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AUTHOR

Lisa Just

Heike Wetzel

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Lisa Just[a,b,*], Heike Wetzel[c]

[a]*Institute of Energy Economics at the University of Cologne gGmbH, Vogelsanger Strasse 321a, 50827 Cologne, Germany*
[b]*Department of Economics, University of Cologne Vogelsanger Strasse 321a, 50827 Cologne, Germany*
[c]*Institute of Economics, University of Kassel, Nora-Platiel-Str. 4, 34109 Kassel, Germany*

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Abstract

In this paper, we use a comprehensive and unique data set of financial, technical and structural characteristics of German distribution network operators from 2011 to 2017 to estimate both the transient and persistent cost efficiency of German distribution network operators. In addition, we analyze the effect of an increasing capacity of distributed generation from renewable energy sources on the total costs of distribution network operators. Our results indicate an average cost reduction potential of approximately 12 percent in the short term and approximately 18 percent in the long term for German electricity distribution network operators. Furthermore, we find that distributed generation from renewable energy sources is a significant cost driver in the production process of network operators. Our study thus contributes to the ongoing debate on incentive regulation and efficiency benchmarking in electricity distribution industries and provides valuable insights for policymakers and regulators.

Keywords: Electricity distribution, regulation, transient cost efficiency, persistent cost efficiency, distributed generation, stochastic frontier analysis

JEL classification: L23, D24, L51, L94

*Corresponding author:
Email address: `lisa.just@ewi.uni-koeln.de`, +49 221 277 29 313 (Lisa Just)

1. Introduction

Electricity networks, which are considered natural monopolies with limited or no competition, are regulated. Over the last few decades, incentive regulation has been the most commonly chosen regulatory framework for gas and electricity network operators worldwide. In 2009, Germany introduced incentive regulation for electricity networks with the aim of preventing excessively high network access charges and increasing the efficiency of network operators. A key element of incentive regulation is the use of efficiency benchmarking techniques that determine individual efficiency targets for each network operator. Regulators use a variety of different econometric methods, such as data envelopment analysis (DEA), stochastic frontier analysis (SFA) and semi-parametric methods, to identify these targets (Kumbhakar and Lien, 2017). Furthermore, within the econometric methodologies, model specifications differ widely with respect to the selection of variables, the assumptions concerning the underlying functional form and the sources of inefficiency considered.

In this paper, we employ state-of-the-art stochastic frontier panel data models to investigate the influence of different model specifications on the estimated individual cost efficiency targets of a large number of German electricity distribution network operators. In particular, we focus on the performance of recently developed SFA models that account for both transient and persistent inefficiency (Colombi et al., 2014; Tsionas and Kumbhakar, 2014; Filippini and Greene, 2016), as opposed to the widely used conventional SFA models that focus only on one source of inefficiency.

A distinction between transient and persistent inefficiency is important for regulatory purposes, as policy implications for improving persistent and transient efficiency are different. Transient inefficiency, for example induced by short-term managerial misbehavior, could be addressed relatively easily by implementing appropriate incentives in the existing regulatory framework. In contrast, persistent inefficiencies indicate structural problems that may require a general adjustment of the regulatory approach (Kumbhakar and Lien, 2017; Filippini et al., 2018).

There are only a few empirical applications that consider different types of efficiency of electricity distribution network operators. Kumbhakar and Lien (2017) use a panel of Norwegian electricity distribution companies between 2000 and 2013. They find differences among models that account for different outcomes in terms of short-term, long-term and overall efficiency and conclude that a proper regulatory design is crucial to obtain correct efficiency measures. Kumbhakar et al. (2020) quantify the cost of input misallocation, differentiating between the persistent and transient technical efficiency of Norwegian electricity distribution firms between 2000 and 2016. The results show evidence of persistent inefficiency and non-negligible costs of input misallocation. Using the data of 28 New Zealand electricity distribution companies from 2000 to 2011, Filippini et al. (2018) analyze the impact of the distinction between transient and persistent efficiency components in terms of price cap regulation. Based on the identification of differences, the authors conclude that the regulator should apply differentiated efficiency measures.

For Germany, there is only one study that distinguishes between transient and persistent efficiency. Using a panel data set with 1,370 observations between 2006 and 2012, Badunenko et al. (2021) investigate the effect of restructuring electricity distribution systems following the German reunification and find that Eastern and Western distribution network operators exhibit the same transient efficiency but vary in their persistent efficiency. However, as in the few earlier studies for Germany that dealt with only one source of efficiency (von Hirschhausen et al., 2006; Hess and Cullmann, 2007; Cullmann, 2012), Badunenko et al. (2021) analyze only technical efficiency and do not consider cost efficiency.

The lack of studies on the cost efficiency of German distribution network operators is largely due to the fact that, unlike in other countries, such as Norway and New Zealand, the German regulator does not publish data on the network operators included in its efficiency benchmarking. In particular, cost-related data must be collected from the annual reports of individual companies, which is a cumbersome process. In this paper, we use a unique and comprehensive panel data set of the financial, technical and structural characteristics of German distribution network operators from 2011 to 2017 that allows us to estimate both persistent and transient cost efficiency for a large segment of German electricity distribution network operators.

Such an analysis is particularly interesting for two reasons: First, with around 900 electricity distribution network operators, Germany has a high number of heterogeneous network operators. Second, over the last two decades, there has been a significant and dynamic increase in distributed generation from renewable energy sources. As the major share of distributed generation is connected to the distribution network and given that network operators are legally obliged to connect and preferably dispatch distributed generation, it is likely that they will be financially affected by an increase of distributed generation. In the short term, the stochastic nature of decentralized generation makes it difficult to ensure safe and reliable grid operation, which increases the need for active intervention by the operator. In the long term, network expansion, modernization and innovation are essential.

The development of distributed generation from renewable energy sources has also been taken into account by the German regulator. While accompanying studies to the German regulatory benchmarking do not find a significant influence of distributed generation on the costs of electricity distribution network operators in the first and second regulation period, they do find one in the third regulation period (Sumicsid and EE2, 2008; Swiss Economics and Sumicsid, 2014; Swiss Economics et al., 2019). For the regulatory benchmarking, however, only cross-sectional data from a single year and a small number of network operators are used.

In this context, our study is the first to use a large panel data set to analyze the impact of a large amount of distributed generation from renewable energy sources on the total costs of German electricity distribution network operators. Second, we analyze how different model specifications in terms of assumptions regarding the underlying functional form and the sources of inefficiency influence the estimated cost function parameters and both transient and persistent cost efficiency estimates. As electricity generation from renewable energy sources is increasing worldwide and electricity network regulation is becoming increasingly complex, our results are of high interest for not only German policy makers but also electricity network regulators globally.

The remainder of the paper is structured as follows: Section 2 offers a brief description of the German incentive regulation and the development of distributed electricity generation, while Section 3 presents the methodology. Section 4 describes the data, and Section 5 reports the empirical results. Finally, Section 6 summarizes the main results and concludes.

