'$ can be reduced to reach the efficient variable input level at point $A'$.

As proposed by Silva and Stefanou (2003, 2007), the input-orientated dynamic directional distance function presented in Equation (6) can be determined by dynamic DEA. Given a sample

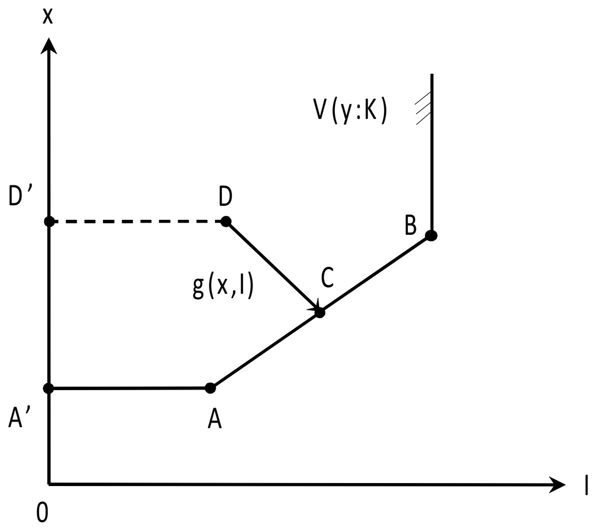


Figure 2: Dynamic directional distance function

of $J$ firms with $M$ outputs, $N$ variable inputs and $F$ quasi-fixed inputs, the dynamic directional distance function $\vec{D}$ for each observation $i$ is obtained by solving the following optimization problem:

$$\begin{aligned}
\vec{D}(y^i, K^i, x^i, I^i; g_x, g_I) = & \max_{(\beta^i, \gamma^j)} \beta^i \\
s.t. \quad & \sum_{j=1}^{J} \gamma^j y_m^j \geq y_m^i, && m = 1, \ldots, M, \quad (i) \\
& \sum_{j=1}^{J} \gamma^j K_f^j \leq K_f^i, && f = 1, \ldots, F, \quad (ii) \\
& \sum_{j=1}^{J} \gamma^j x_n^j \leq x_n^i - \beta^i g_{x_n}, && n = 1, \ldots, N, \quad (iii) \\
& \sum_{j=1}^{J} \gamma^j I_f^j \geq I_f^i + \beta^i g_{I_f}, && f = 1, \ldots, F, \quad (iv) \\
& \gamma^j \geq 0, && j = 1, \ldots, J, \quad (v)
\end{aligned} \tag{7}$$

where $\gamma^j$ are intensity variables assigning a weight to each observation $j$ when constructing the dynamic frontier. The inequality constraints in (i)-(iv) ensure that observation $i$ is located within the feasible production region, while the non-negativity constraints on the intensity variables in (v) indicate that constant returns to scale are assumed. The solution to this program, the maximum value of $\beta^i$, shows to what extent the variable inputs and the gross investments of observation $i$ can be proportionally contracted and expanded relative to the efficient benchmark on the frontier at given outputs and given capital stocks.

*4.2. Dynamic Cost Inefficiency and the Intertemporal Cost Minimization Problem*

Given that the dynamic directional distance function defined in Equation (6) is a valid representation of the input requirement set specified in Section 4.1, a firm's intertemporal cost minimization problem at any base period $t \in [0, \infty)$ can be specified as:

$$
\begin{aligned}
W(y, K_t, w, c, r, \delta) = \underset{(x,I)}{min} \int_t^{\infty} & e^{-r(s-t)}[w'x(s) + c'K(s)]ds \\
& s.t. \\
& \dot{K}(s) = I(s) - \delta K(s), K(t) = K_t \\
& \vec{D}(y, K, x, I; g_x, g_I) \geq 0, s \in [t, +\infty],
\end{aligned}
\tag{8}
$$

where $W$ denotes the value function, $y \in \Re_{++}$ is a vector of outputs in the base period and $K_t \in \Re_{++}$ represents a vector of initial capital stocks (Oude Lansink and Silva, 2013). The vectors of the current input prices for the variable input vector $x(s) \in \Re_{++}$ and the capital stock vector $K(s) \in \Re_{++}$ are represented by $w \in \Re_{++}$ and $c \in \Re_{++}$, respectively. The time-invariant discount rate is $r > 0$, and $\delta$ is a diagonal matrix of depreciation rates $\delta_f > 0, f = 1, \ldots, F$. Finally, $I$ and $\dot{K}$ are vectors of gross and net investments, respectively (Silva and Oude Lansink, 2009; Oude Lansink and Silva, 2013).

