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Abstract

Accounting for network operators' heterogeneity is of crucial importance for regulators. In contrast to observed heterogeneity, the consideration of unobserved differences is far more challenging. Most estimation models try to account for unobserved factors that impact the network operators' costs and performance but neglect the possibility of heterogeneous technologies. Assuming a common technology represented by a joint cost function across network operators implies, e.g., identical marginal costs and economies of scale for all network operators. As it is questionable that this assumption holds in practice, efficiency estimates may be biased as technological heterogeneity is misunderstood as inefficiency. To overcome this misspecification, a latent class model is applied to a comprehensive database of German electricity distribution network operators between the years 2011 and 2017, explicitly accounting for technological differences across network operators. The results indicate that German distribution network operators can be unambiguously classified into three statistically different classes that share a common cost function. The findings show significant differences in the size, capacity of distributed generation from renewable energy sources and identify distributed generation capacity as an important driver of the network operators' technology.

Keywords: Electricity distribution, latent class models, regulation, stochastic frontier analysis, unobserved heterogeneity

JEL classification: L51, L94, D24

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1. Introduction

Electricity distribution is a common example of a market segment that exhibits characteristics of a natural monopoly. In order to avoid monopoly rents and to ensure a cost-efficient operation of the network, distribution network operators are regulated. Thereby, incentive regulation is often used in regulatory practice.

Yardstick competition was one of the first concepts of incentive regulation introduced by Shleifer (1985). Based on the idea of yardstick competition, efficiency benchmarking was implemented in Germany in the year 2009 (Swiss Economics et al., 2019). Efficiency benchmarking aims at determining the individual cost efficiency based on a comparison to the best practice, i.e., firms with the lowest costs. With this simulated competition, benchmarking should lower costs and thus increase efficiency. The efficiency of benchmarking is based on the relatively strong assumption that firms are identical or that heterogeneity across firms is accounted for correctly (Shleifer, 1985). However, as identical firms' premise is rarely fulfilled in practice, regulators are especially concerned about addressing heterogeneity across network operators to achieve reliable efficiency estimates.

In this paper, we estimate the cost efficiency of German network operators, explicitly accounting for technological heterogeneity[1] across network operators. In particular, we investigate whether technological differences across network operators are related to the capacity of distributed generation from renewable energy sources that is installed in the network operators' area. This is particularly challenging, as network operators differ according to many characteristics, some of which are beyond and some within their control. Differences may be, for example, due to technical (e.g., network length, condition of the networks), structural (e.g., number and type of customers, network density, capacity of renewable energy sources), environmental (e.g., weather conditions, landscape), and other characteristics. Some of these differences can be observed by the regulator and can thus be accounted for in the benchmarking procedure. For example, technical data on the network infrastructure must be submitted to the regulator by the network operators, and data on renewable energy sources are publicly available. In contrast, there may be factors that cause differences across network operators but are unobservable, too complex, and too expensive to account for – or no data exists (Cullmann, 2012). Amongst others, only network operators are aware of their network condition. Furthermore, environmental differences may to some extent be observable, albeit expensive (e.g., rain hours, days of snow), but a majority may be unobservable or hard to measure (e.g., ground condition, flat or mountainous landscape). Thus, a residual of heterogeneity remains, that the regulator is not able to account for, i.e., unobserved heterogeneity (Agrell et al., 2014).

As the benchmarking results have a direct financial impact, addressing unobserved heterogeneity is a crucial and challenging task for regulators. Recently developed panel data models provide several approaches to account for unobserved heterogeneity (e.g., Greene

[1]Throughout the paper, the technology of network operators is described by the network operators' cost function. Thus, technological heterogeneity refers to the fact that different cost function parameters may be suitable to describe heterogeneous production processes of network operators.

(2005a,b) and Filippini and Greene (2016)). These models assume that unobserved heterogeneity affects the costs and performance of network operators. However, unobserved heterogeneity may also impact the production process of network operators (Cullmann, 2012). Thereby, the production process, and thus the technology of network operators, is described by the production or cost function of network operators. The aforementioned models assume a common technology, i.e., efficiency frontier, and thus neglect to account for heterogeneous cost and production functions among network operators. In doing so, homogeneous assets, services, and operations of firms (Agrell and Brea-Solis, 2017) as well as identical technological characteristics (e.g., marginal costs and economies of scale) are assumed (Llorca et al., 2014); however, it is questionable whether this holds in practice. For example, an increase in the capacity of distributed generation from renewable energy sources may only have a low cost impact for some network operators while others have a significantly higher cost increase. This difference in marginal costs may, for example, be driven by different plant types (e.g., wind vs. photovoltaic (PV)) or environmental differences (e.g., a mountainous landscape in contrast to a flat landscape). Thus, recent developments such as the dynamic and vast increase in renewable energies and the development of smart and active grids make the assumption of homogeneous conditions for network operators even more difficult (Agrell and Brea-Solis, 2017) and may increase technological heterogeneity. If any technological heterogeneity exists, current regulatory approaches either overlook the differences or misinterpret them as network operators' inefficiency.

To account for technological differences, i.e., heterogeneous cost and production functions, across network operators, so-called latent class models can be applied. Latent class models allow for firms to be sorted into different classes with a common cost or production function. The idea of combining latent class modeling with stochastic frontier analysis models is based on the work of Orea and Kumbhakar (2004) and Greene (2005b). Using data on the Spanish banking system, Orea and Kumbhakar (2004) identify four different classes to account for technological differences across banks between the years 1992 and 2002. They conclude that bank heterogeneity can be fully controlled for, which would otherwise bias efficiency results if technological differences remain uncontrolled. Greene (2005b) applies a latent class model to the U.S. banking industry. He compares different empirical approaches to consider heterogeneity across firms and concludes that a latent class model with two classes can address unobserved heterogeneity in the U.S. banking industry. Assuming that unobserved characteristics may impact German network operators' production process, Cullmann (2012) estimates a latent class model for a panel data set of German distribution network operators from the years 2001 to 2005 to disentangle inefficiency from heterogeneity. She concludes that there are indicators that small and large German distribution operators use different technologies. Llorca et al. (2014) apply a latent class analysis to account for unobserved differences in U.S. electricity distribution operators' technologies between the years 2001 and 2009. They conclude that a latent class analysis outperforms other ex-ante clustering methods and traditional panel data models to address unobserved heterogeneity. The latent class model used can account for environmental differences across network operators without explicitly including them in the cost function. Agrell and Brea-Solis (2017) estimate various latent class models of Swedish electricity distributors between the years

2000 and 2006 and contrast the results with the results of deterministic outlier detection models. In contrast to the one-step approach of, e.g., Agrell and Brea-Solis (2017), Agrell et al. (2014) propose a two-step approach. In the first step, Norwegian power distribution operators are clustered using a latent class model. In the second step, network operators' efficiency is evaluated with the group-specific frontiers using deterministic and stochastic frontier analysis. They find that efficiency estimates for the analyzed Norwegian power distributors are higher and more realistic than a conventional one-step approach. Orea and Jamasb (2017) develop a nested latent class model that can differentiate between fully efficient network operators and those that are, to some part, inefficient. At the same time, they also account for differences in the underlying technology. They estimate the model for Norwegian distribution network operators between the years 2004 and 2011. The possible importance of distributed generation from renewable energy sources was only considered by Agrell and Brea-Solis (2017). They detect a large heterogeneity of injections of power from distributed generation but find no clear pattern regarding their cost impact across classes.

