Do Privatly Owned Firms Outperform Publicly Owned Firms in Electricity Distribution?

Astrid Cullmann Maria Nieswand Julia Rechlitz*

Juni 2016

Preliminary Version
Please do not cite or circulate without corresponding author's permission

Abstract

This paper proposes a flexible semiparametric input distance function model to test for efficiency differences between private and public firms in electricity distribution. In the model, the technology parameters are unknown smooth functions of firm- and time effects which allow a rich and flexible decomposition of sources of firms' efficiency and productivity growth and the link to firm ownership. We validate the model with a new, rich dataset of public and private electric distribution firms operating between 2006 and 2012 in Germany. We find that for both types of ownership technical efficiency is driven by persistent rather than time-varying inefficiency. We find no empirical evidence that public firms operate less efficient than private ones, and thus, our empirical analysis contradicts theoretical predictions.

JEL-Classification: L94, L51, L98
Keywords: Productivity, Ownership, Electricity Distribution, Germany

*Corresponding author. DIW Berlin – German Institute for Economic Research, Mohrenstrasse 58, D-10117 Berlin, Germany; phone: +49-30-89789-611, fax: +49-30-89789-200, email: jrechlitz@diw.de

1 Introduction

More than two decades of deregulation and privatization have massively reshaped especially municipal infrastructure industries in the US and Europe; industries in which local governments have been strongly involved ever since for historical and administrative reasons.
Too often, however, deregulation and privatization have failed to realize the expected cost savings for producers and price reductions for consumers. In response to this observation and income seeking, municipal governments have recently begun to reinforce economic activities by re-purchasing privatized firms (also referred to as deprivatization or remunicipalization), by increasing their shares of ownership in partially privatized firms, or by establishing new publicly owned firms. The issues are perhaps most noticeable in Europe's utility sector, especially in Germany in the last years.
Evaluating the economic activity of the public sector is incrementally linked to discussing the productivity and efficiency of public and private firms. The theoretical literature in the fields of public choice, property rights, and agency theories, predict the latter to perform superior.

Somewhat surprisingly the empirical literature is not conclusive. Much of the relevant empirical literature on public infrastructure industries reports no statistically significant differences in productivity or cost between public and private firms (Ehrlich et al., 1994; Atkinson and Halvorsen, 1986). Some studies show that private firms outperform publicly owned ones (Bagdadioglu et al., 1996; Kumbhakar and Hjalmarsson, 1998), others in turn underline that public firms reach a higher efficiency level (Kwoka, 2005). Any real variations in the empirical findings tend to be attributed to the modeling techniques used, difficulties in disentangling the sources of productivity growth arising from technological progress, scale, or efficiency improvements, or the complex relations between ownership structure and efficiency and changes in productivity.
The rising economic activities of the public sector (the remunicipalization) is combined with an intense policy debate. Especially the competition authorities (in Germany the German Monopolies Commission and the Bundeskartellamt, BKartA) adopt a critical attitude towards this tendency of remunicipalization. They find no sufficient reasons for for an expansion of the public sector and even fear a decreasing efficiency of publicly owned companies, with the consequence of higher costs and higher prices for consumers and therefore welfare loss.
Are the concerns of the German Monopolies Commission justified? Do we need to worry about an efficiency decrease with an expansion of the public sector?
To our knowledge, no one has conducted a thorough empirical investigation that allows

for flexible technologies, and role of ownership for efficiency.

Therefore, we propose a semiparametric input distance frontier model to estimate and decompose efficiency where the coefficients of the function are allowed to vary over time and over ownership types. Our model differs from the earlier studies in two ways. First, we measure efficiency directly in terms of production instead of estimating a cost function. Due to duality and the exogeneity of input ratios, this approach is economically meaningful while not requiring information on input prices (Färe and Primont, 1995; Das and Kumbhakar, 2012). Second, we use flexible techniques to analyze production technology instead of assuming a strict functional form. We explicitly allow for heterogeneous technologies over time which we argue is important in a sector characterized by significant operation changes due to the energy transition and a decentralized energy system. In a model extension we also allow for heterogeneous technologies in private and public firms which might result from the distinct production objectives of publicly owned firms.

We test our model with newly available data on German electricity distribution firms operating between 2006 and 2012. The German case is particularly suitable as a representative illustration of federal efforts to reform a sector characterized by local government activity and the coexistence of private and public companies. The case is also highly policy-relevant because it is important to quantify the sources of efficiency differentials across firms and their development over time in order to develop policies favoring both public and privately owned firms.

Our paper contributes to the published literature by a profound empirical analysis for which the existing methodology was accordingly adapted to the input distance function approach. Our results do not support theoretical predictions, which favors private ownership for efficiency or productivity reasons. We find evidence that technologies of public and private firms are heterogeneous. Taking this into account, we observe that inefficiency is nearly staying constant over the analyzed time period where public firms perform slightly more efficient. Inefficiency is thereby mainly driven by persistent rather than time-varying inefficiency.

The remainder of this paper is structured as follows. Section 2 surveys the relevant literature. Section 3 describes the German situation, the dataset and defines the variables. In Section **??** presents the empirical model and estimation strategy. Section 4 discusses the empirical findings. Section 5 concludes.

2 Literature Review

The ownership-performance debate in the literature on municipal infrastructure industries encompasses studies of property rights, public choice, and agency theory. All theories provide different rationals for the superiority of private firms in terms of efficiency due to differences in objectives, incentives, and control mechanisms. Agency theory assumes that private firms are better able to handle the principal-agent dilemma[1] and consequently are more likely to achieve a higher efficiency level. When property rights are considered, for example, Alchian and Demsetz (1973) and Demsetz (1967) suggest that public ownership attenuates property rights, reducing incentives to minimize costs.[2] The public choice literature, particularly the theory of bureaucracy (Shleifer and Vishny, 1994) assumes that politicians impose their objectives on public organizations in order to gain votes, and that these objectives may be at odds with profit maximization and, consequently, harm efficiency (Villalonga, 2000).[3]

Bartel and Harrison (2005) argue that the environment in which firms operate is important to answer the question of private versus public ownership and performance. Competitive markets force firms to set prices close to marginal costs and provide owners with information on costs and manager effort. Further, owners can create incentives for management to reduce the asymmetric information closing the managerial slack (Hart, 1983; Shirley and Walsh, 2001). In a regulated environment the incentive effect as well as the information effect are diminished.[4] Laffont and Tirole (1993) show that the superiority of private versus public firms depends on the contract settling the provision of the goods or services of a regulated monopoly.[5] Under complete contracts the outcome of private and public firms would be the same. Laffont and Tirole (1991) show that the implementation of a regulator produces a more complex principal agent relationship because private firms now have two principals (the regulator and the owner) who may have opposing objectives. This does not apply to publicly owned firms, since it is assumed that the political

[1]Agents (the managers of public or private firms) seek to maximize their own utility rather than that of the whole firm or its principals (e.g., owners).