The intertemporal cost minimization problem defined in Equation (8) requires a firm to minimize the discounted flow of cost over time subject to two restrictions that have to hold in every time period $s$. The first restriction states that a change in a quasi-fixed factor can only be achieved via investments (disinvestments) and is therefore accompanied by adjustment costs. The second restriction requires the combination of variable inputs and investments to be located within the input requirement set $V(y : K)$.

To derive the combination of variable inputs and gross investments that leads to the current value of the optimal value function within a certain period, the Hamilton-Jacobi-Bellmann (H-J-B) equation can be applied. Oude Lansink and Silva (2013) show that the H-J-B equation for the intertemporal cost minimization problem in Equation (8) can be written as:

$$rW(y, K, w, c) = \min_{(x,I)} \left\{ w'x + c'K + W'_K(I - \delta K) : \vec{D}(y, K, x, I; g_x, g_I) \geq 0 \right\}, \tag{9}$$

where $W'_K = W_K(y, K, w, c)'$ is the vector of shadow values of the quasi-fixed factors. The long-run savings implied in investments are explicitly incorporated in the H-J-B equation, as the shadow value $W_{K_f}$ of the quasi-fixed factor $f$ measures the decrease in the long-run costs if the initial capital stock $K_f$ is increased by a marginal unit.[4]

Similar to the dynamic directional distance function, Equation (9) can be represented by a dynamic DEA model. The corresponding optimization problem for a sample of $J$ firms with $M$ outputs, $N$ variable inputs and $F$ quasi-fixed inputs is given by:

$$\begin{aligned}
rW(y^i, K^i, w^i, c^i) = & \min_{(x,I,\gamma^j)} \quad [w^{i\prime}x + c^{i\prime}K^i + W^{i\prime}_K(I - \delta K^i)] \\
s.t. \quad & \sum_{j=1}^{J} \gamma^j y^j_m \geq y^i_m, \qquad m = 1, \ldots, M, \qquad (i) \\
& \sum_{j=1}^{J} \gamma^j K^j_f \leq K^i_f, \qquad f = 1, \ldots, F, \qquad (ii) \\
& \sum_{j=1}^{J} \gamma^j x^j_n \leq x_n, \qquad n = 1, \ldots, N, \qquad (iii) \\
& \sum_{j=1}^{J} \gamma^j I^j_f \geq I_f, \qquad f = 1, \ldots, F, \qquad (iv) \\
& \gamma^j \geq 0, \qquad j = 1, \ldots, J, \qquad (v) \\
& x_n \geq 0, \qquad n = 1, \ldots, N, \qquad (vi) \\
& I_f \geq 0, \qquad f = 1, \ldots, F, \qquad (vii)
\end{aligned} \tag{10}$$

where $W^{i\prime}_K$ represents a vector of firm-specific shadow values of the quasi-fixed factors. The inequality constraints (i)-(v) have the same interpretation as in Equation (7). The constraints in (vi)

[4] Obtaining reliable estimates for the shadow values of the quasi-fixed factors is methodologically challenging. This is because each shadow value represents a scarcity indicator for the respective quasi-fixed factor and thus depends on the initial capital stock vector, output quantities and input prices. This endogeneity calls for a simultaneous determination of optimal firm-specific input quantities and the firm-specific shadow values of the quasi-fixed factors (Oude Lansink and Silva, 2013). However, a simultaneous determination translates into a nonlinear problem with severe numerical difficulties. For this reason, we use an alternative sequential approach to determine the shadow value of the quasi-fixed factor within our empirical application (see Section (6)).

and (vii) ensure the non-negativity of variable inputs and gross investments.

By using duality theory, Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013) show that a firm-specific dynamic cost inefficiency (CIE) measure can be derived from the solution of Equation (10) as follows:

$$CIE = \frac{w'x + c'K + W_K'(I - \delta K) - rW(y, K, w, c)}{w'g_x - W_K' g_I} \geq \vec{D}(y, K, x, I; g_x, g_I). \tag{11}$$

That is, firm-specific $CIE$ is the deviation of the observed total shadow cost of the actual input choices from the minimum total shadow cost of the optimal input choices, divided by $w'g_x - W_K' g_I$ to construct a unit-free measure.[5] The right-hand side of Equation (11) denotes the firm-specific dynamic technical inefficiency ($TIE$), represented by the dynamic directional distance function. As a consequence, the difference between $CIE$ and $\vec{D}(y, K, x, I; g_x, g_I)$ yields a measure for firm-specific dynamic allocative inefficiency ($AIE \geq 0$). The obtained dynamic allocative inefficiency scores provide an indication as to whether the trade-off between variable input contraction and capital stock extension is optimal in terms of long-run cost minimization.

