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A Comparison of French and German Utilities

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International Benchmarking in Electricity Distribution: A Comparison of French and German Utilities

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October 2008

Abstract

In this paper we present an international cross-country benchmarking analysis for utility regulation of France and Germany, the two largest electricity distribution countries in Europe. We examine the relative performance of 99 French and 77 German distribution companies operating within two different market structures. This paper applies several parametric benchmarking approaches to assess the relative technical efficiency of the utilities, such as deterministic Corrected Ordinary Least Squares (COLS) and Stochastic Frontier Analysis (SFA). Our base model uses the number of employees as a proxy for labor and network length as a proxy for capital as inputs. Units sold and the numbers of customers are considered as outputs. Our model variations and extensions analyze the effect of different characteristics of distribution areas (e.g. population density and the choice of investment in underground cable network). We find that utilities operating in urban areas feature higher efficiency scores and that investment in underground cables increase the technical efficiency of the distribution utilities.

Keywords: international benchmarking, electricity distribution, parametric efficiency analysis

JEL-Codes: L94, L11, C40

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1 Introduction

Recent European sector reforms such as Acceleration Directive 2003 have established a more incentive-based regulatory framework in which distribution utilities are considered as non-contestable regional monopolies. Regulators usually employ benchmarking techniques to compare distribution companies' efficiencies to generate information for incentive-oriented regulations.

A large number of empirical studies at an international level have compared utilities in a single or several countries. Jamasb and Pollitt (2001, 2003) give an extensive comparison of international efficiency studies for the electricity sector, stressing the importance of the proper variable choice. Using panel data compiled from 59 Swiss distribution companies over eight years, Farsi and Filippini (2004) argue that different methodologies may lead to different results. In a similar panel data analysis for six Latin American countries, Estache et al. (2004) show that national regulators can reduce information asymmetry through cross-country efficiency analysis. We note that international cross-country efficiency analysis involves empirical problems due to transnational comparisons. Thus, in general terms cross-country comparisons using firm level data are less common. However, national policy makers have become more interested in cross-country efficiency analyses that allow them to view their industry in broader terms (Jamasb and Pollit, 2003). Estache et al. (2004) acknowledge the empirical problems resulting from differences in definitions and fields of activities and responsibilities of the national distribution companies, and conclude that cross-country comparisons require a high degree of homogeneity. Empirical problems are greater when considering international cost efficiency analyses. Jamasb and Pollit (2003) find that data definition (e.g. accounting rules, depreciation, price deflators, exchange rates, and the like) is a significant problem. Therefore, we limit ourselves in a first step to a comparison of production efficiency in Germany and France.

In addition to monetary variables, technical parameters that can differ across countries must be accounted for; our paper identifies the technical parameters, refining the available data to a consistent and comparable sample. We note that even if distribution companies operate in different regions with similar technical settings, environmental and network characteristics may be only partially observable. Such unobserved heterogeneity is already present at the national level, but the effect can be greater when making international comparisons.[1]

[1] We underline the importance of modeling such unobserved heterogeneity in order to separate the unobserved factors from inefficiencies within international comparisons (see Greene, 2002, 2004 and 2005). Parametric panel data models (Greene's true random effect model and

Quality considerations become more significant within the efficiency comparisons for the different European regulatory authorities. For example, quality as related to benchmarking has been studied by Giannakis et al. (2004) (for UK electricity distribution utilities) and Growitsch et al. (2005). Nevertheless, integration of the quality index in our benchmarking model is not the focus of this paper because of the detail of distribution quality data available for Germany.

To date, no European performance study includes both France and Germany.[2] Thus, this paper is the first productivity analysis of a large number of French and German electricity distributors and their influence in sector liberalization. The two countries' different market structures present the two extremes found in European electricity distribution. France has a vertically integrated dominant operator (ERDF, which is a 100% EDF's subsidiary) with separated distribution activities that are organized into eight more or less homogeneous regional distribution units, while Germany is characterized by many different regional and local distribution companies.

The main objective of our study is to define how the choice of input-output variables can modify the scores and rankings of the companies with respect to the differences in environmental and structural constraints between companies and between the two countries. We hypothesize whether companies operating in urban regions reach higher efficiency scores than in rural areas due to higher population density and the resulting cost advantages. We also estimate the importance of underground cable networks on the relative efficiency scores because such networks generally involve lower maintenance costs. Since financial data is unavailable for German companies, our models incorporate cost drivers such as the number of customers, total power sales, inverse density index, length of the grid, and number of employees.

The next section describes the methodological background for efficiency analysis. Section 3 provides the empirical application, data description, and model specification for the distribution structures in France and Germany that are necessary for international

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latent class models for stochastic frontiers) exist that are able to shed light on the problem, but given that we only dispose of a static data set, we cannot apply any panel data models to model the unobserved heterogeneity. This is a topic for future research.

[2] Jamasb and Pollit (2003) included Italy, Norway, UK Portugal, Spain and Netherlands. Growitsch et al. considered UK, Ireland, Netherlands, Finland, Norway, Sweden, Italy and Spain. Hirschhausen et al. (2008a) analyzed Poland, Czech Republic, Slovakia and Hungary as a unit and compared them with Germany.

comparisons. Results from the basic model and from several extended models estimated with COLS and SFA methods are provided in Section 4. Section 5 concludes.

