Productivity Growth and the Public and Private Ownership of Regulated Firms

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Abstract

This paper proposes a flexible semiparametric input distance function model to account for technology heterogeneity according to public and private ownership of firms. In the model, the technology parameters are unknown smooth functions of firm- and time effects and ownership 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 2005 and 2012 in Germany. We find that public and private firms have different production technologies. Taking this into account, we further 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. Moreover, public firms are characterized by an ongoing productivity change driven mainly by technical progress. Whereas the technical change for private firms appear to stagnate after 2009.

JEL-Classification: L94, L51, L98

Keywords: Productivity, Ownership, Electricity Distribution, Germany

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1 Introduction

Evaluating the economic activity of the public sector is incrementally linked to discussing the productivity and efficiency of public and private firms. The literature in the fields of public choice, property rights, and agency theories, predict the latter to perform superior. 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 had 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 the Europe's utility sector.

Somewhat surprisingly, much of the relevant literature on public infrastructure industries reports no statistically significant differences in productivity or cost between public and private firms (Ehrlich et al., 1994). 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.

To our knowledge, no one has conducted a thorough empirical investigation that allows for flexible technologies, and role of ownership for efficiency, productivity and its components. Therefore, we propose a semiparametric input distance frontier model to estimate and decompose productivity and 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 in private and public firms resulting from the distinct production objectives of publicly owned firms. The model also considers that ownership can neutrally or non-neutrally shift the frontier of the technology without rigidity.

We test our model with newly available data on German electricity distribution firms operating between 2005 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 and productivity 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 decreasing over the analyzed time period where public firms perform slightly more efficient. Inefficiency is thereby mainly driven by persistent rather than time-varying inefficiency. In terms of productivity change and its decomposition, we find technical progress for private and public firms. Publicly owned firms, however, show a more smooth ongoing process while private firms reveal a stagnation after 2008.

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 4 presents the empirical model and estimation strategy. Section 5 discusses the empirical findings. Section 6 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. 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

[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.

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, 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 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 utili-

[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.

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

ties 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, cost function, 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]

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 describes the 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 in 2015 of numerous concession contracts

[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). The model implies that levels of productivity in public-sector firms need not be lower than in the private-sector in the short run, but that productivity growth will be lower for PSEs. In the longer term, of course, lower public-sector productivity growth should eventually lead to lower productivity levels than in the private sector.

for distribution grids[8] and the aim of increasing public influence to implement ecological, socio-economic and fiscal objectives, has reversed the trend. As of 2011, the number publicly owned firms was 935 compared to 655 in 2004, an increase of more than 40 percent. Since 2005, Germany's municipalities acquired about 200 networks.[9]

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)[10] and the physical network characteristics provided by ene't.[11] In total the dataset comprises an unbalanced panel of 1981 observations in the time period of 2005 to 2012. 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, 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 computed by adding up electricity distributed over all voltage levels (see Cullmann, 2010; Jamasb and Pollitt, 2000)), which can be written as

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

[8] 8'000 of about 14'000 concession contracts expired in his 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).

[10] The FDZ data include various cost components, output and revenue structures, 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. We use a subsample of electricity distribution companies.

[11] The ene't data include about 1'200 different network operators with physical information of the distribution networks, grid-specific network charges and other levies, and characteristic attributes of the municipalities served.

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

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

The dummy variable is ownership o:

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

Table 1 shows the summary statistics of the variables.

Table 1: Summary Statistics of the Variables

Var	Median	Mean	SD	Min	Max
q_C	9'669.00	69'580.00	312'009.60	0.00	9'592'000.00
q_E	1'22'100.00	3'064'000.00	68'902'922.00	0.00	5'213'000'000.00
x_N	328.80	2'695.00	13'651.66	0.00	402'400.00
x_T	50.00	1'479.00	24'261.54	0.00	1'746'000.00
x_L^*	-	-	-	-	-
z_C	225.10	351.20	424.08	0.00	10'110.00
z_O	0.04	0.10	0.14	0.00	1.00
o^*	-	-	-	-	-

Note: * Data cannot be disclosed.

4 Empirical Framework

4.1 Stochastic Input Distance Frontier Model

We build our model on the input distance function representation of the transformation function (see Kumbhakar and Sun, 2012).[12] The transformation function is given by $A{*}T(X, Y, t) = 1$, where X is a vector of inputs, Y is a vector of outputs, and t is the time trend. $T()$ is the transformation function.[13] Our assumption that $T()$ is homogeneous of degree 1 in X obtains the input distance function[14] $X_1^{-1} = \Lambda * H(\tilde{X}, Y, t)$, where X_1 is the numeraire input and $\tilde{X}$ is a vector of input ratios, with $\tilde{X}_k = X_k/X_1, k = 2, ..., K$. 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.[15] The firms in this sector minimize cost to produce the exogenously given (determined by demand) output.[16]

We assume labor input X_L as the numeraire input and model the intercept, $\theta(i, t, o)$, as an unknown function of firm- and time-effects which captures both persistent and time-varying inefficiency. The slope coefficient vector, $\phi(t, o)$, is an unknown function of time

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

[13]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 $X_1 = C * g(X_{-1}, Y, t)$.

[14]Introduced by Shephard (1953).