The relationship between dynamic $TIE$, $CIE$ and $AIE$ is illustrated in Figure 3. As in Figure 2, points $A$, $B$ and $C$ denote technically efficient production points located on the frontier of the input requirement set $V(y : K)$, while point $D$ above the frontier indicates a technically inefficient production point. The distance between $D$ and $C$ measures the dynamic $TIE$ of production point $D$.

Further, in order to illustrate dynamic $CIE$, an isocost line $IS_A$ is mapped. The slope of the isocost line is given by the negative ratio of the shadow value of the quasi-fixed factor $W_K$ and the price of the variable input $w$: $-W_K/w$, with $W_K < 0$. Thus, the slope represents the ratio of the savings obtained from variable input contraction and from investing in the capital stock. Isocost lines with higher intercepts represent higher long-run costs. Consequently, only point $A$, at which the frontier is a tangent to the isocost line $IS_A$, represents a dynamic cost-efficient production point. Points $B$ and $C$ denote technically efficient but allocatively inefficient production points with higher costs. Within the illustration, $B$ and $C$ should invest less and focus more on variable

[5] For a detailed discussion on the duality between the dynamic directional distance function and the current value of the optimal value function of the intertemporal cost minimization problem, see Oude Lansink and Silva (2013).

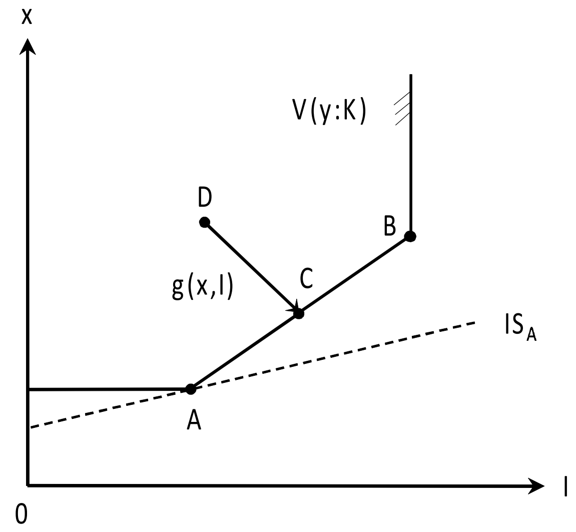


Figure 3: Dynamic $TIE$, $CIE$ and $AIE$

input contraction given the relationship between the shadow value of capital and the price of the variable input. Point $D$, in contrast, suffers from both technical and allocative dynamic inefficiency.

**5. Data for Empirical Application**

We apply the methodology outlined and discussed in Section 4 to a sample of firms within the electricity sector. The sample comprises US electricity transmission and distribution companies for the period 2004-2011. The data is obtained from the FERC Form No.1. After correcting for outliers and eliminating all firms with missing observations during the period considered, the sample consists of an unbalanced panel of 61 firms covering 8 years with 464 observations in total.

Table 1 presents descriptive statistics on the model variables. The choice of output variables for electricity transmission and distribution firms is not straightforward. Different measures, such as peak load of the system, network length, number of customers and total electricity delivered are summarized in Jamasb and Pollitt (2001). In this study, we argue that the total number of customers (aggregated over all segments) and the total electricity flow through the network most appropriately reflect the economic output of our sample firms. We choose two outputs rather than one to account for the heterogeneity of our sample, comprising firms with a focus on either distribution or transmission of electricity.

Table 1: Descriptive statistics

| Variable | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|
| Total Number of Customers (in millions) | 1.05 | 1.07 | 0.12 | 5.25 |
| Total Flow of Electricity (in MWh) | 33.88 | 28.19 | 1.37 | 122.51 |
| OPEX (in million 2002 US$) | 136.12 | 139.54 | 15.34 | 645.16 |
| Capital Stock (in billion 2002 US$) | 3.19 | 3.37 | 0.27 | 20.24 |
| Gross Investments (in billion 2002 US$) | 0.27 | 0.33 | 0.01 | 2.01 |
| Labor Cost Index | 1.21 | 0.16 | 0.88 | 1.70 |
| Producer Price Index | 1.22 | 0.15 | 0.96 | 1.64 |
| Consumer Price Index | 1.16 | 0.06 | 1.05 | 1.25 |

Notes: Information on the components used to compute the figures presented as well as their FERC Form No.1 definitions can be found in the Appendix.