2. The German incentive regulation and distributed electricity generation

In 2009, Germany introduced incentive regulation with the aim of simulating competition among electricity distribution network operators and providing incentives to increase their cost efficiency. To prevent network operators from setting excessively high network tariffs and earning monopoly rents, an annual revenue cap is assigned to each operator.[1]

The starting point of this revenue cap is a regulatory period of five years. The first regulatory period was from 2009 to 2013, the second was from 2014 to 2019 and the third started in 2019 and will end in 2023. The third year of a regulatory period is also the base year t = 0 for the following period. This means that the regulator takes the costs of this year as a starting value for determining the annual revenue caps in the following regulatory period and in a first step breaks them down into two elements: permanently non-controllable costs and controllable costs. Examples of permanently non-controllable costs include concession fees and taxes neither of which can be influenced by a network operator.

In a second step, the regulator carries out an efficiency benchmarking of the controllable costs among the network operators and on this basis further breaks down operator-specific controllable costs into temporarily non-controllable costs and controllable costs. From an efficiency benchmarking perspective, the temporarily uncontrollable costs represent efficient costs, whereas the controllable costs represent inefficient costs. If, for example, the efficiency score for a network operator obtained from the benchmarking is 0.8, the regulator considers 80 percent of the operator's controllable costs efficient and 20 percent inefficient.

Finally, on the basis of the cost evaluation and the efficiency benchmarking, the regulator sets an annual revenue cap RC_{it} for network operator i in year t according to the following formula:

$$RC_{i,t} = C_{pnc,i,t} + (C_{tnc,i,0} + (1 - DF_{i,t})C_{c,i,0} + \frac{B_0}{T})(\frac{CPI_t}{CPI_0} - PF_t) + X_{i,t}, \tag{1}$$

where $C_{pnc,i,t}$ denotes the permanently non-controllable costs in year t and $C_{tnc,i,0}$ and $C_{c,i,0}$ denote the temporarily non-controllable costs and the controllable costs, respectively, in the base year $t = 0$. DF represents a distribution factor that increases from 0.2 up to 1 within a regulatory period and thus defines a reduction path for the controllable (i.e., the inefficient) costs. Furthermore, the formula includes an efficiency bonus B_0 for very efficient network operators that is distributed over the length of the regulation period T, an inflation correction via the consumer price index $\frac{CPI_t}{CPI_0}$, a general sectoral productivity factor PF_t and some additional factors summarized in $X_{i,t}$, which are not discussed in detail here for

[1]The following description in based on the German Incentive Regulation Ordinance (ARegV). More details can also be found in Swiss Economics et al. (2019).

simplicity.[2] Overall, the revenue cap formula shows that the German incentive regulation and thus the network operator-specific revenues strongly depend on a correct determination of the individual efficiency scores of network operators.

To determine individual efficiency scores, electricity network regulators worldwide use non-parametric, parametric and semi-parametric benchmarking techniques. These techniques differ in terms of their flexibility and consideration of stochastic noise. Non-parametric techniques such as DEA are extremely flexible and do not require the assumption of a functional form. However, non-parametric techniques do not take stochastic noise into account and therefore carry the risk of data errors. In contrast, parametric techniques such as SFA take stochastic noise into account but have the disadvantage of requiring a functional form, which can lead to specification errors. The German regulator, the Bundesnetzagentur, uses a mixture of both methods to determine individual efficiency scores. Each network operator is assigned the best efficiency score out of four model specifications that result from two DEA and two SFA specifications ("'best of four principle"').

Furthermore, the model specifications differ considerably in terms of their consideration of the heterogeneity of network operators. Since both supply tasks and regional characteristics can vary considerably from one network operator to another, performing only a simple comparison of the costs would lead to misleading results. For example, network operators operate in different landscapes, have different network sizes, different numbers of customers and so forth. Therefore, it is crucial to consider both the individual and regional characteristics of network operators in the efficiency benchmarking. Accordingly, structural variables that are expected to have an impact on costs must be included in the benchmarking process. In Germany, the Incentive Regulation Ordinance (ARegV) defines the variables that have to be considered (§13 AregV). These variables include the number of exit and metering points, the length of underground cables and overhead lines, the annual peak load, the supply area and the capacity of distributed generation.

In Germany, the consideration of distributed generation is of particular interest, as there has been a significant and dynamic increase in distributed generation in recent years. This increase is mainly due to the support scheme established by the Renewable Energy Source Act (EEG). A guaranteed feed-in tariff for 20 years, a connection obligation and a preferential feed-in have led to a rapid increase in distributed generation. From 2008 to 2017, the number of renewable power plants rose from about 0.5 million to more than 1.7 million. As shown in Figure 1, this increase in facilities is related to an increase in installed capacity from about 35 GW in 2008 to about 108 GW in 2017 (Bundesnetzagentur, 2019a). Renewable energies also play an important role in the consumption mix: In 2017, 36 percent of gross electricity consumption came from renewable sources (Federal Ministry for Economic Affairs and Energy, 2019).

[2] The additional factors include a cost of capital premium for investments after the base year, a quality factor to ensure quality of supply, volatile cost shares and surcharges or discounts on the regulatory account. For a detailed description of all factors included in the revenue cap formula and the calculation of the efficiency bonus, see Incentive Regulation Ordinance (ARegV).

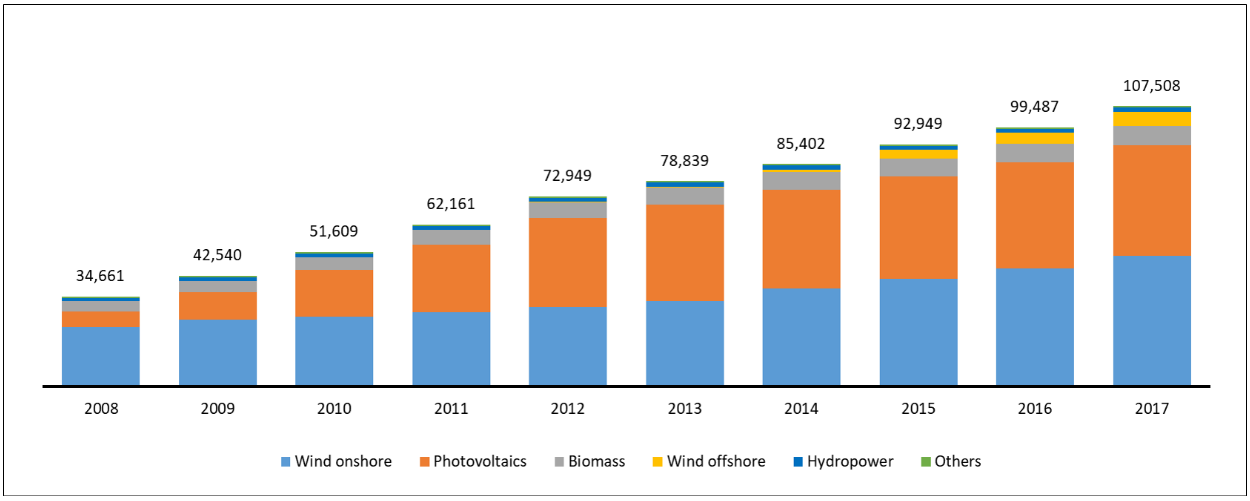


Figure 1: Installed capacity of distributed generation eligible for EEG payments in megawatt [MW]
Source: Bundesnetzagentur (2019a)