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

[16]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.

trend, t and ownership o, and v_{it} is the noise term. The general input distance function in logs is then given by

$$-\ln x_{L,it} \quad = \quad \theta(i,t,o) + \phi(t,o)' \ln B_{it} + v_{it} \tag{8}$$

where $\ln x_{L,it}$ is the labor input for firm i in year t and B_{it} is a vector of covariates (other inputs ratios, x_N/x_L, x_T/x_L; outputs, q_c, q_E and environmental factors, z_D, z_O).
We assume a translog type stochastic input distance function as

$$\begin{aligned} -\ln x_{L,it} \quad = \quad & \theta(i,t,o) \\ + \quad & \sum_{j \in \{N,T\}} \beta_j(t,o) \ln(\tilde{x}_{j,it}) \\ + \quad & \sum_{k \in \{C,E\}} \gamma_k(t,o) \ln(q_{k,it}) \\ + \quad & \sum_{l \in \{D,O\}} \delta_l(t,o) \ln(z_{l,it}) + v_{it} \end{aligned} \tag{9}$$

Equation 9 represents the semiparametric stochastic input distance function: the structure of the distance function is parametric and in a translog form, but the coefficients $\theta(i,t,o)$, $\beta_N(t,o)$, $\beta_T(t,o)$, $\gamma_C(t,o), \gamma_E(t,o)$, $\delta_D(t,o)$ and $\delta_O(t,o)$ are non-parametric functions of o and t.[17] We note that both o and t directly influence the slope parameters as well as the intercept of the function. The relation between o and t and the coefficients is not specified any further. Thus, we do not need to make an assumption ex ante concerning the impact of ownership on the production technology, i.e. ownership structure can influence the production process in various ways. Moreover, the slope coefficients can vary over time and between privately and publicly owned firms.
We interpreted inefficiency in the model as the difference between the minimal input and the actual observed inputs of the firms and assume it is neutral. We capture it by the intercept $\theta(i,t,o)$, which is allowed to vary over time and across firms and can be decomposed into

$$\theta(i,t,o) \quad = \alpha(t,o) - u_{ito} \tag{10}$$

$$\alpha(t,o) \quad = \max_i \; \theta(i,t) \tag{11}$$

[17]The input distance function is only common to all firms in a given year when they have the same ownership type.

where u_{ito} accounts for inefficiency. It implies, that both the coefficients and the inefficiency component, u_{ito}, depend on the ownership structure of the firm, without assuming any functional form.

4.2 Estimation Strategy

We estimate Equation 9 with 10 and 11 in three 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.
3. Decompose the productivity change components based on the estimated input distance frontier from the first two steps.

4.2.1 Step1: Estimation of slopes and intercept

Estimate the slope parameters of the distance function according to the Robinson type transformation (Robinson, 1989).[18] We rewrite Equation 9 as:

$$\begin{aligned} -\ln x^*_{L,it} = & \sum_{j\in\{N,T\}} \beta_j(t,o)\ln(\tilde{x}^*_{j,it}) \\ + & \sum_{k\in\{C,E\}} \gamma_k(t,o)\ln(q^*_{k,it}) \\ + & \sum_{l\in\{D,O\}} \delta_l(t,o)\ln(z^*_{l,it}) + v_{it} \end{aligned} \tag{12}$$

where $\ln(x^*_{L,it}) = \ln(x_{L,it}) - E(\ln(x_{L,it})|i,t,o)$, $\ln(\tilde{x}^*_{j,it}) = \ln(\tilde{x}_{j,it}) - E(\ln(\tilde{x}_{j,it})|i,t,o)$, $\ln(q^*_{k,it}) = \ln(q_{k,it}) - E(\ln(q_{k,it})|i,t,o)$ and $\ln(z^*_{l,it}) = \ln(z_{l,it}) - E(\ln(z_{l,it})|i,t,o)$. Next, we estimate the conditional expectations $E(\ln(x_{L,it})|i,t,o)$, $E(\ln(\tilde{x}_{j,it})|i,t,o)$, $E(\ln(q_{k,it})|i,t,o)$, $E(\ln(z_{l,it})|i,t,o)$ that are estimated applying the Nadaraya-Watson kernel estimator (Sun et al., 2015). After computing the $\ln(x^*_{L,it})$, $\ln(\tilde{x}^*_{j,it})$, $\ln(q^*_{k,it})$, $\ln(z^*_{l,it})$, we estimate Equation 12 (Sun et al., 2015) and obtain the nonparametric functions of the slope coefficients. To estimate the intercept, $\theta(i,t,o)$, in Equation 9, we compute the residuals, $R(i,t,o)$, of the estimated distance function and the observed left side variable, $\ln x_{L,it}$

$$\begin{aligned} R(i,t,o) = -\ln x_{L,it} - & \sum_{j\in\{N,T\}} \hat{\beta}_j(t,o)\ln(\tilde{x}_{j,it}) \\ - & \sum_{k\in\{C,E\}} \hat{\gamma}_k(t,o)\ln(q_{k,it}) \\ - & \sum_{l\in\{D,O\}} \hat{\delta}_l(t,o)\ln(z_{l,it}) \end{aligned} \tag{13}$$