With this paper, we contribute to the existing literature in various ways. First, we analyze whether German electricity distribution network operators use heterogeneous technologies represented by heterogeneous cost functions. In particular, we focus on the capacity of distributed generation from renewable energy sources as a possible source of technological heterogeneity. The analysis of German network operators provides an interesting and relevant case study, as a diverse and large number of electricity distribution network operators have been confronted with changing market environments. Amongst others, this includes the increase in renewable power plants but also the digital transformation over the previous years. This aspect has been neglected by Cullmann (2012), who also accounts for heterogeneous technologies across German network operators. Thus, we are to the best of our knowledge the first to estimate whether structural differences in the technology across German distribution network operators are related to the capacity of distributed generation from renewable energy sources. To address the research question, we apply a latent class stochastic frontier analysis to a large and unique panel of German distribution network operators between the years 2011 and 2017. Second, we compare the results of the latent class analysis with those of two alternative clusters of network operators to gain insights into the importance of accounting for heterogeneous cost function parameters across network operators. With this, we provide valuable insights for the regulation of German distribution network operators and the relevance of considering unobserved heterogeneity.

The paper is organized as follows. Section 2 gives a brief overview of the regulatory framework in Germany. Section 3 describes the methodology applied, while Section 4 introduces the data used in the empirical analysis. Section 5 presents the estimation results, and Section 6 concludes.

2. Regulatory framework in Germany

In 2009, incentive regulation for German electricity distribution operators was introduced by the German regulator, the Bundesnetzagentur, via the Incentive Regulation Ordinance (ARegV). Incentive regulation is based on the economic idea that competition between network operators should be ensured to increase efficiency. Therefore, a revenue cap is assigned to each network operator for one regulation period. By introducing a revenue cap, network operators have the incentive to reduce their costs within the regulation period to increase profits or decrease losses.[2] The calculation of the individual revenue cap is based on a cost assessment of controllable and non-controllable costs as well as an individual efficiency value. In the cost assessment, the regulator reviews the cost situation of each network operator. Subsequently, the individual efficiency value is determined by an efficiency benchmarking of the controllable costs. In practice, regulators apply a variety of parametric and non-parametric approaches. Non-parametric methods such as the data envelopment analysis (DEA) have the advantage of high flexibility as no functional form has to be specified. However, these models do not account for statistical noise, meaning any deviation from the efficiency frontier is considered as inefficiency. In contrast, parametric models such as the stochastic frontier analysis (SFA) require the definition of a functional form but can account for statistical noise. In the case of German benchmarking, a "best-of-four" approach is used: Network operators are assigned the highest efficiency value resulting from four different model specifications, two DEA and two SFA models.

As mentioned above, the efficiency of the benchmarking procedure and the reliability of efficiency estimates are based on the assumption that network operators are comparable. In this context, the German Energy Industry Act (EnWG) states that network operators' financial obligations that result from the benchmarking require their structural comparability (§21a EnWG). Germany is characterized by a high number and high heterogeneity of network operators, who differ according to individual and regional characteristics. Amongst others, the number and structure of customers, the size and condition of networks, the number and installed capacity of renewable power plants connected the grid, and the landscape and its characteristics may vary considerably across network operators. Thus, regulators cannot compare network operators based on their costs only. Some of the differences across network operators can be observed by the regulator, while others cannot. The regulator accounts for observable differences in the benchmarking by including so-called structural variables. These may consist of the area served, length of lines, and the capacity of renewable power plants connected to the grid (§13 ARegV).

Even though regulators account for observed differences across network operators, the issue of possible unobserved heterogeneity remains. The use of panel data models that can account, at least to some extent, for unobserved heterogeneity across network operators is not feasible for Germany, as data restrictions result from only two regulation periods having been completed. In consequence, the Bundesnetzagentur applies a cross-sectional model, which means that network operators are not observed over time but treated as independent observations. As such, the observation and identification of unobserved heterogeneity are impossible. Furthermore, the regulatory approach does not explicitly consider the possibility that network operators differ regarding their technologies and thus their cost and production functions. Nevertheless, regulators try to account for at least some technological heterogene-

[2] The description of the regulation procedure in Germany is based on the Incentive Regulation Ordinance (ARegV) as well as Swiss Economics et al. (2019).

ity. In doing so, the Bundesnetzagentur specifies two groups of network operators according to their size. As such, a group of network operators of the same size should be more homogeneous, and thus better to compare in the benchmarking (Agrell and Brea-Solis, 2017). Network operators with more than 30,000 connected customers are obliged to participate in the regular benchmarking procedure. In contrast, network operators with less than 30,000 customers can participate in the standard benchmarking process or be part of a simplified procedure. In the simplified procedure, network operators are assigned an average efficiency value without the requirement of a cost assessment.[3] This proves that the regulator has the implicit assumption that unobserved technological differences between small and large network operators may exist (Cullmann, 2012). In the past regulation period, only a minority of 20 percent of total network operators participated in the regular benchmarking.

Such an a priori clustering may be easy to implement but is inefficient for various reasons: For one, the classification may be based on the wrong criterion and thus results in misleading groups. In the case of Germany it is questionable whether the network operators' size is correct or sufficient to describe possible technological differences across network operators. Especially over the past years, the increase in distributed generation from renewable energy sources imposes new heterogeneity across network operators: Between the years 2011 and 2017, the installed capacity of renewable power plants increased by 45 GW (Bundesnetzagentur, 2019). Around 98 percent of all renewable power plants are connected to the distribution network (E-Bridge et al., 2014). Moreover, the capacity of renewable power plants is not evenly distributed across network operators, which could lead to some network operators being more affected than others. In the year 2016, 75 percent of the capacity of renewable power plants was installed in network areas of only 15 network operators (IAEW, 2016). The question remains as to whether such a situation may induce structural differences across network operators which are not taken into account under the current regulatory regime and by the size clustering of network operators. Furthermore, efficiency estimates for different groups may be estimated without considering the information of other groups. In this case, the regulator neglects important information as network operators still belong to the same industry and share common characteristics (Kumbhakar et al., 2015). This loss of information may induce inefficiency in the regulatory procedure.

As the benchmarking procedure has a direct financial impact on network operators, an adequate consideration of technological heterogeneity is of crucial importance. In the following, we investigate whether technological heterogeneity represented by different cost functions is present across German network operators using the latent class modeling approach. Furthermore, we analyze whether possible groups of network operators differ significantly regarding observable characteristics (e.g., the capacity of renewable power plants).

3. Methodology

This section first determines the cost function and describes conventional SFA panel data models that assume a common technology, i.e., cost function, and homogeneous technological

[3]The simplified procedure should also protect smaller network operators from excessive effort to be benchmarked. This aspect is, however, not considered in this paper.

characteristics for network operators. In a second step, we focus on latent class models that exhibit the possibility of differences in the cost function parameters across network operators.