A substantial majority of 93 percent of installed renewable power plants are connected to the distribution network (E-Bridge et al., 2014). The German distribution network is operated by almost 900 network operators, which are extremely heterogeneous in terms of size and structure. Due to the increase in distributed generation, there has been an intensive discussion concerning the associated cost consequences for network operators. Challenges arise not only from the pure number of renewable power plants and their capacity but also from the associated increase in volatility in power generation and the changing structure of consumers who simultaneously become generators. Stabilizing the system therefore requires more active intervention by network operators (BDEW, 2016), which could lead to increasing operating costs. Furthermore, increasing connections of renewable power plants could result in a need for network expansions. Due to different network structures (e.g., in urban vs. rural areas), the extent of the necessary network expansions and thus the investment costs may differ considerably (E-Bridge et al., 2014). The heterogeneity of network operators and, moreover, the unequal distribution of distributed generation among network operators may lead to these operators not being equally affected by the increase in distributed generation. Hence, in the following, we analyze whether distributed generation has a cost effect and whether it causes differences in the efficiency of network operators.

3. Methodology

In line with previous studies on the cost efficiency of electricity distribution network operators, we define the total costs of an electricity distribution network operator as a function of input prices, outputs and a number of network characteristics that account for the heterogeneity of an operator's network environment. Using two outputs and five network characteristics, the total cost function can be written as

$$TC = C(QE, QC, ND, SC, DG, I, East, DT) \tag{2}$$

where TC denotes the total costs, QE is the amount of electricity supplied, QC is the number of connection points, ND denotes the network density, SC is the share of underground cable in the total network and DG denotes the installed capacity of distributed generation. Furthermore, we include two dummy variables, I and $East$. I refers to structural differences in terms of whether or not operators are integrated (i.e., operators that operate an electricity and a gas distribution network or only operate an electricity distribution network). In addition, $East$ captures structural differences of operators located in East or West Germany. Finally, the dummy variables DT capture changes over time.

Due to a lack of data, we do not include input prices in our analysis. Thus, we assume that there exist no significant differences in input prices across distribution network operators in Germany, an assumption that has been used in other electricity network studies and is also used by the German regulator (Filippini and Wetzel, 2014; Swiss Economics et al., 2019). A detailed description of the variables and their expected impact on total costs is provided in the following section (see Section 4).

In the next step of the analysis, we define a functional form for the total cost function. In empirical studies on electricity network operators, the Cobb-Douglas and translog functional forms are most commonly used. The Cobb-Douglas functional form is relatively simple and easy to estimate. However, it has the drawback that it imposes a number of a priori restrictions on the structure of the underlying technology. A translog functional form is more flexible but more difficult to estimate. Particularly when it comes to highly correlated variables, the translog function form can easily suffer from multicollinearity problems (Filippini et al., 2018). For reasons of comparison and to investigate the impact of different functional forms on the inefficiency estimates, we use both the Cobb-Douglas and the translog functional forms in our analysis. Based on Equation 2, the translog cost function can be written as

$$\begin{aligned}
lnTC_{it} =& \beta_0 + \beta_{QE} lnQE_{it} + \beta_{QC} lnQC_{it} + \beta_{ND} lnND_{it} + \beta_{SC} lnSC_{it} + \beta_{DG} lnDG_{it} \\
&+ 0.5\beta_{QEQE}(lnQE_{it})^2 + 0.5\beta_{QCQC}(lnQC_{it})^2 + 0.5\beta_{NDND}(lnND_{it})^2 \\
&+ 0.5\beta_{SCSC}(lnSC_{it})^2 + 0.5\beta_{DGDG}(lnDG_{it})^2 + \beta_{QEQC} lnQE_{it} lnQC_{it} \\
&+ \beta_{QEND} lnQE_{it} lnND_{it} + \beta_{QESC} lnQE_{it} lnSC_{it} + \beta_{QEDG} lnQE_{it} lnDG_{it} \\
&+ \beta_{QCND} lnQC_{it} lnND_{it} + \beta_{QCSC} lnQC_{it} lnSC_{it} + \beta_{QCDG} lnQC_{it} lnDG_{it} \\
&+ \beta_{NDSC} lnND_{it} lnSC_{it} + \beta_{NDDG} lnND_{it} lnDG_{it} + \beta_{SCDG} lnSC_{it} lnDG_{it} \\
&+ \beta_I I_i + \beta_{East} East_i + \beta_t T_t + \epsilon_{it},
\end{aligned} \tag{3}$$

where i indicates the firm and t the time period, the βs are the unknown parameters to be estimated and ϵ_{it} is the error term. The Cobb-Douglas functional form is nested in the translog functional form with all second-order and interaction terms dropped from Equation 3. Later, we use postestimation likelihood ratio tests to determine which functional form represents a better fit to the data.

A large number of SFA models for panel data can be used to estimate the defined total cost function. For reasons of comparison, we use three models in our analysis. As shown in Table 1, the models differ in terms of the econometric specification of the error term ϵ_{it} and thus in their measurement of both persistent and transient inefficiency.

Table 1: Econometric specification

	Model I - RE	Model II - TRE	Model III - GTRE
Error term	$\epsilon_{it} = v_{it} + u_i$	$\epsilon_{it} = \omega_i + v_{it} + u_{it}$	$\epsilon_{it} = \omega_i + h_i + v_{it} + u_{it}$
	$v_{it} \sim N[0, \sigma_v^2]$	$v_{it} \sim N[0, \sigma_v^2]$	$v_{it} \sim N[0, \sigma_v^2]$
	$u_i \sim N^+[0, \sigma_u^2]$	$u_{it} \sim N^+[0, \sigma_u^2]$	$u_{it} \sim N^+[0, \sigma_u^2]$
		$\omega_i \sim N[0, \sigma_\omega^2]$	$\omega_i \sim N[0, \sigma_\omega^2]$
			$h_i \sim N^+[0, \sigma_h^2]$
Estimator			
Persistent inefficiency	$E(u_i \mid \epsilon_{i1}, \ldots, \epsilon_{iT})$		$E(h_i \mid \epsilon_{it})$
Transient inefficiency		$E(u_{it} \mid \epsilon_{it})$	$E(u_{it} \mid \epsilon_{it})$

The first model is the random effects (RE) model proposed by Pitt and Lee (1981). In this model, the error term consists of two components: a half-normally distributed time-invariant component u_i which measures persistent inefficiency and a normally distributed time-varying component v_{it} which captures random noise. The model estimates are obtained by maximum likelihood estimation, and, as proposed by Jondrow et al. (1982), the individual level of inefficiency is predicted by the conditional mean of the inefficiency term u_i. The major shortcomings of this model are that it only estimates persistent inefficiency and that all time-invariant individual effects are included in the inefficiency estimates. Consequently, should any time-invariant unobserved heterogeneity exist, the RE model will tend to overestimate the level of persistent inefficiency (Greene, 2005a).