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

The residual term consists of an intercept and a noise term, with $R(i,t) = \theta(i,t,o) + \epsilon_{ito}$. The best predictor for $\theta(i,t,o)$ is $E(R(i,t,o)|i,t,o)$, under the assumption that the noise term is uncorrelated with the intercept and has zero mean. Again, we use the Nadaraya-Watson kernel estimator to estimate the conditional mean of $R(i,t,o)$. The final input distance frontier is then given by:

$$
\begin{aligned}
-\ln(x_{L,it}) &= \hat{\theta}(i,t,o) \\
&+ \sum_{j\in\{N,T\}} \hat{\beta}_j(t,o)\ln\left(\tilde{x}_{j,ito}\right) \\
&+ \sum_{k\in\{C,E\}} \hat{\gamma}_k(t,o)\ln(q_{k,ito}) \\
&+ \sum_{l\in\{D,O\}} \hat{\delta}_l(t,o)\ln(z_{l,ito}) + \hat{v}_{it}
\end{aligned} \tag{14}
$$

4.2.2 Step 2: Decomposing Inefficiency

According to Equation 10, we decompose $\hat{\theta}(i,t,o)$. u_{ito} representing firm specific inefficiency can also cover unobserved heterogeneity which is constant over time and cannot be influenced by the firms. Thus, we separate them from inefficiency, and further decompose u_{ito} into a random firm effect μ_{io} and two inefficiency components both half normally distributed, one which is time persistent η_{io} and one which is time-varying.

Random Firm Effect

The sum of u_{ito} and the noise term v_{ito} is

$$\epsilon_{ito} = \underbrace{\mu_{io} + \eta_{io} + \kappa_{ito}}_{u_{ito}} + v_{ito} \tag{15}$$

We introduce ψ_{io}, χ_{ito}, a_0 with $\psi_{io} = \mu_{io} + [\eta_{io} - E(\eta_{io})]$, $\chi_{ito} = v_{ito} + [\kappa_{ito} - E(\kappa_{ito})]$, $a_0 = E(\eta_{io}) + E(\kappa_{ito})$. Assuming that both η_{io} and κ_{ito} are non-negative variables, we expect that a_0 will be larger or equal to zero. We rewrite Equation 15 where ϵ_{ito} is decomposed into a fixed intercept a_0, which is constant across observations, ownership structure and time; a part which is persistent over time ψ_{io}; and a part which can also change over time κ_{ito}. ϵ_{ito} is given by

$$\epsilon_{ito} = a_0 + \psi_{io} + \chi_{ito} \tag{16}$$

where ψ_{io} represents a firm- and ownership-specific fixed effect entered explicitly in the model. Noting that we can estimate the model using the *LSDV* method,[19] we introduce firm- and ownership-specific dummy variables called D_{io}. D_{io} becomes 1, if firm i with ownership structure o, is observed in the year considered. Moreover, the dependent variable ϵ_{ito} is substituted by $\hat{\epsilon}_{ito} = \hat{u}_{ito} + \hat{v}_{ito}$. We estimate $\hat{u}_{ito}$ by $\hat{u}_{ito} = \hat{\theta}(i,t,o) - \hat{a}_{ito}$ which is in line with the definition of the intercept shown in 10. $\hat{v}_{ito}$ was determined in Equation 14.

$$\hat{\epsilon}_{ito} = a_0 + \sum_{j=1}^{N}\sum_{p=1}^{2} \psi_{io_{jp}} D_{io_{jp}} + \chi_{ito} \tag{17}$$

where index j is an alias of index i and iterates through all firms and index p is an alias of index o and accounts for the two ownership structures. After re-specifying the model according to Equation 17, we estimate it using ordinary least squares (OLS), which yields $\hat{\psi}_{io}$ and $\hat{\chi}_{ito}$.

Persistent Inefficiency

Persistent inefficiency, ψ_{io}, which is that part of the firm-specific inefficiency which is constant over time. We define $\psi_{io} := \mu_{io} + [\eta_{io} - E(\eta_{io})]$. Thus, $-E(\eta_{io})$, the intercept of Equation 18 b_0 is

$$\psi_{io} = b_0 + \mu_{io} + \eta_{io} \tag{18}$$

Using the typical stochastic frontier approach, where b_0 represents the constant term, μ_{io}, the half normally distributed[20] persistent noise term and η_{io} represents the i.i.d. noise term. We estimate the model by substituting ψ_{io} with $\hat{\psi}_{io}$ and determine the time-persistent $\text{TE}_{p,io}$ following Jondrow et al. (1982) as $E(-\mu_{iown}|r_{io})$, with $r_{io} = \hat{\mu}_{io} + \hat{\eta}_{io}$.

Time-varying Inefficiency

Time-varying inefficiency defined as $\chi_{ito} := v_{ito} + [\kappa_{ito} - E(\kappa_{ito})]$ can be decomposed as

$$\chi_{ito} = c_0 + \kappa_{ito} + v_{ito} \tag{19}$$

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

[19]The estimates of the applied LSDV method are equivalent those of the within estimator, which is often applied when estimating fixed effects (Wooldridge, 2012).

[20]With zero mean.

Overall Inefficiency
The overall TE can be calculated as product of

$$TE_{p,io} \cdot TE_{v,ito} = TE_{ito}. \tag{20}$$

Hence, the overall technical efficiency is always strictly smaller than $TE_{p,io}$ and $TE_{v,ito}$ except that at least one of them is equal to one.