3.1. Definition of cost function

We estimate a cost function of electricity distribution network operators that can be described by:

$$TC = TC(QE, QC, ND, DG, DT) \tag{1}$$

where TC denotes the total costs, QE the amount of electricity supplied, QC the number of customers connected to the network, ND the network density, and DG the capacity of distributed generation from renewable energy sources in the specific network area. DT comprises dummy variables that capture changes over time. As frequently done in the literature, QE and QC are defined as outputs (Filippini and Orea, 2014). Due to data restrictions, we abstract from input prices and assume no substantial differences in input prices across electricity distribution network operators. The cost function estimation requires the specification of a functional form. In this paper, a Cobb-Douglas function of the following form is estimated:

$$\begin{aligned} ln\, TC_{it} = \beta_0 + \beta_{QE}\, ln\, QE_{it} + \beta_{QC}\, ln\, QC_{it} + \beta_{ND}\, ln\, ND_{it} + \beta_{DG}\, ln\, DGit \\ + \sum_{t=2}^{T} \alpha_t\, DT_t + \epsilon_{it} \end{aligned} \tag{2}$$

where the subscript i denotes the firm, t the time period, the β's are the unknown parameters to be estimated, and ϵ_{it} is the error term. There exists a broad range of SFA models that can estimate the cost function. In the following, we concentrate on panel data models. In contrast to cross-sectional models, panel data models observe an individual i at different time periods t and are thus able to account for unobserved heterogeneity, at least to some extent. In general, SFA panel data models can be written as:

$$y_{it} = \beta' x_{it} + \epsilon_{it} \tag{3}$$

where y_{it} denotes the costs, x_{it} is a vector of inputs, outputs and firm-specific characteristics and ϵ_{it} is the error term. Thereby, ϵ_{it} comprises unobserved heterogeneity, inefficiency, and random noise. The major concern of panel data models is how to disentangle inefficiency from heterogeneity and random noise. Empirical models differ in their econometric specification of the error term and thus in the way heterogeneity is accounted for (Just and Wetzel, 2020). In earlier panel data models (e.g., Pitt and Lee (1981)), the error term is defined as: $\epsilon_{it} = u_i + v_{it}$. Thereby, inefficiency, u_i, is assumed to be half-normally distributed and constant over time, while stochastic noise, v_{it}, is normally distributed and varies over time. This implies that all time-invariant firm-specific unobserved heterogeneity is considered as inefficiency, and all time-varying effects are absorbed in the stochastic noise term. In order to separate inefficiency and firm-specific heterogeneity, Greene (2005a) and Greene (2005b) introduced individual time-invariant effects with the so-called True Random Effects

(TRE) model where the error term now consists of three parts: $\epsilon_{it} = v_{it} + u_{it} + \omega_i$. v_{it} denotes the normally distributed, time-varying stochastic noise term, u_{it} the half-normally distributed, now time-varying inefficiency term and the additional normally distributed term ω_i captures firm-specific, time constant random variable effects that account for firm-specific heterogeneity. The TRE model is described by:

$$y_{it} = \beta' x_{it} + \omega_i + v_{it} + u_{it} \tag{4}$$

Thus, all effects that are constant over time are considered as firm-specific unobserved heterogeneity. It follows, that time-invariant structural inefficiencies are also regarded as unobserved heterogeneity rather than as inefficiency.[4]

The presented models account for unobserved heterogeneity that may impact individual costs and performance. However, as they assume a common technology represented by a joint cost function and thus a common efficiency frontier across firms, they neglect the possibility that unobserved heterogeneity may influence firms' technology. On the one hand, the TRE model assumes that individual efficiency frontiers may differ according to firm-specific intercepts that capture unobserved heterogeneity. On the other hand, firms are assumed to share the same technological characteristics, e.g., marginal effects, economies of scale, and scopes (Llorca et al., 2014). However, especially in an environment where observed entities are very heterogeneous, the assumption of a common cost function for all network operators may not be valid. For example, the connection of renewable power plants or new customers may induce different costs for network operators depending on, e.g., their specific network conditions or environmental characteristics (e.g., mountains, urban area). In Germany, it may be that, due to the further increase in the capacity of renewable energies, the ongoing digital transformation and also the increasing use of electric vehicles, technological heterogeneity across network operators will even increase. If common technology characteristics are assumed, even though heterogeneous technology characteristics are present, efficiency estimates may be misleading. As technological differences may be considered as inefficiency if a common cost function is wrongly assumed, models will underestimate efficiency. In the following, we discuss a modeling approach that considers differences in firms' technology and its characteristics by allowing for heterogeneous cost function parameters.

3.2. Latent class modeling

Latent class models allow for parameter heterogeneity in the cost function and by this account for different technologies across firms. It is assumed that a latent sorting of network operators in various classes according to differences in cost function parameters exists (Greene, 2007). Network operators that belong to the same class share a common cost function and efficiency frontier. Thus, latent class models control for heterogeneity between groups rather than for individual heterogeneity (Llorca et al., 2014). Each network operator

[4]The most recent panel data models are also able to differentiate between persistent and transient efficiency (Filippini and Greene, 2016).

belongs to one class in which he remains over time. Compared to an arbitrarily a priori clustering of firms, latent class models use all firms' information to determine the cost function of the different classes, irrespective to which class they are assigned.

Under the latent class framework the overall cost function becomes:[5]

$$\begin{aligned} ln\,TC_{it} = \beta_{0j} + \beta_{QEj}\,ln\,QE_{it} + \beta_{QCj}\,ln\,QC_{it} + \beta_{NDj}\,ln\,ND_{it} + \beta_{DGj}\,ln\,DG_{it} \\ + \sum_{t=2}^{T} \alpha_{tj}\,DT_t + \epsilon_{it}|j \end{aligned} \tag{5}$$

where in addition to the introduced notation subscript j denotes the class. The $\beta's$ are estimated for each class j, and the error term is conditioned on class j. For the SFA model, $\epsilon_{it}|j$, is again divided into a random error term, $v_{it}|j$, which is assumed to be normally distributed and independent of the half-normally distributed inefficiency component, u_{it}.

The probability of observing individual i given that it is part of class j is described by $P(i|j)$, which is the conditional likelihood function of individual i.[6]

$$P(i|j) = \prod_{t=1}^{T} P(i,t|j) \tag{6}$$

As a network operator can be a member of every class, the unconditional likelihood function is the sum of the J class likelihood functions multiplied with the prior class probabilities, π_{ij}. Thus, the unconditional likelihood function for individual i is denoted as:

$$P(i) = \sum_{j=1}^{J} \pi_{ij} P(i|j) = \sum_{j=1}^{J} \pi_{ij} \prod_{t=1}^{T} P(i,t|j). \tag{7}$$

Prior class probabilities, π_{ij}, are estimated simultaneously with the parameters of the cost frontiers and are assumed to be constant over time (e.g., Agrell and Brea-Solis (2017)). They are parametrized as multinominal logit model:

$$\pi_{ij} = \frac{exp(\theta_j)}{\sum_{j=1}^{J} exp(\theta_j)}, \theta_J = 0, \sum_{j=1}^{J} \pi_{ij} = 1. \tag{8}$$

θ_j captures all class specific parameters. The restriction, $\theta_J = 0$, is imposed as only J-1 probabilities have to be calculated to specify J probabilities. Furthermore, prior class probabilities have to sum up to one. It is important to note again that a network operator can be a member of only one class in which he remains over time. As the respective class

[5]Alternative model specifications differing in their functional form (Cobb Douglas vs. translog) as well as in the variable definition (e.g., density or number of distributed generation from renewable energy sources) were tested but not able to achieve convergence. Convergence problems of latent class models are reported frequently in the literature (e.g., Llorca et al. (2014), Orea and Kumbhakar (2004), Cullmann (2012), Agrell and Brea-Solis (2017)).

[6]The following model description is based on Greene (2005b) and Greene (2016).

is, however, unknown to the researcher, the prior class probability can be interpreted as the uncertainty of the researcher (Greene, 2005b).