We select the operational expenditure (OPEX) as the variable input. To adjust the variable input expenses for changes in input prices, we deflate OPEX using a weighted average of a labor cost index for the electricity transmission and distribution industry on the state level (LCI)[6] and the producer price index for the electricity transmission and distribution industry (PPI)[7]. The quasi-fixed input, i.e., the capital stock, is approximated by the balance-sheet value of the network assets. The capital stock is deflated by the PPI. Gross investments are computed by taking the sum of net investments (changes in the deflated capital stock) and the deflated depreciation on these assets in the respective year. For the computation of dynamic cost inefficiency and dynamic allocative inefficiency, we use the same deflators outlined above as an approximation for the price of the variable input and the price of capital. However, in order to generate real monetary values, we adjust both input prices for inflation using the consumer price index (CPI).[8] Finally, capital expenditure (Capex) is given by the sum of the deflated annual depreciation and the annual return on the balance-sheet value of the network assets. Following Nillesen and Pollitt (2010), we assume a rate of return of 6 percent for all assets.

[6] The index is calculated from the average annual pay data obtained from the Quarterly Census of Employment and Wages, which is published by the Bureau of Labor Statistics: `http://www.bls.gov/cew/cewind.htm#year=2010&qtr=1&own=5&ind=10&size=0`.

[7] Obtained from the Bureau of Labor Statistics: `http://data.bls.gov/timeseries/PCU221122221122`.

[8] Obtained from the Bureau of Labor Statistics: `http://www.bls.gov/cpi/data.htm`.

## 6. Empirical Results

This section presents and interprets the results of applying the dynamic inefficiency measures outlined in Section 4 to our sample of US electricity distribution and transmission firms. The derived average inefficiency values per year are reported in Table 2.

Table 2: Average Dynamic and Static Inefficiency Scores

| Year | TIE Dynamic | CIE Dynamic | AIE dynamic | TIE/CIE static |
|---|---|---|---|---|
| 2004 | 0.29 | 0.44 | 0.15 | 0.42 |
| 2005 | 0.29 | 0.37 | 0.08 | 0.42 |
| 2006 | 0.26 | 0.36 | 0.10 | 0.41 |
| 2007 | 0.28 | 0.38 | 0.10 | 0.43 |
| 2008 | 0.26 | 0.39 | 0.13 | 0.33 |
| 2009 | 0.29 | 0.37 | 0.08 | 0.41 |
| 2010 | 0.25 | 0.33 | 0.08 | 0.45 |
| 2011 | 0.19 | 0.30 | 0.11 | 0.36 |
| Mean | 0.26 | 0.37 | 0.10 | 0.40 |

The average dynamic technical inefficiency (TIE) of our sample firms ranges between 19% and 29% for the years considered. On average, industrial dynamic technical inefficiency amounts to 26%, indicating that there is substantial potential for the industry to move towards the dynamic technical efficiency frontier by simultaneously contracting variable input usage and expanding gross investments.

We compare and contrast our dynamic technical inefficiency estimates with their static counterparts to assess the impact of considering changes in the quasi-fixed inputs in the benchmarking process. For this purpose, static technical inefficiency is computed for our sample firms, applying DEA to a restricted version of the linear program stated in Equation (7). In this specification, the investment (*iv*) and capital (*ii*) constraints are ignored and the directional vector is set to $g = (x, 0)$. Thus, the efficient static frontier can be achieved by exclusively contracting variable input usage, disregarding changes in the quasi-fixed input. The resulting static benchmarking model is in line with regulatory practice, where the focus frequently lies on benchmarking operational costs.

The average static technical inefficiency values per year are also reported in Table 2. The average technical inefficiency of our sample firms is higher when applying the static measure compared to the dynamic approach. This finding is intuitive, as the dynamic approach to technical inefficiency allows for an additional dimension in the benchmarking process (namely the expansion of gross investments) besides the contraction of variable inputs. On average, dynamic technical inefficiency is around 14 percentage points below the static technical inefficiency. This finding emphasizes that the assessment of the industrial technical inefficiency is significantly altered when adjustments of quasi-fixed inputs via investments are accounted for. The differences in the distribution of technical inefficiency scores between the static and the dynamic approach are illustrated in Figure 4 using kernel density estimates. Clearly, the mean of the dynamic technical inefficiency distribution is smaller than the corresponding static value. Moreover, applying the dynamic measure results in a larger number of fully technically efficient observations, while the number of observations with very high dynamic technical inefficiency scores is rather low.