4.2.3 Step 3: Decomposing Productivity Change

We decompose productivity change into scale change, technical change, and technical inefficiency change. First, we reformulate Equation 9, separating inefficiency from the input distance function as

$$\begin{aligned} -\ln(x_{L,it}) &= \alpha(t,o) \\ &+ \sum_{j\in\{N,T\}} \beta_j(t,o)\ln(\tilde{x}_{j,it}) \\ &+ \sum_{k\in\{C,E\}} \gamma_k(t,o)\ln(q_{k,it}) \\ &+ \sum_{l\in\{D,O\}} \delta_l(t,o)\ln(z_{l,it}) \\ &- u_{ito} + v_{ito} \end{aligned} \tag{21}$$

Taking first differences, we decompose the input change rate into different components for each firm by ownership structure by

$$\begin{aligned} \Delta - \ln x_{L,it} &= \text{technical change } + \text{change of inputs} \\ &+ \text{scale change} + \text{change of environmental variables} \\ &+ \text{change in inefficiency } + \text{residual term.} \end{aligned} \tag{22}$$

Next, we determine technical change TC by the change of the coefficients $\theta(i,t,o)$, $\beta_N(t,o)$, $\beta_T(t,o)$, $\gamma_C(t,o)$, $\gamma_E(t,o)$, $\delta_D(t,o)$ and $\delta_O(t,o)$ as:

$$\begin{aligned} TC \; := \Delta\alpha(t,o) + & \textstyle\sum_{j\in\{N,T\}} \Delta\beta_j(t,o)\ln(\tilde{x}_{j,it}) \\ + & \textstyle\sum_{k\in\{C,E\}} \Delta\gamma_k(t,o)\ln(q_{k,it}) \\ + & \textstyle\sum_{l\in\{D,O\}} \Delta\delta_l(t,o)\ln(z_{l,it}). \end{aligned} \tag{23}$$

Since $\tilde{x}_{N,it}$ and $\tilde{x}_{T,it}$ represent the input use relative to the numeraire input, $x_{L,it}$, input change, IC, in Equation 24 describes a substitution effect as a pure change in inputs as:

$$IC \ := \beta_N(t,o)\Delta \ln\left(\tilde{x}_{N,it}\right) + \beta_T(t,o)\Delta \ln\left(\tilde{x}_{T,it}\right). \tag{24}$$

Scale change SC and the change in environmental variables EC are straightforward to define and given by

$$SC \ := \ \gamma_C \Delta \ln(q_{C,it}) + \gamma_E \Delta \ln(q_{E,it}) \tag{25}$$

$$EC \ := \ \delta_D \Delta \ln(z_{D,it}) + \delta_O \Delta \ln(z_{O,it}) \tag{26}$$

Technical inefficiency change, InC, is given by

$$InC \ := \ \Delta u_{ito} \tag{27}$$

We define the rate of change of technical efficiency TEC as

$$TEC_{ito} := \frac{TE_{ito} - TE_{i(t-1)o}}{0.5(TE_{ito} - TE_{i(t-1)o})} \tag{28}$$

For a given firm with a certain ownership structure, the change of the overall TE corresponds exactly to the change of the time-varying technical efficiency (TE_v). This is reasonable, under the assumption that the change rate of the persistent technical inefficiency (TE_p) is zero.

$$TEC_{ito} = TEC_{v_{ito}} \tag{29}$$

For completeness, we define the residual term RT as

$$RT \ := \ \Delta v_{ito}.$$

5 Empirical Results

5.1 Nonparametric coefficients of the estimated input distance function

Tables 2 and 3 report the mean, median, and quartile values of the estimated smoothed coefficients of the input distance function, for all observations and grouped by ownership respectively. The coefficients and, thus, the elasticities of the input distance functions have the expected signs. The estimated values of the input coefficients, $\hat{\beta}_N(t,o)$ and

$\hat{\beta}_T(t,o)$, are positive and vary in the interval between 0 and 1.[21] It is reasonable that the cost share of the grid, $\hat{\beta}_N(t,o)$, is larger than the cost share of transformers, $\hat{\beta}_T(t,o)$, since transformers are only used to adjust the voltage level and the incurred costs of cables and lines to transmit electricity are higher. Due to duality, the output coefficients, $\hat{\gamma}_C(t,o)$ and $\hat{\gamma}_E(t,o)$, have negative signs.[22] The estimates of the coefficients of the environmental variables, $\hat{\delta}_D(t,o)$ and $\hat{\delta}_O(t,o)$, are also positive. An increase in the customer density by 1 percent leads on average to a decrease in the amount of hours worked by 9 percent. It is reasonable that a distribution grid serving a dense area of customers requires less maintenance intensive, i.e. less labor. An increase of the share of overhead power lines seems to have a negative effect on the number of employees, with the exception of some privately owned firms (lowest quartile of $\hat{\delta}_O(t,o)$ for private firms in Table 3).