From this, the overall likelihood function results:

$$logLF = \sum_{i=1}^{N} logP(i) = \sum_{i=1}^{N} log(\sum_{j=1}^{J} \pi_{ij} \prod_{t=1}^{T} P(i,t|j)). \tag{9}$$

The model is estimated using maximum likelihood. In contrast to the traditional models (e.g., TRE model), the model estimates J different cost frontiers each with an individual probability, i.e., the prior class probability. Thereby, technological heterogeneity is caused by differences in the technology parameters of each frontier, i.e., the β's, and the variance of the inefficiency, σ_u, and error term, σ_v (Agrell et al., 2014).

After the estimation, posterior class probabilities can be computed using Bayes theorem:

$$w(j|i) = \frac{P(i|j)\pi_{ij}}{\sum_{j=1}^{J} P(i|j)\pi_{ij}}. \tag{10}$$

Posterior class probabilities denote the probability of class j given that we have observed individual i. With the posterior class probabilities, it is possible to assign individuals to one class, i.e., the class with the highest posterior probability.

A shortcoming of latent class models is that the number of classes J can not be estimated but has to be defined by the researcher. In the empirical literature the number of classes is most commonly defined using the Akaike (AIC) or Bayesian information criterion (BIC). Both information criteria are suitable for comparing models with different classes as they both favor the model's goodness of fit while they penalize the number of included parameters in the model (Orea and Kumbhakar, 2004). The preferred number of classes is obtained by estimating models with a different number of classes in the first step and comparing them regarding their specific information criterion in the second step. The model with the lowest information criterion is preferable.

4. Data

To answer our research question, we construct a comprehensive database of electricity distribution network operators between the years 2011 and 2017. The database contains financial and technical data for each network operator. We collect the financial data from the network operators' balance sheets and profit and loss accounts. An amendment to the Energy Industry Act (EnWG) in 2011 strengthens the reporting provisions by enforcing network operators to make separate activity reports for gas and electricity distribution. These reporting provisions enable the direct allocation of financial data to the activities associated with electricity and gas, respectively. The professional data provider ene't provides the technical data. The installed capacity of renewable power plants is obtained from the installation register of the Renewable Energy Act (EEG) published by the four transmission system operators (TSO) (50 Hertz Transmission GmbH et al., 2018). The register contains all renewable power plants that are subsidized by the EEG. The data are merged with the financial and technical data through the name of the distribution operator.

According to the ARegV, the regulator should apply outlier detection procedures based on statistical tests (e.g., Cook's distance) and delete observations above a predefined threshold. A standard threshold for Cook's Distance is a value greater than four divided by n (Bollen and Jackman, 1990). After deleting outliers that were detected based on Cook's distance and dropping observations with odd information, our unbalanced panel comprises 1,911 observations. We observe a maximum of 330 electricity distribution operators, which corresponds to more than one-third of the number of German electricity distribution operators.[7]

Table 1 shows the descriptive statistics of the variables included in the total cost function. Total costs, TC, the dependent variable, are the sum of labor costs (personnel expenses), capital costs (sum of material and depreciation expenses), opportunity costs of capital, and costs of other inputs. Thereby, opportunity costs are defined as fixed assets multiplied by the interest rate paid on long-term debt. Monetary values are expressed in year 2010 Euros by deflating them with the consumer price index. We define two outputs: the amount of transferred electricity, QE, measured in megawatt-hours (MWh), and the number of connected customers, QC. As can be seen in Table 1, there is a considerable variation in the size of the variables: While Elektra-Genossenschaft Effeltrich eG, the smallest network operator, transferred 5 GWh electricity in the year 2015 and has approximately 1,000 connection points, the largest network operator, Westnetz, transferred almost 250,000 GWh of electricity in the year 2015 and has with nearly 5,000,000 connection points the highest value in the sample. Even though there are very large network operators, most of the sample consists of smaller network operators: 90 percent of network operators transfer less than 2,537 GWh electricity which corresponds to only 1 percent of the maximum value, and have less than 160,785 connection points. We expect a positive cost impact if the amount of supplied electricity or the number of connected customers increases (e.g., Just and Wetzel (2020)).

We also include structural variables that may influence the costs of network operators but are beyond their control. The network density, ND, is defined as the number of connection points per network kilometer. The sample includes network operators with very dense networks and network operators with a low network density: Netz Leipzig GmbH has 129 connection points per network kilometers, the densest network. In comparison, nvb Nordhorner Versorgungsbetriebe GmbH has only 8 connection points per network kilometers and thus the lowest network density. Due to density effects, we expect network operators with a higher network density to have lower costs, i.e., a negative coefficient (e.g., Filippini and Wetzel (2014), Just and Wetzel (2020)).

In particular, we are interested in the impact of the installed capacity of distributed generation from renewable energy sources, DG. DG comprises the installed capacities of

[7]In the year 2017, the Bundesnetzagentur listed 878 electricity network operators (Bundesnetzagentur, 2020). In our sample, the number of network operators in the year 2017 deviates strongly from the other years as not all network operators have published their annual report for the year 2017 at the time of data collection.

	Mean	Median	Std. dev.	Minimum	Maximum
Total costs (million 2010€)	52.45	11.64	232.36	0.35	5,235.34
Electricity transferred (GWh)	1,911.42	250.03	10,299.59	4.76	247,549.60
Connection points (thousand)	76.68	18.86	269.78	1.04	4,965.61
Network density (connection points/network km)	35.72	33.21	16.86	7.68	129.20
Distributed generation (MW)	96.58	14.64	690.60	0.35	14,827.64

Table 1: Descriptive statistics

PV, wind energy, biomass, hydropower, deep geothermal energy, sewage gas, mine gas and landfill gas that are subsidized by the EEG. The installed capacity of renewable power plants is unequally distributed across network operators, as shown in Table 1. While network operators have, on average, an installed capacity of renewable power plants of 97 MW, 50 percent of the network operators have less than 15 MW installed. On the other hand, Avacon AG has an installed capacity of renewable power plants of 14.8 GW in the year 2015, which is the maximum in the sample. Due to a preferential dispatch and the obligation to connect renewable power plants to the grid, the capacity of distributed generation from renewable energy sources is expected to induce connection costs and challenges in guaranteeing a stable network. Thus, we expect a positive cost impact (e.g., Just and Wetzel (2020)).

5. Results

5.1. Latent classes' cost function estimation

To test whether the assumption of different technologies, i.e., cost functions, is suitable for German network distribution operators, we estimate the latent class model from one to six classes. We determine the number of classes using the BIC criterion (e.g., Agrell and Brea-Solis (2017), Llorca et al. (2014)). Indicated by the lowest BIC, three classes are preferred over more or fewer classes.

The cost function estimation results are obtained using maximum likelihood estimation and are shown in Table 2. The prior class probabilities are simultaneously estimated with the cost function estimates and indicate that 41 percent of the sample belong to class 1, 37 percent to class 3, and 21 percent to class 2 which is the smallest class. The parameters are expressed in natural logarithms and are normalized at their sample median and can thus be interpreted as estimates of cost elasticities at the sample median.