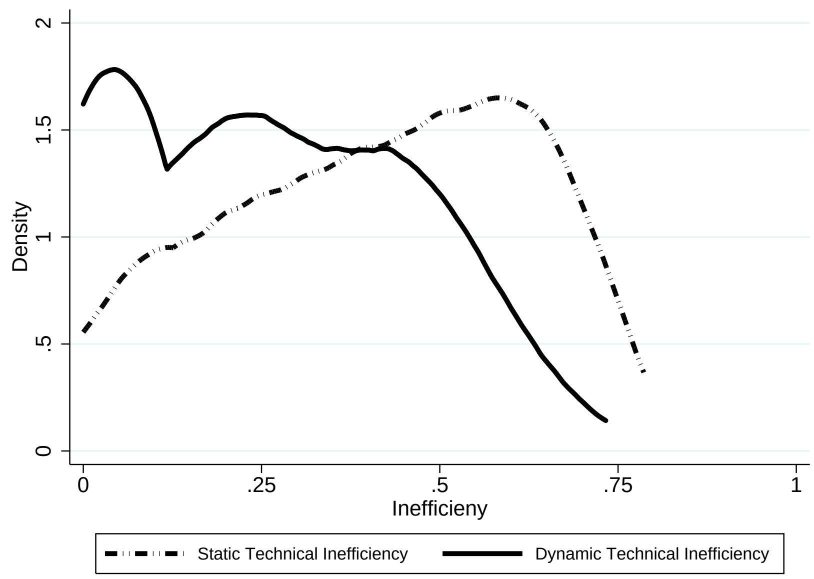


Figure 4: Distribution of Dynamic and Static Technical Inefficiency

*Note:* Kernel density estimate based on an Epanechnikov kernel.

For the assessment of dynamic cost and allocative inefficiencies, we first approximate the firm-specific long-run cost savings induced by a marginal increase in the capital stock by estimating a quadratic dynamic cost function. Differentiating this function with respect to the capital stock yields firm-specific shadow values of capital.[9] Subsequently, in a second step, these values are incorporated into the dynamic DEA model, as described in Equation (10). We rely on this sequential approach in order to circumvent the numerical problems present in a simultaneous determination of optimal firm-specific input quantities and firm-specific shadow values of capital. In addition, the sequential parametric approach avoids imposing the unrealistic assumption of dynamic allocative efficiency that is inherent in an alternative sequential nonparametric approach. The median of the estimated shadow values of capital is about $-0.21$, suggesting that one additional monetary unit of capital leads to long-run cost savings of about 0.21 monetary units on average.

We find that the dynamic cost inefficiency (CIE) of our sample firms is considerably large, with an average dynamic cost inefficiency of 37% (see Table 2).[10] This finding indicates notable potential for savings in long-run costs for the US electricity distribution and transmission industry. The significant level of allocative inefficiency (AIE) in most of the sample years suggests that firms may face problems when choosing the mixture of variable and quasi-fixed inputs given the respective input prices. This means that their trade-off between variable input contraction and capital stock expansion is not in line with the ratio of the variable input price and the shadow value of capital, i.e., the economic benefits of both choices.

Comparing dynamic and static cost inefficiency in our empirical application is complicated by the fact that the dynamic cost inefficiency incorporates allocative inefficiency, while the static cost inefficiency does not.[11] The application of the dynamic cost inefficiency measure yields an average cost inefficiency that is 3 percentage points lower compared to the static measure. In particular, more observations are deemed to be fully cost-efficient when the dynamic input and the shadow value of capital are controlled for. Thus, considering adjustment costs and long-run cost savings induced by investments does affect the outcome of cost inefficiency measurement, although the

[9] A detailed description of the parametric approximation of the firm-specific shadow values of capital is provided in the Appendix.

[10] For a limited number of observations, we find dynamic cost inefficiency values greater than one. This is the case when actual and optimal investments show a huge difference. Considering these observations as extreme cases, we denote them as outliers and do not include them in our further analysis.

[11] Since we use only one variable input measured in monetary terms (OPEX) in our empirical application, the obtained results on the static technical inefficiency can also be interpreted as a static cost inefficiency measure, i.e., inefficiency due to over-usage in cost.

effect is not very pronounced in our application. With regard to benchmarking carried out in regulatory practice, this suggests that X-factors derived from static benchmarking models may deviate from long-run cost minimization targets of the firms under regulation.

The methodological choice of applying either static or dynamic inefficiency measures is expected to most severely affect firms with large investments due to the fact that these firms may face high adjustment costs through changes in the capital stock. Thus, we find it promising to analyze the inefficiency scores obtained from static and dynamic measures for firms with different investment activity. For this purpose, we sort our observations according to their investment shares, defined as the ratio of gross investments and capital stock, and compare the static and dynamic inefficiency scores of different percentiles. The average inefficiency scores for the percentiles considered are reported in Table 3.