Table 2: Estimated Coefficients of the Input Distance Function for all Observations

Coeff	Q25	Median	Mean	Q75	Q99	n
$\hat{\beta}_N(t,o)$	0.2756	0.4732	0.4311	0.5599	0.6367	1981
$\hat{\beta}_T(t,o)$	0.0246	0.0657	0.0675	0.1133	0.1287	1981
$\hat{\gamma}_C(t,o)$	-0.0182	-0.0102	-0.0117	-0.0044	-0.0034	1981
$\hat{\gamma}_E(t,o)$	-0.1672	-0.0518	-0.0972	-0.0277	-0.0242	1981
$\hat{\delta}_D(t,o)$	0.0322	0.0545	0.0913	0.1541	0.1850	1981
$\hat{\delta}_O(t,o)$	0.0005	0.0802	0.1096	0.2303	0.2657	1981

Figure 1 shows the average annual value of the input coefficients $\hat{\beta}_N(t,o)$ and $\hat{\beta}_T(t,o)$. The left panel displays that the cost share of the network on total costs $\hat{\beta}_T(t,o)$ grows constantly for both types of ownership, i.e. we observe increasing expenditure into the grid. From 2006 to 2009 public firms lag behind the privately owned firms, but by 2010 the cost shares of their networks converge towards the values estimated for privately owned firms. The right panel on Figure 1 shows that the cost shares of transformers develop similarly, but on a lower level.[23]

Figure 2 shows the average cost elasticities of the outputs per year, $\hat{\gamma}_C(t,o)$ and $\hat{\gamma}_E(t,o)$. $-\hat{\gamma}_E(t,o)$ is close to zero, independent of the ownership structure. It means that the increase of electricity distributed is not an important cost driver for a distribution system operator. Cost elasticity with respect to connected customers, $\hat{\gamma}_C(t,o)$, is higher.

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

[22] 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.

[23] When expanding a network beyond a certain level, the installed capacity of transformers will also need to be extended.

Table 3: Estimated Coefficients of the Input Distance Function - Public versus Private

Coeff	o	Q25	Median	Mean	Q75	Q99	n
$\hat{\beta}_N(t,o)$	pub	0.2756	0.4168	0.4108	0.5599	0.5910	1619
	priv	0.4732	0.5481	0.5218	0.6162	0.6367	362
$\hat{\beta}_T(t,o)$	pub	0.0246	0.0452	0.0636	0.1133	0.1287	1619
	priv	0.0657	0.0778	0.0851	0.1255	0.1260	362
$\hat{\gamma}_C(t,o)$	pub	-0.0182	-0.0102	-0.0126	-0.0036	-0.0036	1619
	priv	-0.0120	-0.0055	-0.0075	-0.0044	-0.0034	362
$\hat{\gamma}_E(t,o)$	pub	-0.1672	-0.0477	-0.0976	-0.0263	-0.0242	1619
	priv	-0.1383	-0.0615	-0.0952	-0.0478	-0.0297	362
$\hat{\delta}_D(t,o)$	pub	0.0301	0.0367	0.0908	0.1541	0.1850	1619
	priv	0.0519	0.0566	0.0939	0.1415	0.1595	362
$\hat{\delta}_O(t,o)$	pub	0.0005	0.0802	0.1116	0.2303	0.2424	1619
	priv	-0.0046	0.0518	0.1005	0.2089	0.2657	362

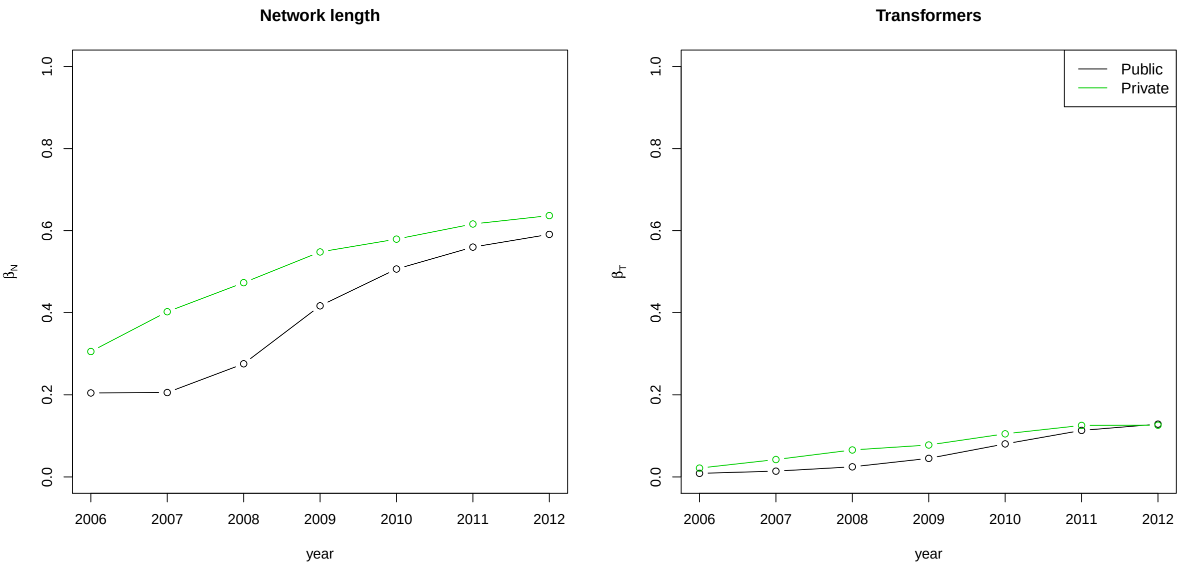
Connecting a customer to the electricity supply network implies that the grid needs to be expanded. The increase in fix costs for installing the new distribution lines by far exceed the variable costs for operation. From 2009 on $\hat{\gamma}_C(t,o)$ increases, peaks in 2011, and then decreases, but on a higher level compared to 2009.[24]
The cost elasticities of $z_{D,it}$ and $z_{O,it}$ correspond to the negative estimated values of $\hat{\delta}_D(t,o)$ and $\hat{\delta}_O(t,o)$. The pattern of $-\hat{\delta}_D(t,o)$, which is inversely related to the temporal progress of the cost elasticity $\hat{\gamma}_C(t,o)$, is explained by the expansion, i.e. increased cost, of the local renewable energy sources. Moreover, it is reasonable that network costs decrease with an increasing consumer density in urban areas and firms in rural areas are more affected by the expansion of renewable energy sources (Büchner et al., 2014). The development of the cost effect of the share of overhead power lines, which is negative during the whole observation period indicates that overhead power lines are less costly than underground cable.