[2]In addition, the property-rights theory postulates that potential divergences of interests between owners and managers in private firms are further reduced by external mechanisms, including a market for ownership rights, that enables owners to sell their shares if they are dissatisfied with managerial performance, face the threat of takeover, or bankruptcy, and an extensive managerial labor market exists. For all of these reasons, the property rights theory posits that private ownership leads to higher efficiency than other types of ownership.

[3]In some public firms, an inefficiently high labor share is observed to decrease unemployment (Shleifer and Vishny, 1994). Nellis (1994) concludes that a competitive market as well as independent and profit-maximizing managers are necessary conditions for efficient publicly owned firms. Vining and Boardman (1992) point out that the greater threat of a takeover or a bankruptcy can encourage managers of privately owned firms to perform more efficiently, whereas the likelihood of a bankruptcy or a takeover of publicly owned firms is rather low (Villalonga, 2000), and the labor market for public manager also seems to be distorted (Vining and Boardman, 1992).

[4]The incentive effect is mainly driven by managerial concern over losing market share due to inefficient performance. The information effect refers to the principal agent relationship between the owners and managers, and hence, becomes more important by assuming a situation of separated ownership and management (Leibenstein, 1966). Managers responsible operational decisions, aim to maximize their utility rather than owner's and firm's utility (Villalonga, 2000).

[5]The regulation scheme is solely a contract with the monopoly describing the rights and obligations.

objectives of the public owner and regulator match well.

Leibenstein (1966) argues that monopolies are likely to be X-inefficient regardless of ownership.[6] Button and Weyman-Jones (1994) relate the theory of X-inefficiency to the measurement of inefficiency by means of parametric and nonparametric frontier methods. Consequently, regardless of ownership, public and private firms in natural monopoly sectors such as electricity distribution, are subject to the same regulatory schemes designed to reduce inefficiency.

The majority of empirical studies on performance differences in the electricity sector have focused on utilities in the United States operating from the 1960s to the 1990s. In general, the conclusions drawn about the performance differences between public and private utilities during this period are rather weak. In fact, Peters (1993) and Pollitt (1995) note that many early studies suffer from small sample sizes, overly restrictive assumptions, and do not account for the impact of market structure, regulation, or vertical integration (see also critique in Atkinson and Halvorsen, 1986). The studies use different estimation methods; topics include managers' turnover rates (De Alessi, 1974), price discrimination (Peltzman, 1971), investment behavior (Rose and Joskow, 1990), and cost efficiency (Neuberg, 1977). A recent study (Kwoka, 2005) using cross-sectional data from 1989 on cost efficiency finds cost advantages for public firms in electricity distribution but cost advantages for private firms outperform in generation. Studies of the EU's power markets are scarce, partly due to the absence of data. In Sweden, Kumbhakar and Hjalmarsson (1998), conclude that private distributors are relatively more cost efficient. Arocena and Waddams-Price (2002), who investigate the cost efficiency of public and private generators in Spain under different regulatory regimes, find no difference under price-cap regulation, whereas public firms are more cost-efficient under cost-plus regulation.

None of the empirical papers account for flexible production functions, or the dynamic perspective of productivity growth within a flexible model, with the exception of Ehrlich et al. (1994) who model a dynamic context.[7]

[6] Leibenstein shows that economic agents may not achieve maximal efficiency in their productive decisions and behavior.

[7] In the model, the level of total factor productivity (TFP) is a function of managerial time allocated to current production, and the rate of TFP growth (TFPG) is positively related to the manager's commitment to investments in plant-specific capital. Public sector managers, according to the model, spend too much time pursuing independent private objectives, which reduces the time spent building plant-specific capital (which raises TFPG in the long run) and has an ambiguous effect on the time spent monitoring current production (which affects the current level of TFP).

3 Dataset and Definitions of Variables

The ongoing, intensive debate concerning deprivatization or remunicipalization makes Germany's electricity sector an ideal setting for studying the relations between ownership type and the differences in productivity and efficiency. This section gives a short overview of the German contex and the current debate and describes the German dataset and defines the variables.

3.1 The German situation

Germany's electricity sector has always been characterized by the existence of publicly and privately owned firms. In the 1990's, many public authorities divested their shares in electricity distribution firms, but the expiration until 2015 of numerous concession contracts for distribution grids[8] and the aim of increasing public influence to implement ecological, socio-economic and fiscal objectives, has reversed the trend. Thus, more and more municipalities are repurchasing the grids from private operators and reveive at the same time an intense support form the local population. Since 2005, Germany's municipalities acquired about 200 networks.[9]

The increase of local government activities in this industry and their economic implications are widely discussed, especially by the the German Monopolies Commission and the BKartA, both warning about public sector inefficiency with a consequence of increased costs and higher prices.

3.2 Dataset and definitions of variables

Our analysis is based on two sources: a new and rich panel dataset provided by the German Federal Statistical Office (FDZ) and the physical network characteristics provided by ene't. The FDZ data include various cost components, output and revenue structures, labor input, and other variables related to the production process. The panel dataset comprises all German utilities with more than ten employees which provide electricity, natural gas, district heating, water supply, sewerage, and waste treatment. The utilities have different degrees of vertical and horizontal integration. Depending on the year of observation, the data represent 80-90 percent of true electricity consumption in Germany.

[8] 8'000 of about 14'000 concession contracts expired in this period. The expirations open a window of time for local public authorities, which can decide whether the existing contract is to be extended, given to another interested private party, or retained. After the concession rights are granted, a concession contract lasts for the next twenty years.