The second model is the true random effects (TRE) model developed by Greene (2005a,b). This model accounts for the shortcomings of the RE model by adding an individual random effect ω_i to the error term. As a result, the normally distributed time-invariant component ω_i captures time-invariant unobserved heterogeneity, and the half-normally distributed time-variant component u_{it} measures transient inefficiency. The model estimates are obtained by maximum simulated likelihood estimation, and, as in the RE model, the individual level of inefficiency is predicted by the conditional mean of the inefficiency term u_{it}. This specification separates time-invariant unobserved heterogeneity from time-varying inefficiency and therefore addresses one of the two limitations of the RE model. However, since all time-invariant individual effects are treated as unobserved heterogeneity, any persistent inefficiency is not included in the inefficiency term. Consequently, while the RE model tends to overestimate inefficiency, the TRE model tends to underestimate it (Farsi et al., 2006).

This problem is accounted for by the third model, the recently proposed generalized true random effects (GTRE) model (Filippini and Greene, 2016). The GTRE model accounts for both persistent and transient inefficiency by adding a fourth component h_i to the error term. Thus, h_i, captures persistent inefficiency and is assumed to be half-normally distributed. As before, v_{it} accounts for random noise, ω_i reflects unobserved time-invariant heterogeneity and u_{it} measures transient inefficiency. As for the TRE model, the model estimates are obtained by maximum simulated likelihood estimation, and the individual levels of persistent and transient inefficiency are predicted by the conditional mean of the corresponding inefficiency terms u_{it} and h_i following the approach outlined in Filippini and Greene (2016).

Individual persistent efficiency scores are calculated as $PE_i = \exp(-\hat{u}_i)$ in the RE model and as $PE_i = \exp(-\hat{h}_i)$ in the GTRE model. Individual transient efficiency scores are calculated as $TE_{it} = \exp(-\hat{u}_{it})$. A value of one indicates 100 percent efficiency, and a value lower than one indicates some degree of inefficiency.

Despite the fact that the GTRE model is the most sophisticated of the three models and addresses several of the shortcomings of the other two models, we retain the RE and the TRE models in our analysis for reasons of comparison. The RE and TRE model are still extremely popular in the field of parametric efficiency analyses, and one contribution of our analysis is showing the impact of different modeling approaches on the estimated efficiency scores in a regulatory framework.

4. Data

For our analysis, we use a comprehensive and unique database of German electricity distribution network operators from 2011 to 2017. Financial data are obtained from the publicly available financial reports of energy firms that operate an electricity distribution network. By law, vertically integrated energy firms in Germany have to publish separate accounts concerning their activities in electricity and gas distribution (§6b Energy Industry Act (EnWG)). These accounts allowed us to collect financial data that are directly connected to the operation of electricity distribution networks and are not combined with other activities that these firms engage in. In addition, we extended the database with technical data from the professional data provider ene't and with data on renewable power plants from the renewable power plant installation register maintained by the four German transmission system operators (50 Hertz Transmission GmbH et al., 2018). The register contains all renewable power plants that are subsidized by the EEG, which applies to more than 95 percent of all renewable power plants in Germany (Bundesnetzagentur, 2019a; Federal Ministry for Economic Affairs and Energy, 2019).

Table 2 shows the number of observed electricity distribution network operators, the total network length, the total number of connection points and the total installed capacity of distributed generation included in our sample by year. In addition, we also present the total numbers for Germany for reasons of comparison. Our sample contains 2,109 observations from 453 distribution network operators. Notably, there are much fewer observations in 2017 than in the other years, as not all firms had published their annual reports for 2017 at the time of data collection. In consequence, the volumes of the other variables are also lower

Table 2: Sample overview

Year	2011	2012	2013	2014	2015	2016	2017
Network operators [number]							
Sample	299	318	326	348	354	351	113
Germany	869	883	883	884	880	875	878
Percent	34	36	37	39	40	40	13
Network length [million km]							
Sample	0.7	0.8	0.8	0.8	1.1	1.1	0.4
Germany	1.9	1.8	1.8	1.8	1.8	1.8	1.8
Percent	37	44	44	44	61	61	22
Connection points [million]							
Sample	21.8	22.6	22.9	25.4	31.7	32.8	13.0
Germany	47.7	48.8	49.9	50.1	50.3	50.7	50.5
Percent	44	46	46	51	63	65	26
Distributed generation [GW]							
Sample	33.8	39.2	38.2	44.3	58.8	66.2	14.9
Germany	62.2	72.9	78.8	85.4	92.9	99.5	107.5
Percent	37	54	48	52	63	67	14

Sources: Bundesnetzagentur (2013, 2014a,b, 2016a,b, 2017, 2019b,a)

in 2017 than in 2016. Overall, the table shows that our sample covers a large proportion of the German electricity distribution sector. In particular, in 2015 and 2016, our sample represents more than 60 percent of the sector in terms of network length, connection points and distributed generation. The scope of our dataset thus renders it quite unique, since, in contrast to other countries, no detailed publicly available data on electricity network operators are provided by the German regulator.

Table 3 shows descriptive statistics of the variables used in the total cost function defined in Equation 3. Total costs (TC) are defined as the sum of variable and capital costs. The variable costs consist of personnel expenses, material expenses and other operating expenses, while the capital costs consist of depreciation and opportunity cost of capital. The opportunity cost of capital is calculated by multiplying fixed assets by the interest rate paid on long-term debt. All monetary values are adjusted for inflation using the consumer price index for Germany and are stated in year 2010 Euros. To define the cost function, we consider two outputs: the number of connection points (QC) and the electricity transferred in gigawatthours (QE). These two outputs reflect the two elements of the joint service of electricity distribution: network connection and electricity supply (Neuberg, 1977). Numerous empirical studies on electricity distribution networks have used this output combination (Filippini and Wetzel, 2014; Hess and Cullmann, 2007; Cullmann, 2012; Growitsch et al., 2012).

Furthermore, to account for the rapidly increasing number of renewable power plants connected to German electricity distribution networks, we include the variable distributed

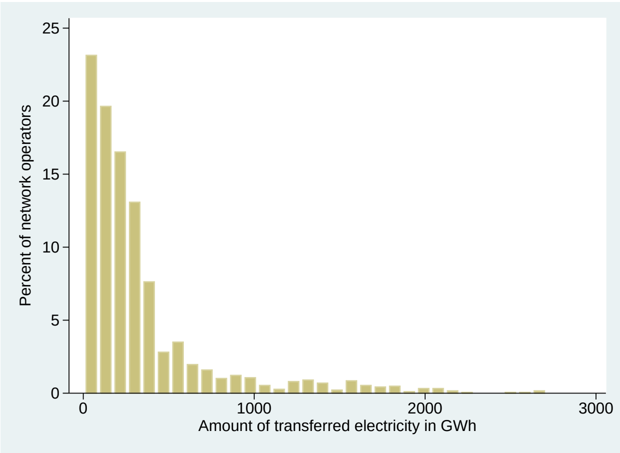
Table 3: Descriptive statistics

	Mean	Median	Std. dev.	Minimum	Maximum
Total costs (million 2010€)	61.54	11.53	263.60	0.25	5,235.34
Electricity transferred (GWh)	1,993.72	244.93	10,191.12	4.76	247,549.60
Connection points (thousand)	80.69	18.58	273.13	0.45	4,965.61
Distributed generation (MW)	140.10	14.70	908.11	0.35	16,120.73
Network density (connection points/network km)	37.12	32.97	24.67	6.49	268.97
Share of cable (cable km/network km)	0.93	0.97	0.09	0.14	1.00
Integrated	0.80			0	1
East	0.19			0	1