5.2 Ownership-specific analysis of efficiency

Figure 3 shows the estimated annual averages of firm-specific technical inefficiency $\hat{u}_{ito}$, for the investigated firms. Although the mean inefficiency of the public firms is smaller, they do not perform less efficiently on average compared to the private firms, considering

[24] 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: Development of Input Coefficients

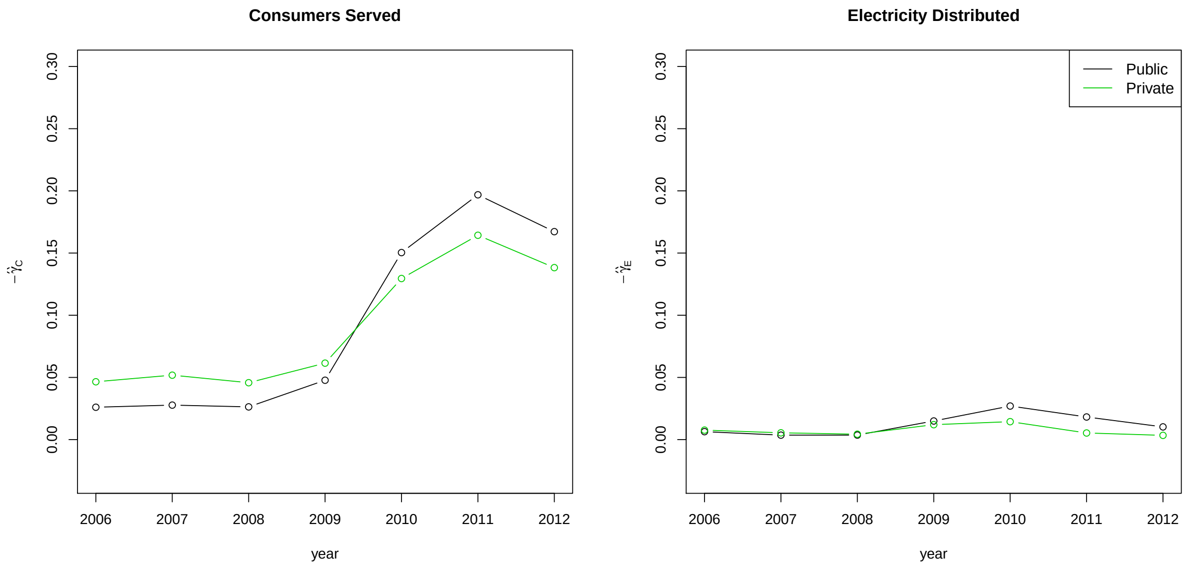


the potential differences in production technologies.

Figure 4 shows the development of technical efficiency and its components, i.e. persistent and time-varying technical efficiency. The left panel presents the annual average of the overall efficiency scores TE, which range from 0.49 to 0.66. TE of the public firms lies above the TE of the private firms. At the start of the observation period, the private firms reduce inefficiency more rapidly than the public firms, but in later years only a small gap separates the two. More detailed, Figure 5 shows a left-skewed distribution of the technical efficiency scores for both groups. Three firms of the private firms are fully efficiently, but no publicly owned firm is fully efficient. In fact, only 19 percent of the public firms achieve efficiency scores larger than 0.80.

Comparing the left and the middle panel in Figure 4 reveals that the persistent technical efficiency $TE_{P,ito}$ follows the same time pattern as the overall TE for both types of firms, except that their estimated values are slightly higher. Since the overall efficiency scores are computed as a product of persistent and time-varying efficiency, which remains nearly constant at a level close to one (right panel of Figure 4), the low average efficiency level probably relate to parts of the internal production processes which are influenced in the long run. Hence, the inefficiencies can be interpreted as quasi-fixed over the whole observation period and that all firms have nearly eliminated all sources of inefficiency which can be influenced in the short run.