All coefficients have the expected sign and are highly statistically significant. We observe differences in the coefficients across the three classes, which suggests differences in marginal costs and thus the technology. In all classes, increasing the outputs leads to an increase in costs. An increase of 10 percent in the supplied electricity induces a cost increase between 0.4 and 1.3 percent. Increasing the number of connected customers by 10 percent yields a very similar cost increase of 6.0 percent for class 1 and 6.7 percent for class 3. Network operators in class 2 face higher connection costs (9.2 percent). According to Cullmann (2012)

Variable	Class 1	Class 2	Class 3
Constant	16.267***	15.589***	16.107***
	(0.017)	(0.027)	(0.018)
ln QE	0.130***	0.044**	0.097***
	(0.010)	(0.021)	(0.008)
ln QC	0.600***	0.918***	0.674***
	(0.012)	(0.029)	(0.011)
ln ND	-0.400***	-0.374***	-0.447***
	(0.016)	(0.038)	(0.015)
ln DG	0.250***	0.052***	0.220***
	(0.008)	(0.014)	(0.007)
2012	0.063***	0.036***	0.038***
	(0.017)	(0.034)	(0.013)
2013	0.076***	0.140***	0.074***
	(0.017)	(0.034)	(0.014)
2014	0.088***	0.115***	0.077***
	(0.017)	(0.033)	(0.013)
2015	0.104***	0.079***	0.073***
	(0.017)	(0.032)	(0.013)
2016	0.148***	0.170***	0.134***
	(0.017)	(0.033)	(0.013)
2017	0.172***	0.354***	0.162***
	(0.023)	(0.051)	(0.019)
Prior Class Probabilities	0.410***	0.218***	0.373***
	(0.026)	(0.022)	(0.026)

Notes: Standard errors in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. The estimations have been performed in NLOGIT 6.

Table 2: Estimation results

differences in connection costs may be due to differences in the customer structure (e.g., industrial vs. household customers). As expected, there are density effects across all three classes, i.e., costs decrease between 3.7 and 4.5 percent when the network density increases by 10 percent. Interestingly, the coefficient of the capacity of renewable power plants varies significantly across classes. While for network operators in class 1 and 3, an increase in the capacity of renewable power plants results in a comparatively high cost increase of 2.5 and 2.3 percent, respectively, it is with 0.5 percent lower for class 2. Environmental conditions (e.g., flat vs. mountainous landscape) and differences in the structure of the capacities of renewable energy plants across classes may be an explanation. For example, wind capacities are predominantly connected to the medium- and high-voltage network while PV is usually connected to the low-voltage network. Thereby, networks of the lower voltage levels have a lower capacity to integrate renewable power plants and are more often confronted with voltage problems than medium- and high-voltage networks. Thus, the same capacity of renewable power plants causes higher costs in the low-voltage network than in the medium- and high-voltage network (Swiss Economics et al., 2019). Positive and significant coefficients of the time dummies indicate a cost increase over time compared to 2011 for all classes.

Besides the differences in the marginal costs of network operators, economies of scale are another technology parameter that indicates whether technological heterogeneity across classes is present. Economies of scale measure the percentage cost increase that results from a simultaneous increase in all outputs by 1 percent.[8] If economies of scale are present ($ES > 1$), network operators would benefit from increasing their size, e.g., by expansion or mergers. In contrast, diseconomies of scale ($ES < 1$) indicate that a reduction of size would be beneficial for network operators. Consequently, $ES = 1$ reveals that network operators operate at their optimal size given the underlying technology (Badunenko and Kumbhakar, 2017). We observe positive economies of scale for all classes, which nevertheless differ. While classes 1 and 3 have similar economies of scale, 1.4 and 1.3, respectively, class 2 has quite lower economies of scale near unity. Thus, efficiency increases are possible for classes 1 and 3 by increasing their size, while network operators in class 2 operate near their optimal size.

The results indicate that the latent class approach exhibits technological heterogeneity among German network operators, captured by three different classes that would have been ignored, assuming a common cost function.[9] Notably, while cost function parameters are similar in classes 1 and 3, they differ for class 2. Thereby, the main difference results from higher marginal costs to connect customers to the network and lower marginal costs of distributed generation capacity from renewable energy sources in class 2. Furthermore, economies of scale are similar in classes 1 and 3 but vary in class 2. Thus, the cost functions, i.e., technologies, of classes 1 and 3 are more alike than the cost function of class 2. In the following, we provide possible explanations for the differences between the technologies of class 2 compared to classes 1 and 3, focusing primarily on the impact of the installed capacity of renewable power plants.

5.2. Characteristics of Classes

Using the estimated posterior class probabilities, we assign network operators to the class with the highest individual probability. The average posterior class probability varies between 95.8 percent for class 3, 96.54 percent for class 2, and 96.92 percent for class 1. Thereby, only five observations of two network operators have a posterior class probability of less than 50 percent. Thus, we conclude that the vast majority of observations can be clearly assigned to one class (Agrell et al., 2014). This results in the following class sizes: Class 1 is with 779 observations the largest class, followed by class 3 which contains 752 observations. Class 2 comprises 380 observations and is thus the smallest class.

Table 3 shows the descriptive statistics of the variables included in the total cost function differentiated by class. The two outputs, electricity supplied and the number of connected

[8] $ES = 1/(\frac{\partial lnTC}{\partial lnQE} + \frac{\partial lnTC}{\partial lnQC})$ (Filippini and Wetzel, 2014).

[9] The impact of considering a common cost function is analyzed in Section 5.4.

	Mean	Median	Std. dev.	Minimum	Maximum
Electricity supplied [GWh]					
Class 1	2,637.13	250.16	15,186.99	24.68	247,549.60
Class 2	1,402.76	260.54	5,091.56	4.76	68,301.84
Class 3	1,416.69	249.05	4,105.17	9.88	31,492.64
Connection points [thousand]					
Class 1	101.85	19.78	387.94	1.63	4,965.61
Class 2	66.92	17.72	175.53	1.04	1,936.85
Class 3	55.55	18.98	111.76	1.54	754.67
Network density [Connection points/network km]					
Class 1	36.56	34.36	18.94	7.68	127.52
Class 2	36.30	32.57	18.81	11.01	129.20
Class 3	34.57	33.24	13.06	11.78	84.60
Distributed generation [MW]					
Class 1	102.89	15.33	581.70	0.47	9,781.43
Class 2	165.50	15.72	1,278.85	0.58	14,827.64
Class 3	55.21	12.34	181.42	0.35	1,635.70

Table 3: Descriptive statistics per class

customers, basically reflect network operators' size. For both variables, we observe significant differences between classes. Class 1 comprises at least some larger operators indicated by the highest average supplied electricity and the highest number of connected customers. Furthermore, the standard deviation of the outputs is highest in class 1 which shows that it consist of large and small network operators. Whereas the picture is clear for class 1, the differences between classes 2 and 3 are not apparent. The average amount of supplied electricity is similar in both classes, while the maximum amount differs significantly: The largest network operator in class 2 delivers more than twice as much electricity than the largest network operator in class 3 (68 TWh vs. 31 TWh). Regarding the number of connected customers, class 3 comprises the smallest network operators: the mean, the standard deviation, and the maximum amount of connected customers are the lowest across classes. The relatively low and similar median values of the outputs across classes indicate that all classes mainly consist of smaller network operators. However, classes 1 and 2 also include some larger network operators. Referring to the estimated economies of scale per class, it seems reasonable that the smallest network operators assigned to class 3 may benefit from a size increase. The positive economies of scale of class 1 may also be driven by the large share of smaller network operators as it seems rather surprising that increasing their size would also benefit the largest network operators.