[9] In a survey of urban administrations with more than 200000 citizens, a large share of the municipalities were planning a remunicipalization in the electricity sector (Lenk et al., 2011).

Table 1: Sample Size

	2006	2007	2008	2009	2010	2011	2012	Sum
Number of Obs.	179	225	280	306	311	293	303	1897
Public	155	187	237	264	263	245	260	1611
Private	24	38	43	42	48	48	43	286
Number of Obs. BNetzA	876	877	855	862	866	869	883	

Table 2: Definitions of Variables

Variable	Name	Type	Defintion
q_C	number of consumers	output variable	in Thous.
q_E	electricity distributed	output variable	in Mwh
x_N	network length	input variable	in km
x_T	installed capacity of transformers	input variable	in MVA
x_L	amount of worked hours	input variable	in hours
z_D	consumer density	operation environment	per km2
z_O	share of overhead lines	operation environment	km per km
own	ownership structure		Dummy

We use a subsample of electricity distribution companies. Due to the unbundling requirements, meaning that all integrated firms had to separate, legally unbundle, the network operation we use information only on the network part of the firms. The ene't data include physical information of the distribution networks, grid-specific network charges and other levies, and characteristic attributes of the municipalities served. We merged the two data sets and ended up with an unbalanced panel of 1897 observations in the time period of 2006 to 2012 (Table 1).

To asses efficiency and productivity, we use firms' production data as opposed to costs and prices because the data on inputs and outputs are generally reliable, readily available, and well defined. Further, inputs price data are not available and require constructing proxies from other data sources. In this case, quantity data are more reliable than the price data. To model the production process we use the output and input variables and the exogeneous factors derived from the empirical literature on efficiency analysis of electricity distribution companies (see Cullmann, 2010; Jamasb and Pollitt, 2000)).

The typical outputs of a distribution system operator are the number of customers served q_C (the total number of a firm's connected customers summed up over all voltage levels: high voltage, hv, medium voltage, mv, low voltage, lv), which is written as

$$q_C = q_{C,hv} + q_{C,mv} + q_{C,lv}, \tag{1}$$

and the annual amount of distributed electricity q_E (the total annual amount of electricity measured in MWh distributed through firm's grid computed by adding up electricity distributed over all voltage levels, which can be written as

$$q_E = q_{E,hv} + q_{E,mv} + q_{E,lv}. \tag{2}$$

The common input factors are labor x_L (amount of hours worked in a firm) and capital (approximated by the grid length x_N and the installed capacity of transformers x_T summed up over the voltage levels and type of line (underground cable x_{UC} versus overhead lines x_{OL})), which can be written as

$$\begin{aligned} x_{OL} &= x_{OL,hv} + x_{OL,mv} + x_{OL,lv} \\ x_{UC} &= x_{UC,hv} + x_{UC,mv} + x_{UC,lv} \\ x_N &= x_{UC} + x_{OL}. \end{aligned} \tag{3}$$

x_T (total installed capacity of transformers in the distribution grid measured in MVA summed up over the voltage levels) is

$$x_T = x_{T,hv} + x_{T,mv} + x_{T,lv}. \tag{4}$$

Two exogenous factors controlling for heterogeneity between the firms are z_D (computed as fraction of the number of consumers q_C and the geographical area served, z_A), which can be written as

$$z_D = q_C / z_A \tag{5}$$

with

$$z_A = z_{A,hv} + z_{A,mv} + z_{A,lv}$$

and z_O (share of overhead power lines representing a different technology compared to underground cable calculated as the share of overhead power lines x_{OL} on the length of the complete distribution grid x_N), which is written as

$$z_O = x_{OL}/x_N. \tag{6}$$

ownership *own* is defined as a dummy variable which takes the value of one if the firm is publicly owned with more than 50 % share in nominal capital. Table 3 shows the summary statistics of the variables.

$$o = \begin{cases} 1 & \text{if firm publicly owned} \\ 0 & \text{otherwise, privately owned} \end{cases} \tag{7}$$

Table 3: Summary Statistics of the Variables

		Variable	25% Quart.	Median	Mean	75% Quart.	Std. Dev.
Customers	publ	q_C	7996	15707	25572.3	26775.5	36998.09
	priv		2888.5	14360.5	45905.73	44176	72686.13
Electricity	publ	q_E	96729.13	192643	432171.3	372440.8	1158509
	priv		40624.16	240329.1	1033875	891961	2158137
Network	publ	x_N	252.93	431.3	673.98	731.55	928.03
	priv		182.8	518.65	1676.31	1425.5	2788.16
Labor	publ	x_L^*	47672	94241	133304.2	163870	141701.2
	priv		8097.5	22328.5	91693.31	108181	163029.2
Density	publ	z_D	486.18	1061.6	1164.58	1669.6	814.42
	priv		466.24	832.89	1085.25	1508.99	895.5
Overhead	publ	z_O	0.02	0.06	0.08	0.12	0.08
	priv		0.04	0.12	0.2	0.32	0.21

Note: * Data cannot be disclosed.

3.3 Stochastic Input Distance Frontier Model

We build our model on the input distance function representation of the transformation function (see Kumbhakar and Sun, 2012).[10] The transformation function is given by $A * T(X, Y, Z, t) = 1$, where X is a vector of inputs, Y is a vector of outputs, Z a vector of environmental factors, and t is the time trend. $T()$ is the transformation function.[11] Our assumption that $T()$ is homogeneous of degree 1 in X obtains the input distance

[10] All of the primal formulations can be derived from a transformation function by using different normalizing (identifying) restrictions (Kumbhakar and Sun, 2012).

[11] To estimate the transformation function $A * T() = 1$ requires identifying the restrictions. Under the assumption that $T()$ is separable in Y we get a production function $Y = B*f(X, t)$. Under the assumption that one of the input, e.g., X_1 is separable from other inputs, we can express the transformation function as an input requirement function $X_1 = C * g(X_{-1}, Y, t)$.

function[12] $X_1^{-1} = \Lambda * H(\tilde{X}, Y, Z, t)$, where X_1 is the numeraire input and $\tilde{X}$ is a vector of input ratios, with $\tilde{X}_p = X_p/X_1, p = 2, ..., P$.