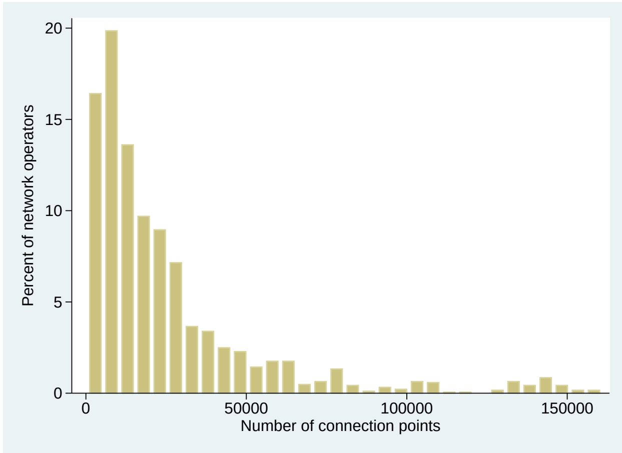
generation (DG). DG is measured in megawatts and comprises the installed capacity of wind energy (on and offshore), solar power, biomass, hydropower, deep geothermal energy, mine gas, landfill gas and sewage gas. Since connecting fluctuating renewable energy sources to the network incurs both connection and system stability costs, we expect a positive sign for the distributed generation coefficient, indicating higher costs for distribution operators with a higher amount of distributed generation connected to the network.

Figure 2 presents frequency distributions of the two outputs and the distributed generation. For clarity, the graphs are limited to the 90 percent percentiles and thereby show that approximately 90 percent of network operators transfer less than 3,000 GWh electricity, have fewer than 165,000 connection points and less than 80 MW installed capacity of distributed generation connected to their network in all years. The right-skewed distributions shown in Figure 2 illustrate the high number of small network operators in the sample. The median values in Table 3 show that about 50 percent of the distribution network operators transferred less than 245 GWh electricity, have fewer than 19,000 connection points and less than 15 MW installed capacity of distributed generation connected to their network in all years. These numbers show the highly fragmented structure of the German electricity distribution sector. Nevertheless, our data set also includes a number of very large distribution network operators. The largest network operator in the sample is Westnetz, which transferred 247 TWh of electricity and had almost 5 million connection points in 2015. With more than 16 GW installed capacity of distributed generation connected to its network, Avacon AG is the distribution network operator with the highest capacity of distributed generation in the sample.

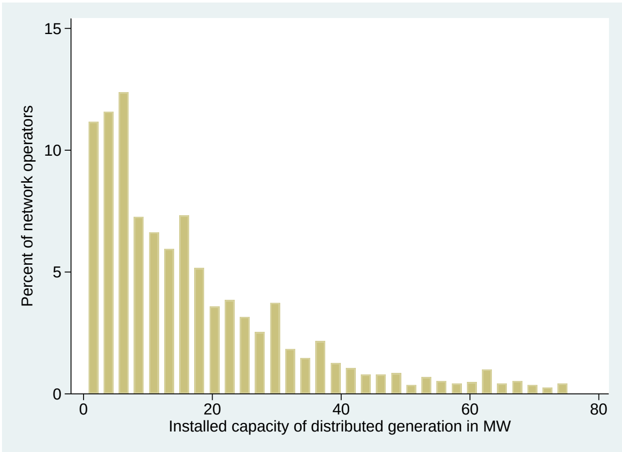
In addition to the large differences in the levels of the two outputs and the installed capacity of distributed generation connected to the networks, we also see large differences in the other structural variables included in our analysis. Network density varies from very dense networks with up to 270 connection points per network km to very low density networks with only six connection points per network km. A similar picture emerges for the share of underground cables in the total network, which ranges between 14 and 100 percent. We expect a negative sign for the network density coefficient, indicating that networks with higher density can benefit from density effects and can therefore operate at lower costs than



(a) Transferred electricity in GWh



(b) Number of connection points



(c) Installed capacity of distributed generation in MW

Figure 2: Frequency distributions of transferred electricity, connection points and distributed generation

other networks (see, e.g., Filippini and Wetzel (2014)). In contrast, we expect a positive sign for the cable share coefficient, indicating higher construction and operating costs for networks with a higher share of underground cables (see, e.g., von Hirschhausen et al. (2006); Hess and Cullmann (2007)).

The variable 'integrated' equals one if a network operator operates both an electricity and a gas distribution network and zero otherwise. As indicated in Table 3, about 80 percent of the electricity distribution operators in our sample are integrated (i.e., operate an electricity and gas distribution network). Assuming that integrated operators can benefit from scope economies, we expect a negative sign for the integrated coefficient, indicating lower costs for integrated operators than for non-integrated operators (see, e.g., Triebs et al., 2016; Fetz and Filippini, 2010).

Finally, the variable 'east' equals one if the network is located in East Germany (including Berlin) and zero otherwise. By including this variable, we account for differences that might stem from the history of socialism and the related modernization investments in East Germany after the German reunification. Thus, we expect a positive sign for the east coefficient, indicating higher costs for networks in East Germany than for networks in West Germany (see, e.g., von Hirschhausen et al. (2006); Hess and Cullmann (2007)). About 20 percent of the electricity networks in our sample are located in East Germany. Overall, our data show that the German electricity distribution sector is not only highly fragmented but also characterized by a high degree of heterogeneity.

5. Results

5.1. Cost function estimation

The estimated results for the Cobb-Douglas and the translog specifications of the three econometric models are presented in Table 4. Since total costs and the regressors are in logarithmic form and the regressors are normalized at their sample median, the coefficients can be interpreted as cost elasticities evaluated at the sample median. The first-order coefficients for the two outputs have the expected signs and are highly statistically significant in all estimations. The estimated coefficients for the electricity supplied vary between 0.142 and 0.156 in the Cobb-Douglas specification, indicating that a 10 percent increase in the number of kilowatt-hours supplied increases total costs by about 1.4 to 1.6 percent. The corresponding coefficients in the translog specification are slightly lower, indicating a total cost increase of about 0.8 percent as a result of a 10 percent increase in electricity supplied. Similar to many other studies (e.g. Filippini and Wetzel, 2014; Badunenko et al., 2021), the estimated coefficients for the second output, the number of connection points, are much higher. Across both cost function specifications, the estimated coefficients vary between 0.563 and 0.712. Hence, a 10 percent increase in the number of connection points is estimated to increase total costs by about 5.6 to 7.1 percent.

The estimated coefficients for the network characteristics (network density, share of cable and integrated network operator) also have the expected signs, and most of them are statistically significant at least on the 10 percent level. Only in the Cobb-Douglas specification the coefficients for the share of cable are not statistically significant. Overall, our estimation results indicate that network operators with a higher network density and integrated network operators that provide both electricity and gas supply services have lower costs, while network operators with a higher share of cable face higher costs. In particular, for integrated network operators, the estimated coefficients suggest costs that are about 4 to 9 percent lower.