The mean and median network density show only slight variation across classes. However, the distribution of the network density is narrower in class 3 than in class 1 and 2: The standard deviation is lowest, and also the maximum value is with 84 connection points per network kilometer considerably smaller than those in class 2 and 1 (129 and 128 connection points per network kilometer, respectively). Thus, most of the network operators in class 3 have a relatively low network density.

We see significant differences in the cost impact of the installed capacity of renewable power plants across classes and are now interested, whether classes also differ according to the amount of renewable power plants' installed capacity. Class 3 is with an average installed capacity of 55 MW and a median capacity of 12 MW clearly characterized as the class with the lowest installed capacity. With 166 MW, the average installed capacity in class 2 is three-time higher, and with 103 MW in class 1 almost twice as high as in class 3. Besides, class 2 also contains network operators with the highest distributed generation capacity from renewable energy sources having a maximum of 14.8 GW compared to 9.8 GW in class 1 and only 1.6 GW in class 3. All classes contain network operators with very low distributed generation capacities from renewable energy sources, resulting in comparatively low median values and large standard deviations.

In sum, class 1 contains the largest network operators with high, but not the highest, installed capacity of renewable power plants. Network operators allocated to class 2 have the highest installed capacity of renewable power plants and are of relatively medium size. The picture is evident for class 3, consisting of small network operators operating networks with low density and low distributed generation capacities from renewable energy sources.

Even though we observe differences in class characteristics across classes, we are interested in whether the deviations are statistically significant different from zero. Hypothesis tests (t-tests) on mean equality across classes show that classes statistically differ, at least in some parts. As shown in Table 4, the minor differences are found between classes 1 and 2 that only differ significantly in the average number of connected customers (QC). In contrast, classes 1 and 3 statistically differ in the mean of all variables. Class 2 and 3 do not vary statistically in their size but their network density and installed capacities of distributed generation from renewable energy sources. Thus, a classification of German network operators according to their size only may be misleading.

	Class 1 & Class 2		Class 1 & Class 3		Class 2 & Class 3	
Variable	mean difference	p-value	mean difference	p-value	mean difference	p-value
QE	1,234.37	0.1233	1,220.43	0.0333 **	-13.94	0.9604
QC	34.93	0.0946 *	46.30	0.0017 ***	11.37	0.1860
ND	0.26	0.8234	1.99	0.0171 *	1.73	0.0717 *
DG	-62.62	0.2523	47.68	0.0318 **	110.29	0.0205**

Notes: ***, ** and *: Significant at the 1%-, 5%-, and 10%-level.

Table 4: Differences in means of variables across classes

We conclude that there is technological heterogeneity between German network operators related to differences in the size, the network density, and the capacity of distributed generation from renewable energy sources identified by differences in the cost function parameters. Furthermore, differences in class characteristics are present. As we are particularly interested in the impact of distributed generation capacity from renewable energy sources, we try to find even more related differences across classes. Therefore, we analyze whether classes differ according to the installed capacities of PV and wind power.[10] Especially wind and PV plants have very heterogeneous demands on network operators as they differ in the voltage level of the network they are usually connected to and in further characteristics, e.g., plant-specific size, locational requirements, and so forth. The summary statistics are shown in Table 5.

	Mean	Median	Std. dev.	Minimum	Maximum
Installed PV capacity [MW]					
Class 1	53.24	10.05	264.86	0.47	3,339.93
Class 2	34.04	9.49	183.56	0.39	2,222.87
Class 3	28.27	8.85	77.29	0.35	755.90
Installed wind capacity [MW]					
Class 1	35.11	0	289.07	0	5,579.58
Class 2	118.20	0.55	1,015.48	0	11,753.48
Class 3	19.86	0	84.96	0	824.36
Wind share					
Class 1	0.10	0	0.16	0	0.69
Class 2	0.17	0.02	0.23	0	0.91
Class 3	0.13	0	0.20	0	0.89

Table 5: Descriptive statistics of non-included variables per class

As for the total installed capacity of renewable power plants, wind and PV capacities are lowest for class 3. However, the differences between class 1 and 2 become clearer now: In class 2, the high installed capacity is driven by wind capacities that are, on average, almost five times higher than in class 3 and more than twice as high as those in class 1. In contrast, class 1 comprises the highest average and median installed capacity of PV. The differences in the installed wind capacities across classes clarify the heterogeneous cost function parameters. The high wind capacities lead to lower marginal costs of distributed generation capacities from renewable energy sources in class 2 (see Table 2). Due to voltage problems that occur more often in the low-voltage level and the limited capacity to integrate renewable power plants, the same capacity of renewable power plants causes higher costs in the low- than in the medium- and high voltage network (Swiss Economics et al., 2019). These findings are supported by the wind share per class, defined as the installed wind capacity divided by the total installed capacity of renewable power plants. In class 2, 17 percent of the installed capacity of distributed generation from renewable energy sources comes from wind power compared to 10 and 13 percent in class 1 and 3, respectively. Thus, network operators of class 2 may have lower marginal costs of the capacity of distributed

[10] Convergence problems and characteristics of the data impede the inclusion of these variables in the total cost function.

generation from renewable energy sources due to a high capacity and share of wind power connected to the medium- and high-voltage level. In contrast, classes 1 and 3 have a lower capacity of wind power and a higher share of capacities connected to the low-voltage level, resulting in a higher cost impact.

The previous findings indicate that heterogeneity among German network operators exists regarding their cost function parameters. Especially class 2 seems to differ significantly from the other classes. These differences may be driven by the high installed wind capacities in class 2. To validate the results and demonstrate the general impact of wind capacities on network operators' costs, we estimate a standard random effects model abstracting from any efficiency effects. We split the sample into network operators with and without wind capacities and estimate Equation 2 separately for both groups and compare the results.[11] The "wind group", i.e., network operators with installed wind capacities larger than zero, comprises 880 observations, and the "no-wind group", i.e., network operators with no installed wind capacity, contains 1,031 observations.[12] The results support the previous findings: Network operators without any installed wind capacities face higher marginal costs from increasing distributed generation capacity from renewable energy sources than network operators with installed wind capacities. In the case of network operators having no wind, the effect measures mainly the impact of an increase in PV capacities which induce higher costs than wind capacities. As previously mentioned, these differences result from the wind capacities connected to the medium- and high-voltage network, while PV is usually connected to the low-voltage network.

To sum up again: Network operators with the highest capacity of renewable power plants, mainly driven by wind power, are medium-sized and attributed to class 2. Thereby, the high capacity of wind power explains the lower marginal costs of the capacity of renewable power plants in class 2. Class 1 comprises the largest network operators with a high capacity of distributed generation from renewable energy sources in general and PV in particular. In contrast, class 3 includes operators combining the lowest installed capacity of renewable power plants, small size, and the lowest network density. The higher marginal costs of the capacity of renewable power plants in classes 1 and 3 are driven by the comparatively higher share of capacities from renewable energy sources connected to the low voltage level.

5.3. Efficiency estimates

Besides the differences in parameter estimates and class-specific characteristics, we are interested in differences in the efficiency estimates. In a latent class framework there are as many frontiers as classes. Thus, the estimation of (in)efficiency is not as straightforward as in the standard SFA models. Inefficiency can be estimated based on two approaches: First, network operators are benchmarked against the frontier of the class with the highest posterior class probability, i.e., the "most-likely" frontier. Second, the network operator is benchmarked against a "weighted-average" frontier consisting of the probability-weighted

[11]The distribution of wind capacities across network operators and the low variation of network operators' wind capacities over time prevent the estimation of a single model, including the capacities of wind and PV.