Input distance functions are extensively used for modeling inefficiency (Kumbhakar and Sun, 2012). To analyze efficiency within the electricity distribution sector the input distance function formulation is economically appropriate because for the firms on this sector the inputs are endogenous and output electricity distributed and number of customers is exogenous.[13] The firms in this sector minimize cost to produce the exogenously given (determined by demand) output.[14]

The input distance function (IDF) in logs is given by

$$-\ln X_{1,it} = \theta(i,t) + \phi'(t) \ln B_{it} + v_{it} \tag{8}$$

where $\ln X_{1,it}$ is the numeraire input for firm i in year t, $\theta(i,t)$ is the intercept, $B_{it} = [\tilde{X}, Y, Z]$ is a vector of covariates including $p = 2, \ldots, P$ inputs, $q = 1, \ldots, Q$ outputs, and $k = 1, \ldots, K$ environmental factors, and v_{it} is a noise term. $\phi(t)$ is the slope coefficient vector which is an unknown function of t. Therefore, the IDF is allowed to vary over time, but has the same shape for all firms in time period t. Further, the IDF is semi-parametric, because it is of some functional form that needs to be assumed, but coefficients are nonparametric functions of t. Hence, there is no a priori assumption on how time affects the shape of the IDF.

To construct a yearly frontier technology, we define

$$\theta(i,t) = \alpha(t) + m(i,t) \tag{9}$$

with

$$\alpha(t) = \max_i\{\theta(i,t)\}.$$

Given that $\alpha(t)$ is the largest intercept $\theta(i,t)$ among the firms in period t, $m(i,t)$ can be interpreted as some time and firm-specific distance to a yearly frontier technology. Since m depends on i and t, it captures time and firm-specific effects, which can be caused by fixed effects, μ_i, transient inefficiency, u_{it}, and persistent inefficiency η_i.

[12] Introduced by Shephard (1953).

[13] The firms are legally obliged to connect and serve all the customers.

[14] Das and Kumbhakar (2012) show that under cost minimization, input ratios are exogenous. Färe and Primont (1995) show that the input distance function is dual to the cost function and therefore, the input distance function is ideal to use when input prices are not available or do not vary much.

Hence, for the IDF specified in (8), $m(i,t)$ is defined by

$$m(i,t) = \mu_i - u_{it} - \eta_i. \tag{10}$$

Further, adding $m(i,t)$ and the noise term v_{it}, defines the composed error term ϵ_{it}, which, therefore, captures all deviations from the yearly frontier technology as

$$\epsilon_{it} = m(i,t) + v_{it} = v_{it} + \mu_i - u_{it} - \eta_i. \tag{11}$$

By substituting $\theta(i,t)$ in (8) by (9) and (10) and rearranging, we obtain

$$-\ln X_{1,it} = \alpha(t) + \phi(t)' \ln B_{it} + \underbrace{v_{it} \underbrace{+\mu_i - u_{it} - \eta i}_{m_{it}}}_{\varepsilon_{it}}$$

3.4 Estimation Strategy

We estimate Equation 8 with 9 in two steps based on Sun et al. (2015):

1. Estimate the slopes and intercept of the input distance function.
2. Estimate the inefficiency by separating the firm-effects from both persistent and time-varying inefficiency by making distributional assumptions on the inefficiency components and on the random firm-effects.

Further, to productivity measures, we

3. (Future work:) decompose the productivity change components based on the estimated input distance frontier from the first two steps.

3.4.1 Step1: Estimation of slopes and intercept

Assuming a Cobb-Douglas type stochastic input distance function, equation 8 becomes

$$\begin{aligned} -\ln X_{1,it} &= \theta(i,t) \\ &+ \sum_{l \in P_{|-p=1}} \beta_p(t) \ln(B_{p,it}) \\ &+ \sum_{l \in Q} \gamma_q \ln(B_{q,it}) \\ &+ \sum_{l \in K} \delta_k \ln(B_{k,it}) + v_{it}. \end{aligned} \tag{12}$$

To estimate the slope parameters of the distance function according to the Robinson type transformation (Robinson, 1989).[15], we rewrite Equation 12 as:

$$\begin{aligned} -\ln X^*_{1,it} &= \sum_{l \in P_{|-p=1}} \beta_p(t) \ln\left(B^*_{p,it}\right) \\ &+ \sum_{l \in Q} \gamma_q(t) \ln(B^*_{q,it}) \\ &+ \sum_{l \in K} \delta_k(t) \ln(B^*_{k,it}) + v_{it}. \end{aligned} \tag{13}$$

where, for estimation purposes, the expected conditional mean of each variable is subtracted from the original variable's values, i.e., $\ln(X^*_{1,it}) = \ln(X_{1,it}) - E(\ln(X_{1,it})|i,t)$ and $\ln(B^*_{it}) = \ln(B_{it}) - E(\ln(B_{it})|i,t)$.

We estimate the conditional expectations $E(\ln(X_{1,it})|i,t)$ and $E(\ln(B_{it})|i,t)$ by applying the Nadaraya-Watson kernel estimator (Sun et al., 2015). Estimating equation 13 as a semi-parametric smooth coefficients model without intercept (Sun et al., 2015), provides the nonparametric functions of the slope coefficients, i.e. $\hat{\beta}(t)$, $\hat{\gamma}(t)$, and $\hat{\delta}(t)$.

To estimate the intercept, $\theta(i,t)$, in Equation 12, we compute the residuals, $\hat{v}_{it}$, of the estimated distance function using the observed left and right side variable, $\ln X_{1,it}$ and lnB_{it}, and the estimated coefficients as

$$\hat{v}_{it} = -\ln X_{1,it} - \sum_{q} \hat{\beta}_p(t) \ln\left(B_{p,it}\right) \tag{14}$$

$$- \sum_{l \in Q} \hat{\gamma}_q(t) \ln(B_{q,it}) \tag{15}$$

$$- \sum_{l \in K} \hat{\delta}_k(t) \ln(B_{k,it}).$$

The residual term $\hat{v}_{it}$ consists of an intercept and a noise term, i.e., $v_{it} = \theta(i,t) + \omega_{it}$. The best predictor for $\theta(i,t)$ is its conditional mean $E(v_{it}|i,t)$, under the assumption that the noise term ω_{it} is uncorrelated with the intercept and has zero conditional mean, i.e., $E(\omega_{it}|i,t) = 0$. Again, we use the Nadaraya-Watson kernel estimator to estimate the conditional mean of v_{it}. Using the predictors of $\theta(i,t)$, i.e. $\hat{\theta}(i,t)$, and equation 9, we obtain $\hat{\alpha}(t)$ being the annual maximum observed $\hat{\theta}(i,t)$ and $\hat{m}_{it}$, which can be interpreted as total distance from an observation to the estimated input distance frontier

[15]Estimation of a frontier with time-varying coefficients, but without intercept.

due to inefficiency and firm effects.