As expected, the estimated coefficients for the dummy variable "‘east"’ are positive in all models. However, within the translog specification, only one of three coefficients is statistically significant, indicating costs about 5 percent higher for operators located in East Germany compared to operators located in West Germany. Within the Cobb-Douglas specification, all coefficients are statistically significant and indicate a cost difference of about 5 to 7 percent. The estimated time dummy coefficients are very similar across all models and suggest a significant cost increase over time. In 2017, the network operators are estimated to have had costs about 14 to 18 percent higher when compared to the costs in 2011.

Table 4: Estimation results

	Cobb-Douglas			Translog		
Variable	RE	TRE	GTRE	RE	TRE	GTRE
Constant	15.789***	16.288***	16.303***	15.728***	16.172***	16.134***
	(0.024)	(0.017)	(0.016)	(0.029)	(0.031)	(0.016)
$ln\, QE$	0.142***	0.144***	0.156***	0.080***	0.080***	0.084***
	(0.014)	(0.007)	(0.007)	(0.021)	(0.008)	(0.008)
$ln\, QC$	0.657***	0.581***	0.563***	0.712***	0.629***	0.635***
	(0.018)	(0.009)	(0.009)	(0.031)	(0.011)	(0.011)
$ln\, ND$	−0.265***	−0.267***	−0.264***	−0.236***	−0.282***	−0.299***
	(0.020)	(0.010)	(0.010)	(0.036)	(0.014)	(0.013)
$ln\, SC$	0.068	0.014	0.010	0.318**	0.114*	0.193***
	(0.067)	(0.038)	(0.037)	(0.153)	(0.060)	(0.053)
I	−0.066***	−0.090***	−0.064***	−0.055*	−0.068***	−0.038***
	(0.024)	(0.010)	(0.010)	(0.029)	(0.011)	(0.010)
$ln\, DG$	0.158***	0.224***	0.225***	0.173***	0.221***	0.219***
	(0.012)	(0.005)	(0.005)	(0.017)	(0.006)	(0.006)
East	0.060**	0.052***	0.073***	0.004	0.008	0.050***
	(0.025)	(0.010)	(0.010)	(0.030)	(0.011)	(0.010)
2012	0.014	−0.001	0.006	0.016	0.010	0.011
	(0.023)	(0.021)	(0.020)	(0.024)	(0.021)	(0.019)
2013	0.064***	0.046***	0.051***	0.065***	0.059***	0.060***
	(0.018)	(0.018)	(0.017)	(0.020)	(0.018)	(0.016)
2014	0.086***	0.062***	0.068***	0.087***	0.076***	0.076***
	(0.018)	(0.017)	(0.016)	(0.019)	(0.017)	(0.016)
2015	0.098***	0.069***	0.077***	0.099***	0.082***	0.085***
	(0.020)	(0.017)	(0.017)	(0.022)	(0.018)	(0.017)
2016	0.162***	0.133***	0.139***	0.163***	0.148***	0.146***
	(0.021)	(0.018)	(0.018)	(0.022)	(0.019)	(0.017)
2017	0.181***	0.142***	0.155***	0.179***	0.161***	0.162***
	(0.028)	(0.024)	(0.023)	(0.034)	(0.025)	(0.023)
Log likelihood	6.221	100.948	91.792	66.793	167.132	139.139

Notes: To conserve space the first-order coefficients are presented only. The second-order and interaction coefficients are available from the authors upon request. Standard errors in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. The estimations have been performed in NLOGIT 6.

Finally, with regard to distributed generation, all coefficients are statistically significant at the 1 percent level and show a positive sign. The coefficients vary between 0.158 and 0.225, which indicates that a 10 percent increase in the installed capacity of distributed generation results in a total costs increase by about 1.6 to 2.3 percent. These results show that distributed generation is a significant cost driver in the production process of German electricity distribution network operators and thus should be included in the benchmarking procedure.

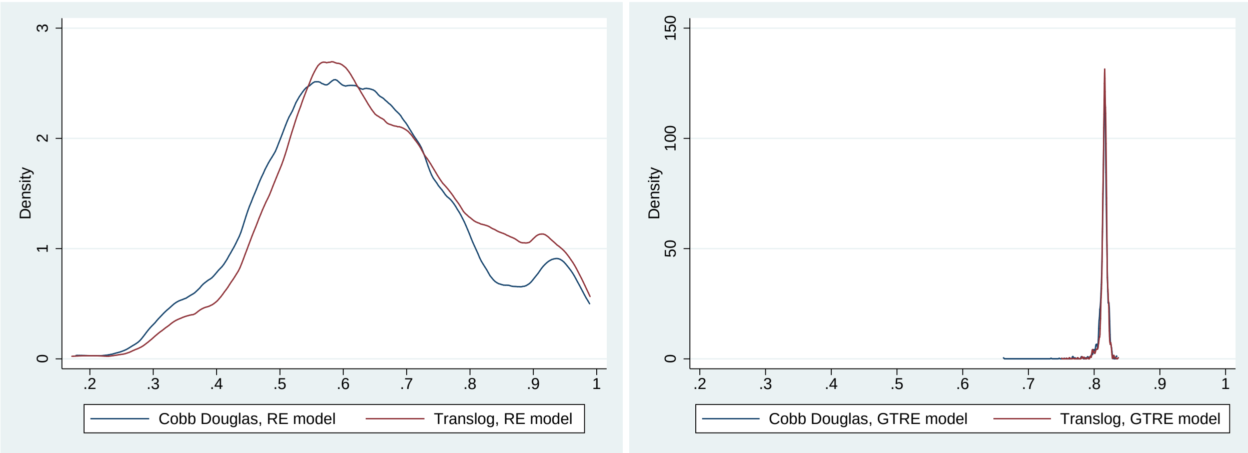
5.2. Cost efficiency

Table 5 shows descriptive statistics for both the transient and persistent efficiency scores, which are estimated with the three econometric and the two functional form specifications. First, it can be seen that the estimates from the Cobb-Douglas and the translog specifications are very similar in all models. The highest difference in the average efficiency level of about 3.25 percentage points is shown for the TRE model. This result indicates that with respect to the estimated efficiency levels, the choice between a Cobb-Douglas and a translog specification when it comes to functional form is of minor importance in the case of German electricity distribution network operators. This result is also supported by the Kernel density estimates shown in Figure 3. For all models, the distribution obtained from the Cobb-Douglas specification is very similar to the distribution obtained from the translog specification. Nevertheless, post-estimation likelihood-ratio tests indicate that, in all models, the translog specification is preferred over the Cobb-Douglas specification.