[12]The detailed estimation results are depicted in Table 9 in the Appendix.

average of all classes (Greene, 2002). The higher the posterior class probabilities, the lower are the differences between the two approaches (Orea and Kumbhakar, 2004). In our case, the mean posterior class probability varies between 95.8 and 96.9 percent per class. To be consistent with network operators' assignment to a particular class, we chose the approach with the "most-likely" frontier. Due to the high posterior probabilities, differences between the two methods are only of minor importance. The individual inefficiency is estimated using the approach of Jondrow et al. (1982), where individual inefficiency is predicted by the conditional mean of the estimated inefficiency term, $u_{i,t}$.

	Mean	Std. dev.	Minimum	Maximum
Total sample	0.9033	0.0977	0.3169	0.9891
Class 1	0.8962	0.0700	0.6254	0.9891
Class 2	0.7959	0.1358	0.3169	0.9833
Class 3	0.9649	0.0154	0.8907	0.9891

Table 6: Cost efficiency estimates

Table 6 shows the summary statistics of efficiency estimates per class and of the whole sample. Comparing the efficiency estimates across classes, it is remarkable that class 2 has a relatively low efficiency (79.6 percent). In contrast, class 3 contains very efficient network operators with efficiency estimates that only vary between 89.1 and 98.9 percent. The average efficiency of network operators in class 1 is 89.6 percent and thus close to the overall sample average of 90.3 percent. The differences across classes are illustrated by the distribution of efficiency estimates shown in Figure 1, which differ substantially. Network operators in class 3 show a very narrow distribution around very high efficiency values, while the distribution of class 2 is much flatter and at a lower level. Hypotheses tests (t-tests) with the hypothesis of equal average efficiency estimates across classes confirm the results: The null-hypothesis of equal efficiency has to be rejected for all class comparisons (class 1 with 2, class 2 with 3, and class 1 with 3) at the 1 percent significance level. Thus, efficiency estimates differ significantly between classes.

As we observe differences in the efficiency and installed capacity of distributed generation of renewable energy sources across classes, we are interested in whether these are related. Analogous to Just and Wetzel (2020), we compare the efficiency of network operators with different shares of distributed generation from renewable energy sources but cannot find significant differences in the efficiency. Thus, the results indicate that differences in network operators' efficiency are not driven by the installed capacity of renewable power plants.

5.4. Comparison with two- and one-class model

To validate our results, we compare them with those of two different model specifications. First, we estimate a latent class model with only two classes. In Germany, network operators are clustered in two groups according to their size, revealing the indirect assumption of structural differences between small and large network operators. Thereby, the regulator

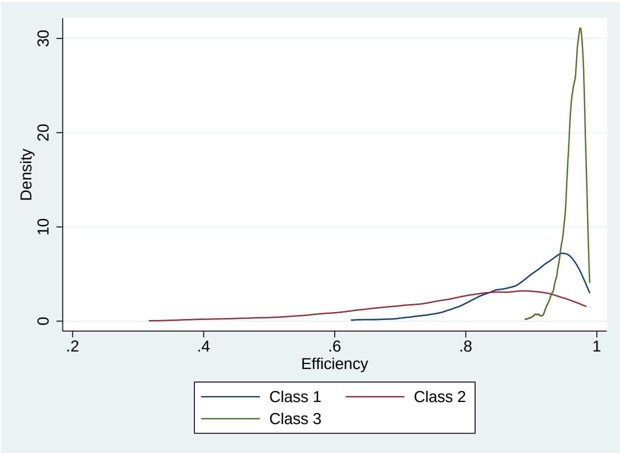

Figure 1: Kernel density estimates of cost efficiency

defines the clustering criterion as 30,000 connected customers. As we have pointed out, such an exogenous clustering is inefficient per definition. Thus, we are rather interested in whether a latent class model with two classes would reflect the regulator's assumption that network operators' size is the relevant clustering criterion. Second, we estimate a True Random Effects (TRE) model where network operators are considered one group, i.e., a one-class model. Even though the TRE model allows individual frontiers due to a random shift of the constant, the cost function, i.e., technology, is assumed to be equal for all network operators. The detailed estimation results of the two-class and the TRE model can be found in the Appendix.

We first analyze the results obtained by the two-class model. The estimation of a latent class model with two classes yields the following class sizes: Class A consists of 1,248 network operators and class B of 663.[13] The summary statistics of both classes are shown in Table 7. It is striking that the average differences between the two classes are smaller compared to the differences across classes in the three-class model. However, class A contains small network operators with lower installed capacities of distributed generation from renewable energy sources, while class B consists of large network operators with comparably higher installed capacities of distributed generation from renewable energy sources. Again, the installed capacity of wind power is not included in the cost function but shows significant variation across the two classes. The high capacities of distributed generation from renewable energy sources in class B are driven by high wind capacities being more than twice as high as in class A. Analogous to the results of the three-class model, network operators in class B face lower marginal costs of the installed capacity of distributed generation from renewable energy sources than network operators in class A (see Table 10 in the Appendix). The heterogeneous impact of distributed generation capacity from renewable energy sources is

[13]We name the classes A and B rather than 1 and 2 to avoid confusion with the names of the three-class model.

neglected in the TRE model, assuming a joint cost function, i.e., technology, for all network operators. The results show that the estimated marginal costs of increasing distributed generation capacity from renewable energy sources are smaller than in class A and larger than in class B. Thus, the TRE model overestimates the cost impact of distributed generation from renewable energy sources for network operators with relatively high wind capacities and underestimates it for those with lower wind capacities (see Table 11 in the Appendix).[14]

Referring to our question of whether an endogenous clustering reflects the German regulator's assumption, we have to state that this is rather not the case. Classes differ in the number of connected customers, but the specific sampling criterion of 30,000 connection points seems not to be relevant here. Even though class A consists of relatively small operators, nearly one-third has more than 30,000 connection points, and even 66 percent of the rather large network operators in class B have less than 30,000 connection points. Thus, we cannot confirm the German regulator's clustering criterion if we assume the existence of two classes.

	Mean	Median	Std. dev.	Minimum	Maximum
Electricity supplied [GWh]					
Class A	1,895.16	239.14	11,649.46	9.88	247,549.60
Class B	1,942.03	261.46	7,101.38	4.76	68,301.84
Connection points [thousand]					
Class A	67.59	18.41	257.71	1.60	4,965.61
Class B	93.80	20.20	290.56	1.04	2,382.71
Network density [Connection points/network km]					
Class A	34.60	31.56	17.16	7.68	127.52
Class B	37.84	35.66	16.08	11.01	129.20
Distributed generation [MW]					
Class A	89.78	14.69	479.75	0.35	9,781.43
Class B	109.36	14.45	907.70	0.58	14,827.64
Installed wind capacity [MW]					
Class A	31.44	0	237.21	0	5,579.58
Class B	72.34	0.01	770.44	0	11,753.48

Table 7: Descriptive statistics per class of the two-class model

As efficiency estimates have direct financial consequences for network operators, we are furthermore interested in the impact of different clustering approaches on efficiency estimates. Therefore, we compare the three-class model's efficiency estimates with those of the two-class model and the one-class model, i.e., the TRE model, which assumes equal technology characteristics and thus a common cost function for network operators. Thus, technological heterogeneity, of which our previous results indicate that it is present, is considered as inefficiency. In consequence, we expect a lower efficiency in the TRE model than

[14]The estimation results of the TRE model are obtained by maximum simulated likelihood estimation.

in the latent class models. Average efficiency estimates across the three models are shown in Table 8. The average efficiency estimates differ only slightly but are, as expected, highest for the three-class model. The two-class model yields, on average, slightly higher efficiency values than the TRE model. This may be because the two-class model considers technological heterogeneity among network operators, which is attributed to inefficiency in the TRE model. Applying t-tests to test the equality of efficiency estimates across the different models, we find that efficiency between the three- and the two-class model and between the three-class model and the TRE model differ significantly at the 1 percent level. Differences between the two-class model and the TRE model are only slightly significant at the 10 percent level.