3.4.2 Step 2: Decomposing Inefficiency

According to equation 10, we aim to decompose the total distance $\hat{m}_{it}$ into three components where the firm effect η_i can also be interpreted as unobserved heterogeneity which is constant over time and which cannot be influenced by the firms. Thus, we aim to separate it from inefficiency. For estimation purposes, however, we the overall deviation from the IDF, i.e., ϵ that we obtain by adding $\hat{m}_{it}$ and $\hat{v}_{it}$ following equation 11.
To decompose 11 empirically, we re-define ϵ_{it} as:

$$\epsilon_{it} = a_0 + \psi_{i0} + \chi_{it} \tag{16}$$

where a_0 is an intercept which is time-invariant and the same across all observations. It captures the expected means of each of the components, i.e., $a_0 = E[v_{it}] + E[\mu_i] + E[-u_{it}] + E[-\eta_i]$. Assuming that noise v_{it} and firm effects μ_i are variables of zero mean, yields $a_0 = E[-u_{it}] + E[-\eta_i]$. Further, ψ_{i0} captures all time-invariant observation-specific components in 11 and defined as $\psi_{i0} = \mu_i - [\eta_i + E[-\eta_i]] = \mu_i - \eta_i - E[-\eta_i]$. χ_{it} captures instead all time-varying observation-specific effects and given by $\chi_{it} = v_{it} - [u_{it} + E[-u_{it}] = v_{it} - u_{it} - E[-u_{it}]$.

Random firm effects ψ_{i0} represents a firm-specific fixed effect entered explicitly in the model. To obtain an estimate of the firm effects, we introduce firm-specific dummy variables D_i that becomes 1, if firm i is observed in the year considered.
Hence, 16 becomes

$$\epsilon_{it} = a_0 + \sum_{j=1}^{N} \psi_{i0} D_{i_j} + \chi_{it} \tag{17}$$

where index j is an alias of index i. We estimate the model using ordinary least squares (OLS) while the dependent variable ϵ_{it} is substituted by $\hat{\epsilon}_{it} = \hat{m}_{it} + \hat{v}_{it}$. From that, we obtain $\hat{\psi}_{i0}$ and $\hat{\chi}_{it}$.

Persistent inefficiency Persistent inefficiency, η_i, is part of the firm effect ψ_{i0}. With $\psi_{i0} = \mu_i + [\eta_i - E(\eta_i)]$ and $b_0 = -E[-\eta_i]$, we further define

$$\psi_{i0} = b_0 + \mu_i - \eta_i \tag{18}$$

Using the typical stochastic frontier approach for production functions, where b_0 represents the constant term, μ_i, the i.i.d. persistent noise term (firm effect) and η_i represents half normally distributed noise, i.e., persistent inefficiency. We estimate the model by substituting ψ_{i0} with $\hat{\psi}_{i0}$ obtained from 17 and determine the persistent TE_p following Jondrow et al. (1982) as $E(-\eta_i|r_i)$, with $r_i = \hat{\mu}_i + \hat{\eta}_i$.

Transient inefficiency Similar to determining persistent inefficiency estimates, we use the definition $\chi_{it} = v_{it} + [u_{it} - E(u_{it})]$ and define

$$\chi_{it} = c_0 + v_{it} - u_{it} \tag{19}$$

with the intercept $c_0 = -E(-u_{it})$, u_{it} following a half normal distribution representing the inefficiency term and v_{it}, normally distributed term with zero mean, accounting for noise. To estimate Equation 19, χ_{it} is replaced by its estimate $\hat{\chi}_{it}$. Time-varying inefficiency, TE_t is again determined by computing $E(-u_{it}|e_{it})$ (Jondrow et al., 1982). e_{it} describes the complete residual term, with is composed of $u_{it} + v_{it}$.

Overall inefficiency The overall TE_o is the product of TE_p and TE_t, i.e.

$$TE_{p,i} \cdot TE_{t,it} = TE_{o,it}. \tag{20}$$

Hence, the overall technical efficiency is always strictly smaller than TE_p and TE_t except that at least one of them is equal to one.

4 Empirical results

In a first stage we estimate a common technology for public and private firms. In this model the coefficients of the input distance function depend only on time t and the intercept on time t and firm effects.

4.1 Common technology for public and private firms

4.1.1 Interpretation of estimated coefficients

Table 4 reports the estimated smoothed coefficients of the input distance function, for each year (2006-2012). The coefficients and, thus, the elasticities of the input distance functions have in all years the expected signs. The estimated value of the input coefficient $\hat{\beta}_N(t)$ is positive and varies in the interval between 0 and 1.[16] It is reasonable that the cost share of the grid, $\hat{\beta}_N(t)$, is larger than the cost share of labor, $\hat{\beta}_L(t) = 1 - \hat{\beta}_N(t)$, since network operation is a capital-intensive industry. Due to duality, the output coefficients,

[16]The coefficients of the inputs can be interpreted as the share of total costs (Fare et al., 1993).

$\hat{\gamma}_C(t)$ and $\hat{\gamma}_E(t)$, have negative signs.[17] Cost elasticity with respect to connected customers is higher than for electricity delivered. This seems to be intuitive as it is more cost intense to build new connection than to increase the distributed electricity through an existing grid.[18] The estimate of the coefficient of the environmental variables $\hat{\delta}_D(t)$ is positive indicating that an increase in the customer density leads to a decrease in the amount of hours worked. It is reasonable that a distribution grid serving a dense area of customers requires less maintenance, i.e. less labor. The influence of overhead cables is not that consistent over the observed time period, i.e. the value of the coefficient $\hat{\delta}_O(t)$ changes its sign 2010 from positive to negative.