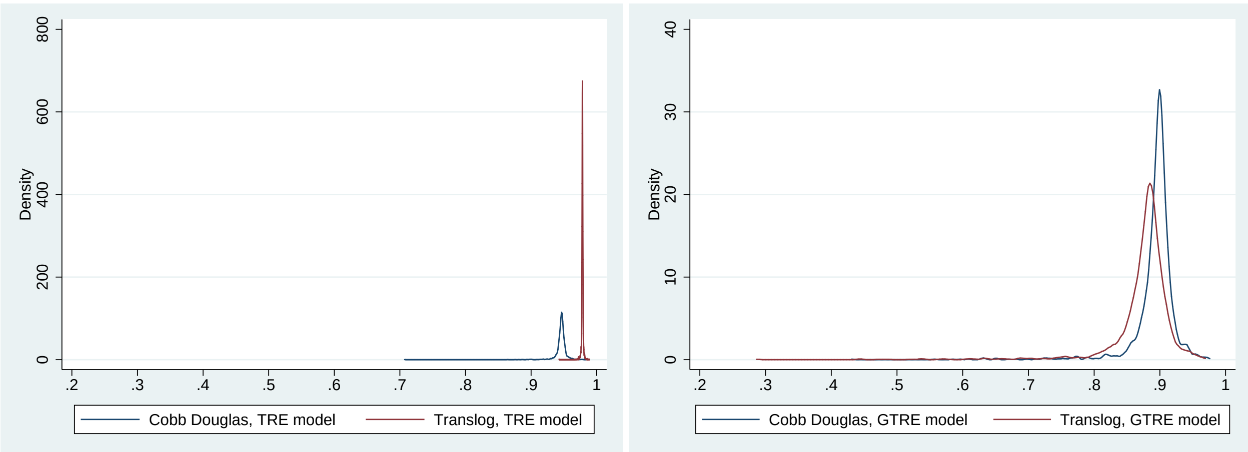
Table 5: Cost efficiency scores

	Mean	Std. dev.	Minimum	Maximum
Persistent efficiency				
Cobb-Douglas, RE model	0.6343	0.1597	0.1782	0.9888
Translog, RE model	0.6601	0.1583	0.1716	0.9895
Cobb-Douglas, GTRE model	0.8146	0.0082	0.6619	0.8346
Translog, GTRE model	0.8153	0.0059	0.7505	0.8369
Transient efficiency				
Cobb-Douglas, TRE model	0.9458	0.0096	0.7073	0.9844
Translog, TRE model	0.9783	0.0014	0.9427	0.9892
Cobb-Douglas, GTRE model	0.8933	0.0350	0.4309	0.9760
Translog, GTRE model	0.8750	0.0478	0.2861	0.9693

A completely different picture emerges when comparing the estimated efficiency values across the three econometric models. Focusing on the mean values obtained with the translog specification, our results show that the mean values of persistent efficiency vary from 66.01 percent in the RE model to 81.53 percent in the GTRE model. This difference of about



(a) Persistent efficiency



(b) Transient efficiency

Figure 3: Kernel density estimates

15.52 percentage points is due to the fact that, in the RE model, all unobserved time-invariant heterogeneity is included in the efficiency scores, while this is not the case in the GTRE model. Hence, our results indicate that the RE model significantly underestimates the persistent efficiency of German electricity distribution operators.

A similar picture emerges for the estimates of transient efficiency obtained from the TRE and GTRE models. For the translog specification, the mean value in the TRE model is about 10.33 percentage points higher than in the GTRE model. As the GTRE model is the more sophisticated model in that it accounts for both persistent and transient efficiency, this result suggests that the TRE model overestimates the transient efficiency of German electricity distribution operators.

In addition to the differences in the efficiency levels, possible differences in the efficiency rankings are also relevant (see, e.g., Filippini et al., 2018). Table 6 reports the correlations among the estimated efficiency levels estimated by the three econometric and the two functional form specifications. The correlation coefficients for the Cobb-Douglas and the translog specifications vary between 0.88 and 0.97 in the three econometric specifications and thus indicate only minor differences in the efficiency rankings obtained from the two functional forms. Only slightly lower correlation coefficients are shown for transient efficiency as estimated by the TRE and the GTRE models, namely 0.88 for the Cobb-Douglas and 0.80 for the translog specification. However, the lowest correlation coefficients among the estimated efficiency levels and hence the largest differences in the efficiency ranking are observed for persistent efficiency. The correlation coefficient between the RE and GTRE model is 0.61 for the Cobb-Douglas specification and 0.65 for the translog specification.

Table 6: Correlation coefficients

Persistent efficiency	Cobb-Douglas, RE model	Translog, RE model	Cobb-Douglas, GTRE model	Translog, GTRE model
Cobb-Douglas, RE model	1	0.918	0.614	0.624
Translog, RE model	0.918	1	0.558	0.654
Cobb-Douglas, GTRE model	0.614	0.558	1	0.882
Translog, GTRE model	0.624	0.654	0.882	1
Transient efficiency	**Cobb-Douglas, TRE model**	**Translog, TRE model**	**Cobb-Douglas, GTRE model**	**Translog, GTRE model**
Cobb-Douglas, TRE model	1	0.965	0.878	0.815
Translog, TRE model	0.965	1	0.834	0.802
Cobb-Douglas, GTRE model	0.878	0.834	1	0.931
Translog, GTRE model	0.815	0.802	0.931	1

Overall, our results show that, in particular, the econometric specification of the model significantly influences the estimated efficiency scores for German electricity distribution operators. In comparison, the choice of the functional form is of minor importance. Nevertheless, with regard to the estimated coefficients, some differences can also be identified in this context.

In addition, if we consider the results of the translog GTRE model as being most reliable, we find an average transient efficiency of about 88 percent, while the average persistent efficiency is lower, at about 82 percent. This result suggests that German electricity distribution network operators could reduce their total costs by an average of about 12 percent by improving their short-term management performance and by about 18 percent by long-term restructuring efforts. One reason for the higher level of persistent inefficiency could be the highly fragmented structure of the sector. Indeed, the estimated results in Table 4 indicate that the sector is characterized by economies of scale.[3] Therefore, one way to increase the level of persistent efficiency could be to merge small operators into larger units.

[3]Economies of scale (ES) are defined as the proportional increase in total costs brought about by a proportional increase in outputs, holding all other explanatory variables fixed: $ES = 1/(\frac{\partial lnTC}{\partial lnQE} + \frac{\partial lnTC}{\partial lnQC})$. Economies of scale are present if ES is greater than 1 (Filippini and Wetzel, 2014).

5.3. *Distributed generation*

With regard to distributed generation, the results presented in Table 4 show that the installed capacity of renewable power plants is a significant cost driver. In addition, we are interested in whether there are significant differences in the transient efficiency levels among network operators with a high and a low installed capacity of distributed generation. Table 7 presents the estimated mean values of transient efficiency for distribution networks with a very low (below 2.69 MW), a low (between 2.69 and 5.82 MW), a high (between 30.43 and 75.55 MW) and a very high capacity of distributed generation (above 75.55 MW).[4] It can be seen that, in all model specifications, the mean efficiency values are very similar for the considered four groups of distribution network operators. Furthermore, non-parametric Wilcoxon rank-sum tests indicate that at least at the 5 percent level of significance, the hypothesis that the mean transient efficiency level is the same for the four considered capacity levels of distributed generation cannot be rejected. Hence, we do not observe any significant differences in the efficiency levels of distribution network operators with high and low installed capacity of distributed generation, at least as long as the installed capacity of distributed generation is included as a cost driver in the total cost function.