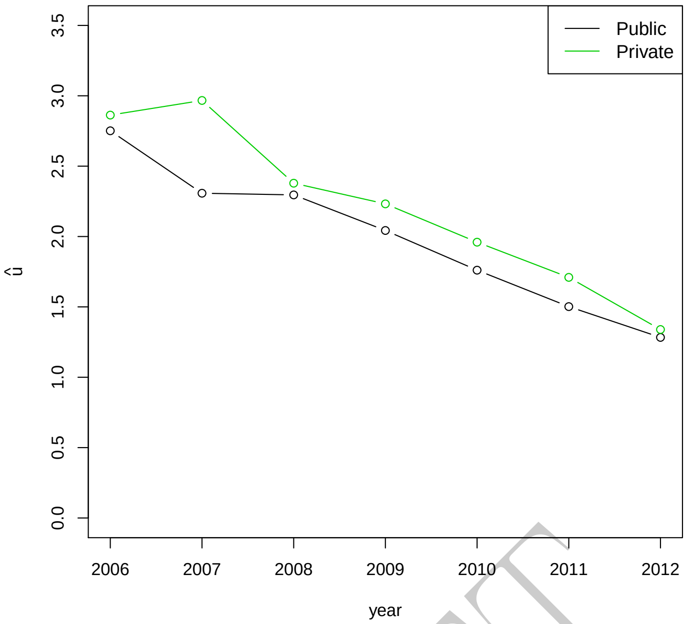
Figure 2: Cost Elasticities of Consumers Served and Electricity Distributed



5.3 Ownership-specific analysis of productivity change and components

Figures 6 and 7 show the main findings for the results of decomposing productivity change into its components, i.e. technical change TC, input change IC, scale change SC, change in environmental variables EC, and inefficiency change InC. The index of the average rate of technical change in Figure 6 decreases over time. We interpret TC in the context of an input distance function, i.e., a rate decrease infers technical progress. Beginning in 2009, decentralized renewable energy expansion and associated grid optimization took place throughout Germany. The figure also indicates that the technical process of the publicly owned firms is characterized by an ongoing, more uniform, process than for the private firms. For private firms technical progress even appear to stagnate after 2009. The panel of Figure 7 display input change and inefficiency change as index scores, respectively. The input change (left panel) reflects the change in inputs relative to the numeraire input labor multiplied by the estimated input coefficients, which can be interpreted as a substitution effect. The input change for the public firms remains constant over time, whereas there is a slight decrease for the private firms towards the end of the observation period. Given that the coefficient of network length β_N is increasing (left panel of Figure 1), this result reflects that a substitution effect as a constant level of input change can only be achieved with a decreasing ratio of network length to hours worked. The right panel of Figure 7 shows that the private firms' average change rate of inefficiency increases slightly from 2007 to 2008 and then steadily decreases, whereas the public firms' average

Figure 3: Development of the Inefficiency Term u

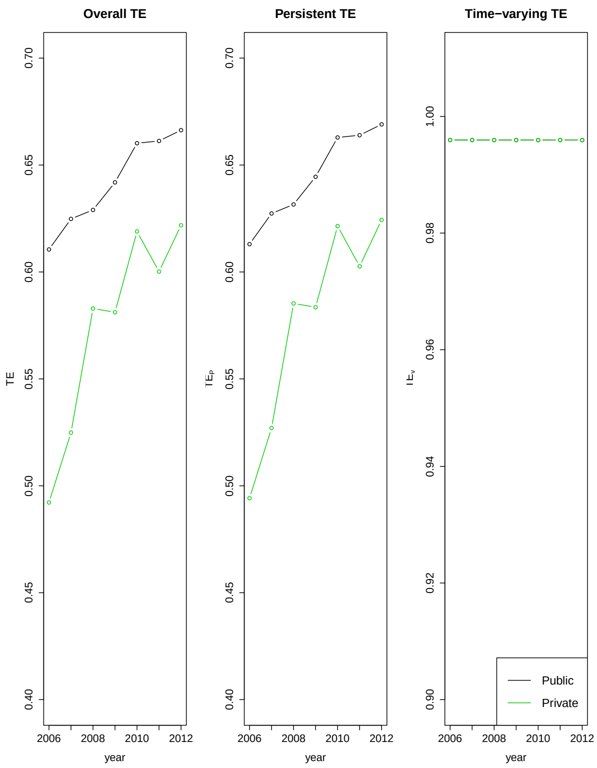


change rate declines from 2007 to 2012. Overall, the development of the average change rate of inefficiency is in line with the time pattern of inefficiency shown in Figure 3. SC and EC, however, remain unchanged for public and private firms throughout the whole observation period and therefore not presented in the paper.

6 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 and productivity across ownership type. The proposed model was flexible enough to differentiate between time-persistent and time-varying ineffifficiency and to decompose productivity change into components, i.e. technical change, input change, scale change, and inefficiency change. The model was validated with a unique and newly constructed dataset of Germany's public and private electricity distribution firms operating between 2005 and 2012. Our dataset contains 1981 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. However, while public firms are characterized by an ongoing tech-

Figure 4: Development of the Technical Efficiency



nical progress, private firms appear to stagnate with respect to technical progress after 2009. 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.