Table 4: Estimated Coefficients of the Input Distance Function

Year	$\hat{\beta}_N$	$\hat{\gamma}_C$	$\hat{\gamma}_E$	$\hat{\delta}_D$	$\hat{\delta}_O$
2006	0.4512	-0.0087	-0.0029	0.0159	0.0138
2007	0.5407	-0.0056	-0.0065	0.0151	0.0391
2008	0.6530	-0.0035	-0.0108	0.0124	0.0674
2009	0.7300	-0.0137	-0.01486	0.0196	0.0479
2010	0.7705	-0.0346	-0.0166	0.0366	-0.0085
2011	0.8051	-0.06528	-0.0235	0.0575	-0.0419
2012	0.8392	-0.1050	-0.0409	0.0782	-0.0526
Average					

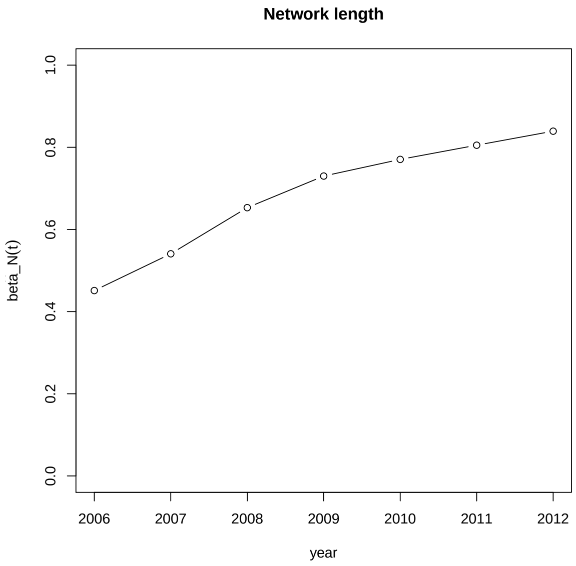
Figure 1 shows the evolution of the input coefficients $\hat{\beta}_N(t)$. It displays that the cost share of the network on total costs increase constantly over the years, i.e. we observe increasing expenditure into the grid. This can be explained by the energy transition (Energiewende) and the grid transformation towards increased decentralized generation and the obligation to connect more and more renewables.
Figure 2 shows the evolution of the output coefficients $\hat{\gamma}_C(t)$ and $\hat{\gamma}_E(t)$ over time. While $\hat{\gamma}_C(t)$ decreases significantly after 2009[19], $\hat{\gamma}_E(t)$ only slightly decreases over time.
The coefficients vary significantly over time which indicates that a flexible semiparametric

[17] Due to duality between both the distance function and the cost function (Fare et al., 1993), the slope coefficient of the output is the first derivative of the distance function with respect to this output, which corresponds to the negative cost elasticity.

[18] Connecting a customer to the electricity supply network implies that the grid needs to be expanded. The increase in fix costs for installing the new distribution lines by far exceed the variable costs for operation.

[19] While large power plants are normally connected to the transmission network, small renewable energy sources are mostly connected to the distribution grids. In its *Monitoringbericht 2014*, the Bundesnetzagentur (2014) reports that the number of firms needing to integrate renewable energy sources grow rapidly since 2009. Hence, the forced expansion of decentralized capacity of small renewable energy sources will increase cost elasticity of the consumers served.

Figure 1: Input Coefficient, $\hat{\beta}_N(t)$, over time



input distance function, allowing the technology parameters to vary over time capturing transformations in the production process is appropriate.

4.1.2 Analysis of efficiency scores

With the inefficiency decomposition defined in (16), we derive time-varying as well as persistent firm-specific inefficiency estimates. Our results show that the firms do not exhibit persistent inefficiency under the assumption of a common technology. Persistent efficiency estimates $TE_{P,i}$ are always close to one.[20] It implies that all firms have nearly eliminated all sources of inefficiency which can be influenced in the long run.

Thus, the overall efficiency is mainly driven by transient efficiency. Table 5 shows the summary statistics on the estimated transient technical efficiency scores $TE_{t,it}$, for public and private firms separately. In general, we observe a median efficiency between 0.7912 and 0.8864 while it is slightly increasing during the observed time period. Beside some variations in the lower and upper quantiles, efficiency estimates do not appear to be very different when comparing public and private firms, e.g., the mean efficiency in 2012 for public firms is 0.8731 and 0.8700 for private firms.

We further test, whether public and private firms on average perform significantly different from each other by means of Wilcoxon rank sum test with continuity correction. The Null hypothesis is that the location shift between the group means is zero. With a p-value of 0.2376 we cannot reject the Null. This result is also supported by Figure 3

[20] For clarity, we do not report the results.

Figure 2: Output coefficient, $\hat{\gamma}_C(t)$ and $\hat{\gamma}_E(t)$, over time