Table 7: Comparison of mean transient efficiency by installed capacity of distributed generation

	Installed capacity of distributed generation				Wilcoxon very low vs. very high	Wilcoxon low vs. high
	Very low (N=210)	Low (N=210)	High (N=317)	Very high (N=318)		
Transient efficiency	Mean	Mean	Mean	Mean	p-value	p-value
Cobb-Douglas, TRE model	0.9460	0.9460	0.9454	0.9452	0.132	0.743
Translog, TRE model	0.9783	0.9783	0.9783	0.9782	0.077	0.803
Cobb-Douglas, GTRE model	0.8933	0.8931	0.8932	0.8903	0.640	0.331
Translog, GTRE model	0.8759	0.8729	0.8767	0.8705	0.750	0.285

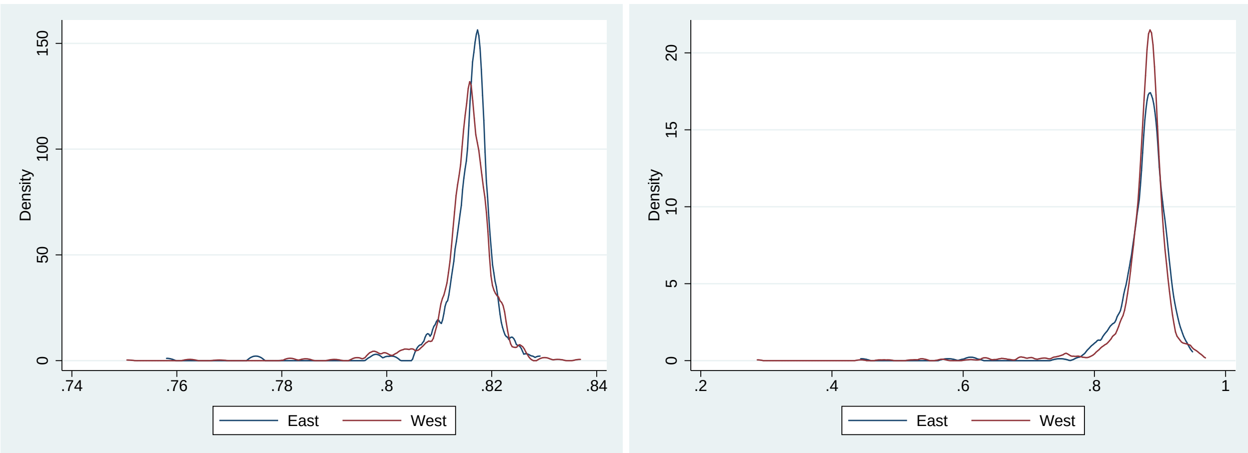
5.4. *Locational differences*

Finally, we consider efficiency differences between distribution network operators located in East and West Germany. Badunenko et al. (2021) find that East German distribution network operators on average perform better than West German distribution network operators in terms of persistent efficiency but not in terms of transient efficiency. Figure 4 shows the Kernel density estimates of the persistent and transient efficiency scores obtained from the translog GTRE model with the estimates being displayed separately for East and West German distribution network operators. The distributions are very similar for both kinds of efficiency. This finding indicates that there are hardly any significant differences in terms of

[4]The thresholds are chosen based on the 10^{th}, 25^{th}, 75^{th} and 90^{th} percentiles of the variable "'distributed generation"'.

both transient and persistent efficiency between Eastern and Western electricity distribution operators. This finding is also supported by complementary Wilcoxon rank-sum tests for all other model specifications.

Regarding persistent efficiency, this result is contrary to that obtained by Badunenko et al. (2021). This inconsistency may be due to the fact that our observation period starts in 2011 and runs until 2017, while the observation period of Badunenko et al. (2021) starts in 2006 and ends in 2011. Thus, the data of Badunenko et al. (2021) are much closer to the date of the German reunification and thus to the beginning of the restructuring of the electricity sector in East Germany than ours. Furthermore, the empirical models differ: While Badunenko et al. (2021) use an input distance function approach and hence focus on technical efficiency measures, we apply a cost function approach and consider cost efficiency measures.



(a) Persistent efficiency

(b) Transient efficiency

Figure 4: Comparison of distribution network operators in East and West Germany

6. Conclusions

Efficiency benchmarking techniques are an essential component of incentive regulation in many network industries, such as telecommunications, water, electricity and gas. Regulators around the world use a variety of econometric methods and model specifications, and academic research is continuously contributing to the development of these techniques. Particularly for regulated sectors, recent developments in stochastic frontier panel data models are of special interest, as such advancements make it possible to distinguish between transient and persistent inefficiency in a single model.

Using a comprehensive and unique data set of financial, technical and structural characteristics of German distribution network operators from 2011 to 2017, we estimated both the transient and persistent cost efficiency of German distribution network operators. Our results indicate an average cost reduction potential of about 12 percent in the short term and about 18 percent in the long term when both sources of inefficiency are accounted for in a single model. These results are robust to the choice of a Cobb-Douglas or translog functional form. However, the comparison with econometric models that account for either only transient or only persistent efficiency shows significant differences in terms of efficiency estimates and suggests that ignoring one or the other source of inefficiency can lead to false efficiency targets in incentive regulation. In accordance with Filippini et al. (2018) and Kumbhakar et al. (2020), we therefore conclude that the German regulator should consider both transient and persistent cost efficiency in its regulatory approach and use different measures to address inefficiencies resulting from both short-term management mistakes and from long-term structural problems.

Due to the significant and dynamic increase in decentralized generation from renewable energy sources in Germany over the last two decades, we were also interested in the effects of an increasing capacity of distributed generation on the total costs of distribution network operators. As expected, we find that distributed generation is a significant cost driver in the production process of German electricity distribution network operators. Our results indicate that a 10 percent increase in distributed generation capacity leads to a total costs increase of about 1.6 to 2.3 percent. In terms of cost efficiency, however, we did not find any significant differences among network operators with high and low installed distributed generation capacity in transient efficiency. These results indicate that distributed generation has no impact on cost efficiency, at least in Germany. However, it is important, particularly in contexts with a high share of distributed generation, to take distributed generation into account in the cost function and thus in the regulatory approach.

We conclude that the distinction between transient and persistent efficiency is highly relevant for German electricity distribution companies. Transient and persistent inefficiency have different causes and different policy implications in terms of improving efficiency. Furthermore, generally speaking, regulatory approaches globally and not just in Germany should be constantly adapted to novel circumstances, such as the increasing expansion of renewable energies. Electricity distribution network operators worldwide are facing major challenges in transforming power supply systems towards a sustainable energy supply. Not only on the generation side, the increase in the use of new technologies will necessarily lead to adjustments and thus to different cost structures. Increased electric mobility or the use of heat pumps and electricity storage systems will also have an impact. Such future developments must be taken into account in further research and regulation and thus also in the efficiency comparison of electricity distribution network operators.

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

Alte Wagenfabrik
Vogelsanger Str. 321a
50827 Köln
Germany

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

CORRESPONDING AUTHOR

Lisa Just
Lisa.just@ewi.uni-koeln.de

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