Table 3: Average Dynamic and Static Inefficiency Scores for Investment Ratio Percentiles

| Cumulative Percentile of Investment Ratio | Observations | TIE Dynamic | CIE Dynamic | AIE Dynamic | TIE/CIE Static |
|---|---|---|---|---|---|
| Total Sample | 464 | 0.26 | 0.37 | 0.11 | 0.40 |
| 5 | 441 | 0.25 | 0.36 | 0.11 | 0.40 |
| 25 | 348 | 0.22 | 0.33 | 0.11 | 0.39 |
| 50 | 232 | 0.21 | 0.33 | 0.12 | 0.41 |
| 75 | 116 | 0.17 | 0.28 | 0.11 | 0.44 |
| 95 | 24 | 0.07 | 0.20 | 0.13 | 0.44 |

The comparison reveals that firms with high investment ratios suffer heavily when investments are neglected in the assessment of technical inefficiency. While the static inefficiency values differ only slightly among the different percentiles, the dynamic technical and dynamic cost inefficiency values show significant variation. For instance, dynamic average technical inefficiency of the upper investment ratio quartile is 27 percentage points lower than its static counterpart. For the case of the upper fifth percentile, the difference in technical inefficiency between the dynamic and static measure even increases to 37 percentage points. In contrast, firms with small investment shares are less exposed to the choice of the technical inefficiency measure. With regard to cost inefficiency, a similar pattern arises. For the case of the upper fifth percentile, the difference in cost inefficiency between the dynamic and static measure amounts to 24 percentage points, while for the total sample the difference is only 3 percentage points.

## 7. Conclusion

The objective of this study was to investigate the impact of using static vs. dynamic inefficiency measures in the context of benchmarking used for incentive-based regulation schemes. We therefore applied the concept of dynamic inefficiency developed by Silva and Oude Lansink (2009) and Oude Lansink and Silva (2013) to a sample of US electricity distribution and transmission firms in order to obtain dynamic technical and dynamic cost inefficiency estimates using dynamic DEA. We then compared our dynamic inefficiency estimates with their static counterparts .

Most importantly, our empirical results reveal that the consideration of investments and the corresponding adjustment costs significantly affect the outcome of benchmarking exercises, both in terms of technical and cost inefficiency. In specific, firms with large investments are extremely vulnerable to the choice of the inefficiency measure underlying the benchmarking process and suffer from X-factors that are too strict when static benchmarking models are applied by the regulator. As a result, firms subject to X-factors derived from static benchmarking models may have incentives to deviate from the long-run cost minimization by cutting investments.

This finding emphasizes that the application of dynamic inefficiency measures in the context of incentive-based regulation may be beneficial. Dynamic inefficiency measures have the advantage that they are consistent with the multi-period optimization of firms and explicitly address adjustment costs from changes in quasi-fixed inputs. Thus, X-factors derived from dynamic benchmarking models can resolve the mismatch between benchmarking methods used in regulation and the optimization of firms with regard to the time horizon of decision making. Moreover, the dynamic approach allows for a comparison of the optimal and the actual mix of static and dynamic factor usage via estimating dynamic allocative inefficiency. This enables the regulator to shift incentives in the regulatory design towards the desired direction.

In addition, our empirical findings point towards a significant potential for long-run cost savings for the US electricity distribution and transmission industry. The computation of the dynamic directional distance function reveals an average dynamic technical inefficiency of 26%, while average dynamic cost inefficiency amounts to 37%. The rather high level of dynamic inefficiency may be attributed to a lack of efficient regulation within the industry considered. For instance, incentive-based regulation of electricity transmission and distribution firms is not in place in many states in the US (Kwoka, 2009). However, when interpreting the results of our inefficiency measures, one should keep in mind that our sample firms are rather heterogeneous. We therefore recommend a cautious interpretation of the inefficiency scores obtained.

Our study has generated valuable insights into the application of static and dynamic measures of inefficiency and the implicit consequences on derived X-factors in incentive-based regulatory schemes. Nevertheless, various extensions of our research seem promising, such as the application of dynamic inefficiency measurement to other industries in which the role of adjustment costs is expected to be different. Another interesting opportunity for further research would be to apply the static and dynamic methods to a more homogeneous sample and to draw concrete conclusions with regard to the financial effects for the firms under incentive-based regulation schemes.

## References


Averch, H. and Johnson, L. L. (1962). Behavior of the firm under regulatory constraint. *The American Economic Review*, 52(5):1052–1069.

Burger, A. and Geymüller, P. (2007). Assessing the effects of quality regulation in Norway with a quality regulated version of dynamic DEA. Working Paper 2007.4, Research Institute for Regulatory Economics, WU Vienna University of Economics and Business.

Cambini, C. and Rondi, L. (2010). Incentive regulation and investment: evidence from european energy utilities. *Journal of Regulatory Economics*, 38(1):1–26.

Cambridge Economic Policy Associates (CEPA), Sinclair Knight Merz (SKM), and GL Noble Dentom (2010). The economic lives of energy network assets: a report for ofgem.

Ernst & Young (2013). Mapping power and utilities regulation in Europe.