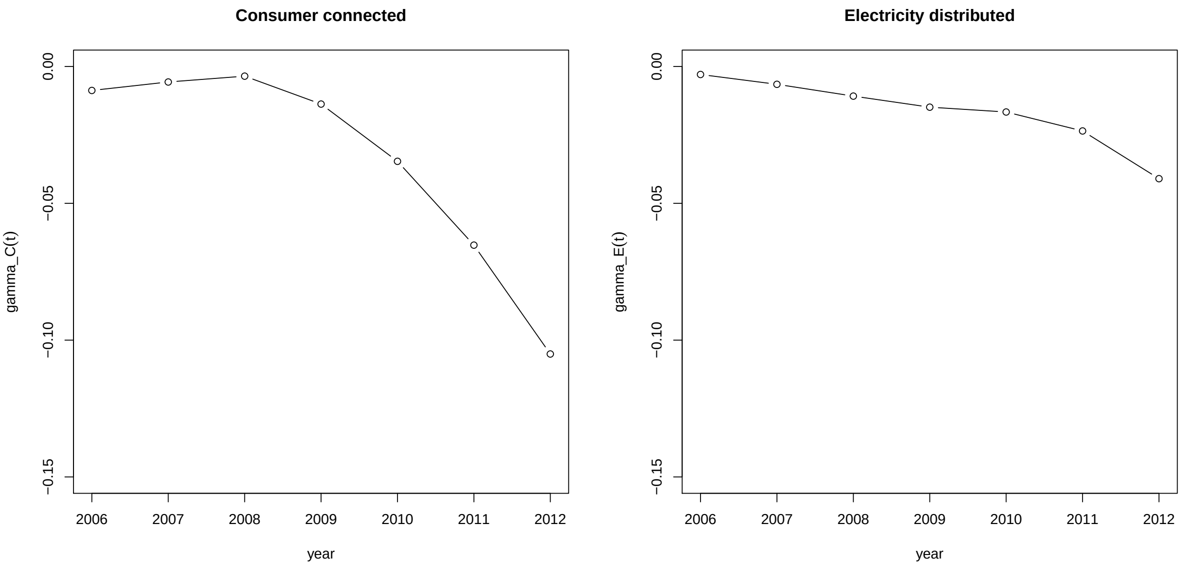


Table 5: Transient Efficiency Scores $TE_{t,it} = exp(-u_{it})$

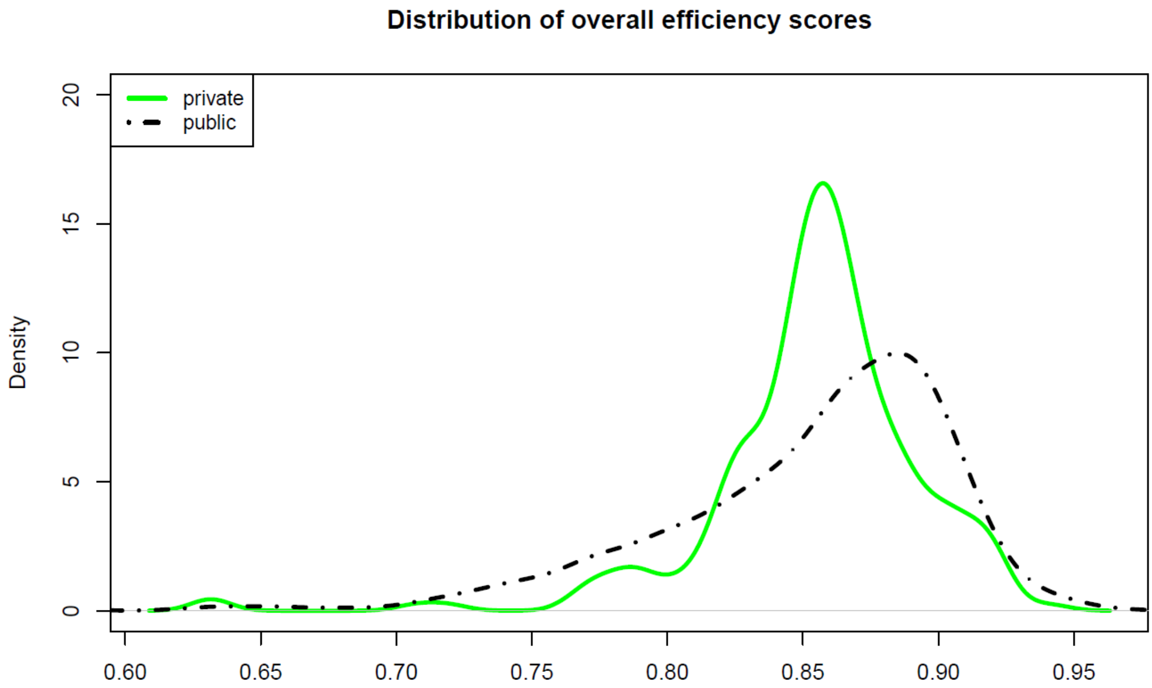
Year	Own	1% Quart.	25% Quart.	Median	Mean	75% Quart.	99% Quart
2006	Public	0.5957	0.5957	0.7912	0.7899	0.8317	0.9272
	Private	0.6345	0.8361	0.8738	0.8468	0.9101	0.9267
2007	Public	0.6554	0.7773	0.8081	0.8153	0.8504	0.9621
	Private	0.7711	0.8152	0.8666	0.8567	0.8976	0.8976
2008	Public	0.7308	0.8240	0.8240	0.8240	0.8811	0.9313
	Private	0.8199	0.8392	0.8504	0.8501	0.8613	0.8914
2009	Public	0.8068	0.8721	0.8864	0.8830	0.8991	0.9350
	Private	0.7939	0.8493	0.8668	0.8638	0.8820	0.9214
2010	Public	0.7295	0.8499	0.8726	0.8660	0.8922	0.9371
	Private	0.7880	0.8445	0.8580	0.8557	0.8665	0.9161
2011	Public	0.6931	0.8585	0.8847	0.8724	0.9020	0.9382
	Private	0.8102	0.8588	0.8688	0.8666	0.8752	0.9184
2012	Public	0.6722	0.8598	0.8831	0.8731	0.9028	0.9404
	Private	0.8147	0.8559	0.8689	0.8700	0.8830	0.9235

showing the distribution of the overall technical efficiency scores $TE_{o,it}$. Our results show that we cannot find statistical evidence that publicly owned DSOs operate their networks less efficient compared to private firms, and hence, invalidate the concerns of the German Monopolies Comission and the Bundeskartellamt.

4.1.3 Productivity decomposition

tbd

Figure 3: Distribution of the Technical Efficiency Scores, public vs. private



4.2 Assuming different technologies for public and private firms

tbd

5 Conclusion

The aim of this paper was to gain a fuller understanding of the technology and short- and long-term performance differences between publicly and privately owned firms. We proposed a semiparametric input distance function model to allow for a rich decomposition of efficiency across ownership type. The proposed model was flexible enough to differentiate between time-persistent and time-varying inefficiency. The model was validated with a unique and newly constructed dataset of Germany's public and private electricity distribution firms operating between 2006 and 2012. Our dataset contains 1897 observations of German electricity distribution firms. The results showed that while the two ownership types operated under different production technologies, a high persistent inefficiency in both types sustained productivity change. The results also indicate that the different ownership types show a different input mix over time. The lack of empirical evidence that public firms operated less efficiently than private ones questions the predictions from theoretical models and provides new grounds for ongoing political discussion on economic activities of the public sector.