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Figure 5: Histogramm: TE of Public and Priavte DSOs

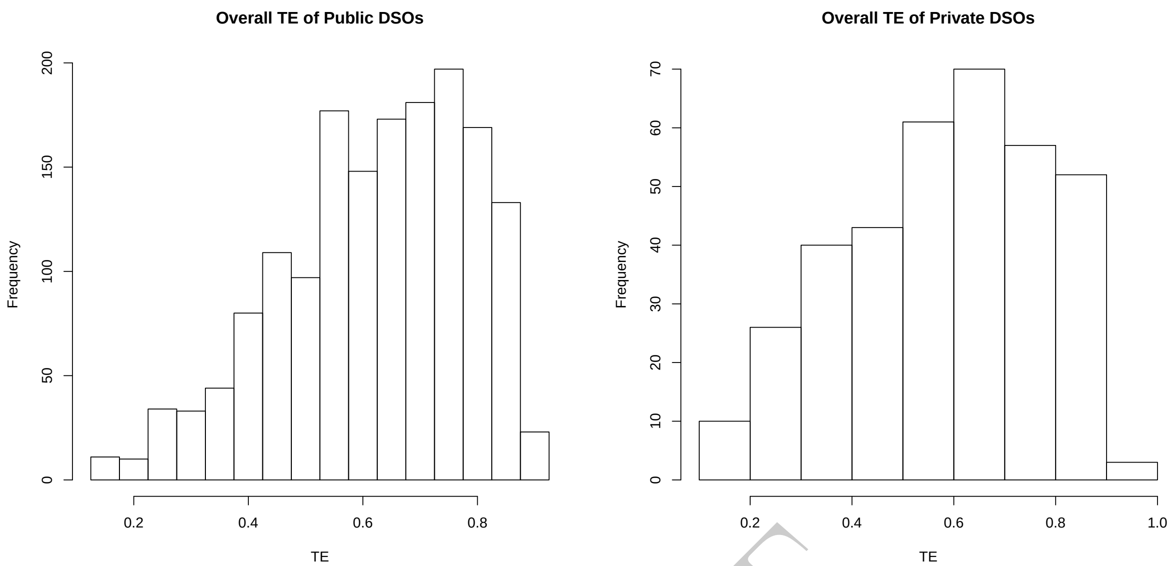


Figure 6: Technical Change

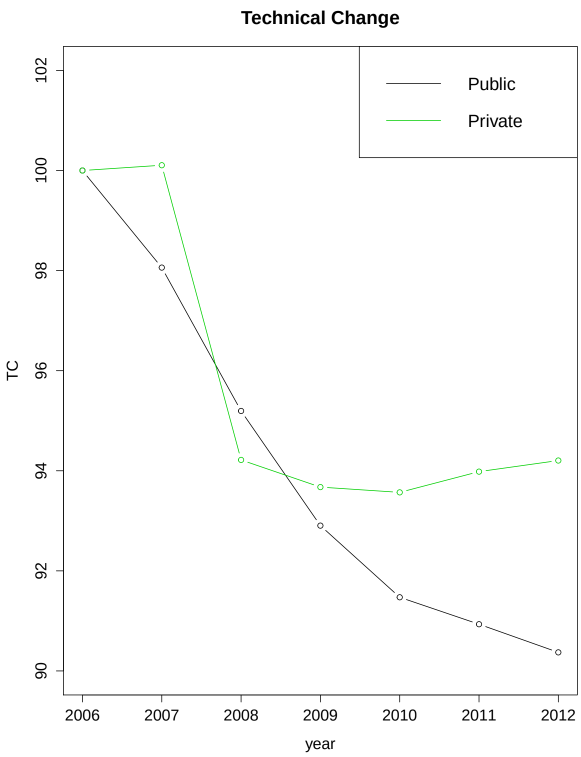
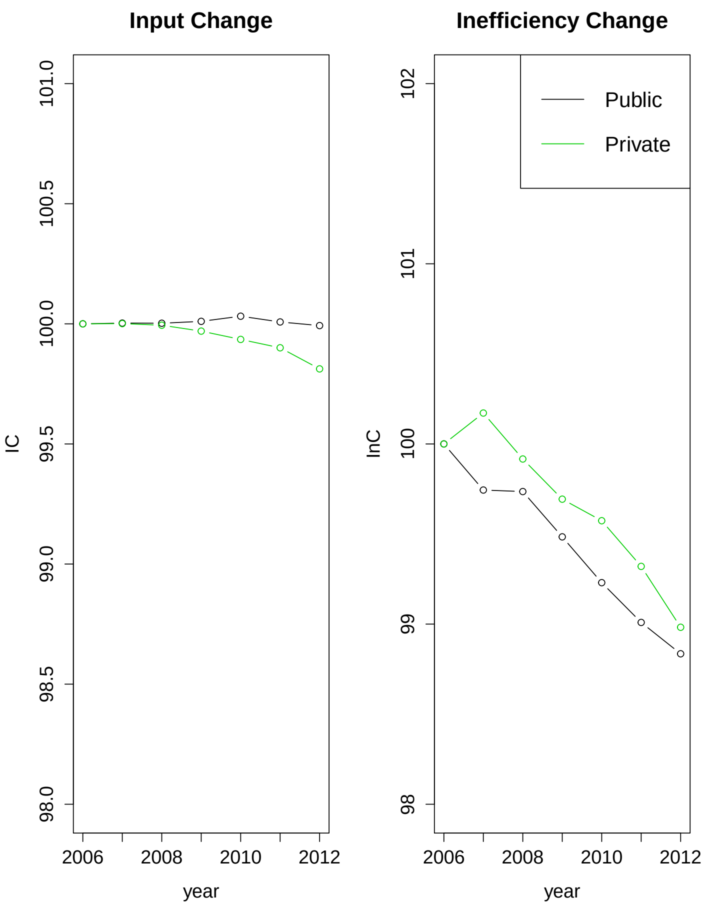


Figure 7: Input Change



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