Fallah-Fini, S., Triantis, K., and Johnson, A. L. (2013). Reviewing the literature on non-parametric dynamic efficiency measurement: state-of-the-art. *Journal of Productivity Analysis*, 41(1):1–17.

Färe, R. and Grosskopf, S. (1997). Efficiency and productivity in rich and poor countries. In Jensen, B. and Wong, K., editors, *Dynamics, economic growth, and international trade*, pages 243–263. The University of Michigan Press, Ann Arbor.

Färe, R. and Primont, D. (1995). *Multi-Output Production and Duality: Theory and Applications*. Kluwer Academic, Boston.

Geymüller, P. (2007). The efficiency of european transmission system operators. An application of dynamic dea. Working Paper 2007.3, Research Institute for Regulatory Economics, WU Vienna University of Economics and Business.

Guthrie, G. (2006). Regulating infrastructure: The impact on risk and investment. *Journal of Economic Literature*, 44(4):925–972.

Jamasb, T. and Pollitt, M. (2001). Benchmarking and regulation: international electricity experience. *Utilities Policy*, 9:107–130.

Jamasb, T. and Pollitt, M. (2007). Incentive regulation of electricity distribution networks: lessons of experience from britain. *Energy Policy*, 35:6163–6178.

Joskow, P. (2008). Incentive regulation and its application to electricity networks. *Review of Network Economics*, 7(4):547–560.

Joskow, P. (2011). Incentive regulation in theory and practice - Electricity distribution and transmission networks. Nber chapters, National Bureau of Economic Research, Inc.

Kwoka, J. (2009). Investment adequacy under incentive regulation. Northeast University–September.

Leland, H. (1974). Regulation of natural monopolies and the fair rate of return. *The Bell Journal of Economics and Management Science*, 5:3–15.

Nagel, T. and Rammerstorfer, M. (2009). Modeling investment behavior under price cap regulation. *Central European Journal of Operations Research*, 17(2):111–129.

Nemoto, J. and Goto, N. (1999). Dynamic data envelopment analysis: Modelling intertemporal behavior of a firm in the presence of productive inefficiencies. *Economic Letters*, 64:51–56.

Nemoto, J. and Goto, N. (2003). Measurement of dynamic efficiency in production: An application of data envelopment analysis to japanese electric utilities. *Journal of Productivity Analysis*, 19:191–210.

Nillesen, P. and Pollitt, M. (2010). Using regulatory benchmarking techniques to set company performance targets: the case of us electricity. *Competition & Reg. Network Indus.*, 11:50.

Oude Lansink, A. and Silva, E. (2013). Dynamic efficiency measurement: A directional distance function approach. cef.up working paper series 7/2013, Center for Economics and Finance at the University of Porto.

Roques, F. A. and Savva, N. (2009). Investment under uncertainty with price ceilings in oligopolies. *Journal of Economic Dynamics and Control*, 33(2):507–524.

Sengupta, J. K. (1994). Evaluating dynamic efficiency by optimal control. *International journal of systems science*, 25(8):1337–1353.

Sengupta, J. K. (1999). A dynamic efficiency model using data envelopment analysis. *International Journal of Production Economics*, 62(3):209–218.

Shleifer, A. (1985). Theory of yardstick competition. *The RAND Journal of Economics*, 16:319–327.

Silva, E. and Oude Lansink, A. (2009). Dynamic efficiency measurement: A directional distance function approach. Unpublished. Wageningen University.

Silva, E. and Stefanou, S. (2003). Nonparametric dynamic production analysis and the theory of cost. *Journal of Productivity Analysis*, 19:5–32.

Silva, E. and Stefanou, S. (2007). Nonparametric dynamic efficiency measurement: Theory and application. *American Journal of Agricultural Economics*, 89:389–419.

Thomas, A. L. (1969). *The allocation problem in financial accounting theory.* American Accounting Association, Evanston.

Vogelsang, I. (2010). Incentive regulation, investments and technological change. CESifo Working Paper 2964, München.