Acknowledgements

This research is part of the project 'Municipal infrastructure companies against the background of energy policy and demographic change (KOMIED)' funded by the Leibniz Commission (SAW-2013-DIW-5). The paper has been presented at the North Americal Workshop on Productivity Analysis 2016 (NAPW) and at the Lunch Seminar at University Neuchatel. We gratefully acknowledge Pio Baake, Tomaso Duso, and Christian von Hirschhausen for their valuable comments and suggestions. We thank Ann Stewart for language assistance. The usual disclaimer applies.

6 Bibliography

Alchian, A., Demsetz, H., 1973. The property right paradigm. The Journal of Economic History 33 (1), 16–27.

Arocena, P., Waddams-Price, C., 2002. Generating efficiency: Economic and environmental regulation of public and private electricity generators in spain. International Journal of Industrial Organisation 20 (1), 41–69.

Atkinson, S. E., Halvorsen, R., 1986. The relative efficiency of public and private firms in a regulated environment: The case of us electric utilities. Journal of Public Economics 29 (3), 281–294.

Bagdadioglu, N., Price, C. M. W., Weyman-Jones, T. G., 1996. Efficiency and ownership in electricity distribution: a non-parametric model of the turkish experience. Energy Economics 18 (1), 1–23.

Bartel, A. P., Harrison, A. E., 2005. Ownership versus environment: Disentangling the sources of public sector inefficiency. The Review of Economics and Statistics 87 (1), 135–147.

Bundesnetzagentur, 2014. Monitoringbericht 2014. Tech. rep., Bundesnetzagentur.

Button, K. J., Weyman-Jones, T. G., 1994. X-efficiency and technical efficiency. Public Choice 80, 83–104.

Cullmann, A., 2010. Benchmarking and firm heterogeneity: a latent class analysis for German electricity distribution companies. Empirical Economics 42 (1), 147–169.

Das, A., Kumbhakar, S. C., 2012. Productivity and efficiency dynmaics in indian banking: an input distance function approach incorporating quality of inputs and outputs. Journal of Applied Econometrics 27 (2), 205–234.

De Alessi, L., 1974. Mangerial tenure under private and government ownership in the electric power industry. Journal of Political Economy 82 (3), 645–653.

Demsetz, H., 1967. Toward a theory of property rights. American Economic Review 57, 347–359.

Ehrlich, I., Gallais-Hamonno, G., Liu, Z., Lutter, R., 1994. Productivity growth and firm ownership: An analytical and empirical investigation. Journal of Political Economy 102 (5), 1006–1038.

Fare, R., Grosskopf, S., Lovell, C. A. K., Yaisawarng, S., 1993. Derivation of shadow prices for undesirable outputs: A distance function approach. The Review of Economics and Statistics 75 (2), pp. 374–380.
URL `http://www.jstor.org/stable/2109448`

Färe, R., Primont, D., 1995. Multi-output production: theory and applications. Kluwer.

Hart, O. D., 1983. The market mechanism as an incentive scheme. The Bell Journal of Economics, 366–382.

Jamasb, T., Pollitt, M., 2000. Benchmarking and regulation: international electricity experience. Utilities Policy 9 (3), 107–130.

Jondrow, J., Lovell, C. K., Materov, I. S., Schmidt, P., 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. Journal of econometrics 19 (2), 233–238.

Kumbhakar, S. C., Hjalmarsson, L., 1998. Relative performance of public and private ownership under yardstick competition: electricity retail distribution. European Economic Review 42 (1), 97–122.

Kumbhakar, S. C., Sun, 2012. Estimation of tfp growth: a semiparametric smooth coefficient approach. Empirical Economics 43 (1), 1–24.

Kwoka, J. E., 2005. The comparative advantage of public ownership: Evidence from US electric utilities. Canadian Journal of Economics/Revue canadienne d'économique 38 (2), 622–640.

Laffont, J.-J., Tirole, J., 1991. Privatization and incentives. Journal of Law, Economics, & Organization, 84–105.

Laffont, J.-J., Tirole, J., 1993. A theory of incentives in procurement and regulation. MIT press.

Leibenstein, H., 1966. Allocative efficiency vs." x-efficiency". The American Economic Review, 392–415.

Lenk, T., Rottmann, O., Albrecht, R., 2011. Rekommunalisierung in der Energieversorgung. PublicGovernance–Zeitschrift für öffentliches Management, 6–11.

Nellis, J., 1994. Is privatization necessary? World Bank Viewpoint 17, 1999.

Neuberg, L., 1977. Two issues in the municipal ownership of electric power distribution systems. Bell Journal of Economics 8 (1), 303–323.

Peltzman, S., 1971. Pricing in public and private enterprises: Electric utilities in the united states. Journal of Law and Economics 14 (1), 109–147.

Peters, L., 1993. Non-profit electric utilities in the united states: Pricing and efficiency. Annals of Public and Cooperative Economics 64 (4), 575–604.

Pollitt, M., 1995. Ownership and Performance in Electric Utilities: The International Evidence on Privatization and Efficiency. Oxford University Press.

Robinson, P. M., 1989. Nonparametric estimation of time-varying parameters. Springer.

Rose, N., Joskow, P., 1990. The diffusion of new technologies: Evidence from the electric utility industry. RAND Journal of Economics 21 (3), 354–373.

Shephard, R. W., 1953. Cost and production functions. Princeton University Press.

Shirley, M. M., Walsh, P., 2001. Public vs. private ownership: the current state of the debate. World Bank Policy Research Working Paper (2420).

Shleifer, A., Vishny, R. W., 1994. Politicians and firms. The Quarterly Journal of Economics, 995–1025.

Sun, K., Kumbhakar, S. C., Tveterås, R., 2015. Productivity and efficiency estimation: A semiparametric stochastic cost frontier approach. European Journal of Operational Research 245 (1), 194–202.

Villalonga, B., 2000. Privatization and efficiency: differentiating ownership effects from political, organizational, and dynamic effects. Journal of Economic Behavior & Organization 42 (1), 43–74.

Vining, A. R., Boardman, A. E., 1992. Ownership versus competition: Efficiency in public enterprise. Public choice 73 (2), 205–239.