	Mean	Std. dev.	Minimum	Maximum
Three-class model	0.9033	0.0977	0.3169	0.9891
Two-class model	0.8982	0.0601	0.5997	0.9857
One-class model (TRE)	0.8960	0.0611	0.3414	0.9855

Table 8: Comparison of cost efficiency estimates

Even though efficiency estimates may, on average, differ only slightly, differences for individual network operators may be more prominent. If we account for two technology classes represented by two different cost functions, 75 percent of the network operators will face lower efficiency estimates than with three technology classes. Suppose only one class is considered, and thus, differences in the underlying cost function are ignored at all. In that case, 69 percent of the network operators will have lower efficiency estimates than in the three-class model. Thus, individual efficiency estimates are sensitive to the model specification. The results correspond to our expectation and previous research: The consideration of technological differences reduces unobserved heterogeneity within the classes, and therefore, the heterogeneity conventional models may consider as inefficiency (Agrell et al., 2014).

6. Conclusions

The regulation of electricity distribution network operators is most commonly based on incentive regulation, of which benchmarking is an essential element. The use of benchmarking procedures requires the existence of a set of comparable network operators. As this assumption is seldom fulfilled in practice, addressing the heterogeneity among network operators in benchmarking is one of the major concerns and challenges for regulators. If differences among network operators are observable, the regulator accounts for them directly in the benchmarking procedure. To deal with unobserved heterogeneity is far more challenging.

Unobserved heterogeneity may impact network operators in various ways. First, it can affect the costs and performance and second, the production process. The second aspect is, however, often neglected in the regulatory practice, with a common technology, i.e., production process, being assumed among network operators instead. This implies, for example, that all network operators are represented by the same cost function and thus face the same marginal costs, e.g., to connect new customers or distributed generation plants. However, network operators differ substantially in many aspects that are likely to influence the production process and thus contradict this assumption. For example, network operators in a mountainous landscape face higher connection costs than those in a rather flat landscape. Moreover, costs of distributed generation from renewable energy sources differ according to the plant type: Wind capacities at higher voltage levels induce lower costs than PV in a low-voltage network. These differences remain uncontrolled for if regulators assume a common technology, i.e., cost function.

Technological differences may even increase due to changing market conditions. Increasing distributed generation from renewable energy sources as well as the use of electric vehicles and heat pumps would require an adaption of network operators. The ability to adapt may also be influenced by unobserved differences among network operators. These developments together with the structural diversity of network operators raise doubts on the assumptions of homogeneous conditions among network operators at the moment and even more in the future. If technological heterogeneity remains uncontrolled and a joint cost function is assumed for all network operators, efficiency estimates would be biased and have direct financial consequences for network operators.

In this paper, we estimate the cost efficiency of German network operators and explicitly account for technological differences represented by heterogeneous cost functions among network operators. Based on a latent class model, our results show that German network operators can be unambiguously classified into three statistically different classes sharing a common technology, i.e., cost function, based on size and distributed generation variables. We find significant differences in the size, installed capacity of distributed generation from renewable energy sources, and efficiency estimates across classes. The results indicate that distributed generation from renewable energy sources is a relevant driver of technological heterogeneity among classes. First of all, differences in the installed capacity of renewable power plants across classes are partly driven by the total capacity but especially by differences in the installed capacities of wind power. Furthermore, we observe a heterogeneous cost impact of an increase in distributed generation from renewable energy sources across classes related to their installed wind capacities. Thus, clustering German network operators solely according to their size, as done by the German regulator, leads to misleading results. The importance to account for technological heterogeneity among German network operators is confirmed by comparing the results of the three-class model with those of a one- and two-class model. Efficiency values are highest in the three-class model as, at least some, technological heterogeneity is overlooked and thus considered as network operators' inefficiency in the one- and two-class model.

We conclude that German network operators use heterogeneous technologies represented by different cost function parameters. The consideration of technological differences reduces unobserved heterogeneity within classes, avoiding the misspecification of heterogeneity as inefficiency in conventional models. As efficiency estimates have a direct financial impact on network operators, the importance of correctly accounting for heterogeneity can be clearly seen in the results. In this context, the application of latent class analysis may provide valuable insights for regulators to detect and address technology differences among network operators in Germany and worldwide.

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Appendix

Variable	wind group	no-wind group
Constant	16.203***	16.320***
	(0.024)	(0.023)
$ln\,QE$	0.127***	0.138***
	(0.021)	(0.023)
$ln\,QC$	0.684***	0.599***
	(0.032)	(0.032)
$ln\,ND$	-0.459***	-0.346***
	(0.041)	(0.037)
$ln\,DG$	0.184***	0.247***
	(0.021)	(0.019)
2012	0.024*	0.011
	(0.013)	(0.014)
2013	0.063***	0.036***
	(0.014)	(0.014)
2014	0.071***	0.040***
	(0.014)	(0.015)
2015	0.076***	0.046***
	(0.014)	(0.015)
2016	0.143***	0.112***
	(0.015)	(0.016)
2017	0.170***	0.140***
	(0.020)	(0.023)

Notes: Standard errors in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. The estimations have been performed in STATA 12.

Table 9: Estimation results of wind and no-wind group

Variable	Class A	Class B
Constant	16.184***	15.771***
	(0.016)	(0.031)
$ln\, QE$	0.135***	0.117***
	(0.010)	(0.019)
$ln\, QC$	0.568***	0.781***
	(0.017)	(0.027)
$ln\, ND$	-0.315***	-0.235***
	(0.019)	(0.033)
$ln\, DG$	0.265***	0.105***
	(0.007)	(0.013)
2012	0.047***	0.028
	(0.016)	(0.029)
2013	0.060***	0.098***
	(0.016)	(0.029)
2014	0.072***	0.103***
	(0.016)	(0.029)
2015	0.075***	0.101***
	(0.016)	(0.029)
2016	0.125***	0.191***
	(0.016)	(0.030)
2017	0.131***	0.303***
	(0.023)	(0.045)
Prior Class Probabilities	0.630***	0.370***
	(0.028)	(0.028)

Notes: Standard errors in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. The estimations have been performed in NLOGIT 6.

Table 10: Estimation results of the two-class model

Variable	TRE
$Constant$	16.129***
	(0.006)
$ln\,QE$	0.144***
	(0.004)
$ln\,QC$	0.632***
	(0.006)
$ln\,ND$	-0.391***
	(0.007)
$ln\,DG$	0.199***
	(0.003)
2012	0.037***
	(0.009)
2013	0.078***
	(0.008)
2014	0.083***
	(0.008)
2015	0.087***
	(0.008)
2016	0.150***
	(0.008)
2017	0.176***
	(0.013)

Notes: Standard errors in parentheses. ***, ** and *: Significant at the 1%-, 5%-, and 10%-level. The estimations have been performed in NLOGIT 6.

Table 11: Estimation results of the TRE model