## Appendix A. Parametric approximation of the firm-specific shadow values of capital

The dynamic cost function in a quadratic functional form is given by

$$
\begin{aligned}
W_{it} = {} & \alpha_0 + \alpha_{QE}\, QE_{it} + \alpha_{QC}\, QC_{it} + \alpha_K\, K_{it} + \alpha_w\, w_{it} + \alpha_c\, c_{it} \\
& + \frac{1}{2}\alpha_{QE,QE}\, QE_{it}\, QE_{it} + \frac{1}{2}\alpha_{QC,QC}\, QC_{it}\, QC_{it} + \frac{1}{2}\alpha_{K,K}\, K_{it}\, K_{it} \\
& + \frac{1}{2}\alpha_{w,w}\, w_{it}\, w_{it} + \frac{1}{2}\alpha_{c,c}\, c_{it}\, c_{it} + \alpha_{QE,QC}\, QE_{it}\, QC_{it} + \alpha_{QE,K}\, QE_{it}\, K_{it} \\
& + \alpha_{QE,w}\, QE_{it}\, w_{it} + \alpha_{QE,c}\, QE_{it}\, c_{it} + \alpha_{QC,K}\, QC_{it}\, K_{it} + \alpha_{QC,w}\, QC_{it}\, w_{it} + \alpha_{QC,c}\, QC_{it}\, c_{it} \\
& + \alpha_{K,w}\, K_{it}\, w_{it} + \alpha_{K,c}\, K_{it}\, c_{it} + \alpha_{w,c}\, w_{it}\, c_{it} + \alpha_t\, t_t + \frac{1}{2}\alpha_{t,t}\, t_t^2,
\end{aligned} \tag{A.1}
$$

where the subscripts $i$ and $t$ denote the firm and year, respectively; $W$ represents long-run costs; $QE$ is the flow of electricity; $QC$ is the number of customers; $K$ is the capital stock; $t$ is a time trend; and $c$ and $w$ are the price of capital and the price of the variable input, respectively.

Representing the dynamic cost function by $g(\cdot)$, we estimate the parameters of Equation A.1 by solving the following minimization problem:

$$
\begin{aligned}
& min \sum_{t=1}^{T}\sum_{i=1}^{N} \epsilon_{it}^2 \\
& s.t.\; W_{it} = g(\cdot) + \epsilon_{it} && \forall i,t, \quad (i) \\
& \partial\, g(\cdot)/\partial\, QE_{it} \geq 0 && \forall i,t, \quad (ii) \\
& \partial\, g(\cdot)/\partial\, QC_{it} \geq 0 && \forall i,t, \quad (iii) \\
& \partial\, g(\cdot)/\partial\, w_{it} \geq 0 && \forall i,t, \quad (iv) \\
& \partial\, g(\cdot)/\partial\, c_{it} \geq 0 && \forall i,t, \quad (v) \\
& \partial\, g(\cdot)/\partial\, K_{it} \leq 0 && \forall i,t, \quad (vi)
\end{aligned} \tag{A.2}
$$

The problem minimizes the sum of the squared residuals of the quadratic dynamic cost function subject to a set of inequality constraints that impose monotonicity required by economic theory. The shadow value of capital is then approximated by the first derivative of the cost function with respect to the capital stock:

$$\frac{\partial g(\cdot)}{\partial K_{it}} = \alpha_K + \alpha_{K,K} K_{it} + \alpha_{QE,K} QE_{it} + \alpha_{QC,K} QC_{it} + \alpha_{K,w} w_{it} + \alpha_{K,c} c_{it}. \tag{A.3}$$

## Appendix B. Data sources

Table B.1: Data sources

| Variable | Source |
|---|---|
| **Total Number of Customers (in millions)** | |
| = avg. no. customers per month | FERC Form No.1: 301 - 12 (g) |
| **Total Flow of Electricity (MWh)** | |
| = sales of electricity | FERC Form No.1: 301 - 12 (d) |
| + transfer of electricity received | FERC Form No.1: 329 - TOTAL (i) |
| - transmission of electricity by others | FERC Form No.1: 332 - TOTAL (d) |
| **OPEX (in million 2002 US$)** | |
| = transmission expenses for electric operation and maintenance | FERC Form No.1: 321 - 112 (b) |
| + distribution expenses for electric operation and maintenance | FERC Form No.1: 322 - 156 (b) |
| **Capital Stock (in billion 2002 US$)** | |
| = transmission plant balance (begin of year) | FERC Form No.1: 206 - 58 (b) |
| + distribution plant balance (begin of year) | FERC Form No.1:206 - 75 (b) |
| **Gross Investments (in billion 2002 US$)** | |
| = gross investments in transmission | |
| = transmission plant balance (end of year) | FERC Form No.1: 207 - 58 (g) |
| - transmission plant balance (begin of year) | FERC Form No.1: 206 - 58 (b) |
| + transmission plant depreciation expenses | FERC Form No.1: 336 - 7 (b) |
| + gross investments in distribution | |
| = distribution plant balance (end of year) | FERC Form No.1: 207 - 75 (g) |
| - distribution plant balance (begin of year) | FERC Form No.1: 206 - 75 (b) |
| + distribution plant depreciation expenses | FERC Form No.1: 336 - 8 (b) |
| **Labor Cost Index** | Bureau of Labor Statistics |
| **Producer Price Index** | Bureau of Labor Statistics |
| **Consumer Price Index** | Bureau of Labor Statistics |