2 Parametric Benchmarking Methods

Efficiency analysis (benchmarking) has played an essential role in defining regulatory policies mainly in industries characterized by natural monopolies and/or by public ownership such as energy. In the electricity sector, efficiency analysis is particularly important in the migration to a competitive industry structure with market-oriented regulation for both transmission and distribution. A wide range of different nonparametric and parametric benchmarking methods have been utilized (e.g. Coelli et al., 2005) to assess the relative efficiency of different decision-making units. They have been particularly useful in the regulatory processes in the UK, Switzerland, the Nordic States, the Netherlands, and Austria. Until now, in the empirical application within a regulatory framework the nonparametric data envelopment analysis (DEA)[3] has outperformed SFA (see Farsi et al., 2007). Nevertheless, we explicitly focus on the parametric approach for the following reasons: regulators are beginning to employ parametric methods to assess the cost drivers of distribution companies; assessing the impacts of different parameters on efficiency scores is useful; and SFA results are important because the deterministic DEA are sensitive to outliers and sampling variations.

We apply the two common parametric approaches (COLS and SFA). The technological possibilities of firms and industries can be summarized by means of production functions that represent the technical relationship between the level of inputs and the resulting level of outputs.[4] There are several different algebraic formats to describe the technology of the industry; the most important are the linear, the quadratic, the normalized quadratic, the generalized Leontief and the constant elasticity of substitution (CES) functions. Empirical applications most frequently use Cobb-Douglas and the Translog functions, depending on different assumptions about returns to scale and substitution elasticities. The Translog

[3] DEA is a non-parametric approach determining a piecewise linear efficiency frontier along the most efficient utilities by means of linear programming to derive relative efficiency measures of all other utilities.

[4] The principal properties of production functions that underpin the economic analysis are nonnegativity, weak essentiality, non-decreasing and concave in the different inputs (for a detailed mathematical analysis on production function characteristics see Coelli et al., 2005). An econometric production function estimation from observed input-output combinations therefore determines the average level of outputs that can be produced from a given level of inputs (Schmidt, 1986).

function is defined by a second order (all cross-terms included) log-linear form and represents a relatively flexible functional form that does not impose assumptions about constant elasticities of production or elasticities of substitution between inputs (see Coelli et al., 2005). Thus, it allows the data to indicate the actual curvature of the function rather than imposing *a priori* assumptions.

The Cobb-Douglas production function is characterized by more restrictive assumptions about returns to scale and the elasticity of substitution. The elasticity of substitution has a constant value of 1 (i.e. the functional form assumption imposes a fixed degree of substitution on all inputs). The elasticity of production is constant for all inputs (i.e. a 1 percent change in input level will produce the same percentage change in output irrespective of any other arguments of the function; Coelli et al., 2005). We note that Cobb-Douglas is a special case of the Translog production. The Cobb-Douglas function can be expressed by

$$\ln y_i = \beta_0 + \sum_{j=1}^{2} \beta_j \ln x_{ji} \qquad (1)$$

where y_i represent the aggregated output index and x_1, x_2 the capital and labor input respectively.

Within the COLS approach we assume a given functional form of the relationship between inputs and outputs and estimate the unknown parameter of the function by ordinary least squares (OLS) regression, and the residual (the estimated error) represents technical inefficiency. The efficient frontier is constructed by adding the value of the largest positive estimated error v_i (see Jamasb and Pollit, 2003 for an extensive overview). To derive the relative performance of an individual firm, we assess the distance from the observation point to the efficient frontier captured by the estimated error.

SFA is another parametric method used to estimate the efficient frontier and the efficiency scores.[5] Within this approach the unknown parameters of the function are estimated by maximum likelihood techniques. Contrary to OLS regression, the SFA model decomposes the residuals into a symmetric component representing statistical noise and an asymmetric

5 The development of the SFA model specification was independently proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977).

component representing inefficiency (Greene, 2004, 2005). The most general formulation (proposed by Aigner et al., 1977; also Greene, 2004, 2005) is

$$\begin{aligned} & y = \beta' x + v - u, \\ & u = |U| \\ & U \sim N\ [0, \sigma_u{}^2] \\ & v \sim N[0, \sigma_v{}^2] \end{aligned} \qquad (2)$$

where x represents the explanatory variables (inputs in the case of a production frontier), y the observed production of a firm, u the nonnegative random variable associated with inefficiency, and v the symmetric random error accounting for noise. The latter is assumed to be independently and identically distributed normal random variables. As the model is usually specified in natural logs, the u can be interpreted as the percentage deviation of observed performance y from the unit's own frontier performance (see Greene, 2002).[6]

SFA allows the computation of efficiencies of the individual decision units or the entire industry. A common measure of technical efficiency is the ratio of the observed output to the corresponding stochastic frontier output (Coelli et al., 2005). For both approaches relative to the production frontier, the measures of technical efficiency TE are generally defined as

$$TE = E(y|u, x) / E(y|u = 0, x) = EXP(-u) \qquad (3)$$

where E is the conditional expectation, TE assumes a value between 0 and 1 and indicates the observed output of the i-th unit relative to the output which could be produced by a fully efficient unit using the same input vector. The above measures of technical efficiency rely upon the predicted value of the unobservable u (see Coelli et al., 2005) that is determined by means of conditional expectations of the functions of u, conditional upon the observed value of the whole error term, $v - u$.[7]

[6] A large number of variants of the SFA model with regard to the distributional specifications of the inefficiency u have been proposed in the literature. In addition to the half normal distribution of u there are three other common alternatives: the truncated normal (Stevenson 1980), the exponential, and the gamma models (Greene, 1990). An extensive survey can be found in Kumbhakar and Lovell (2000) who also provide the likelihood functions for the different models for estimation purposes.

[7] Jondrow et al. (1982) and Battese and Coelli (1992) derive the conditional predictor of u in detail.

3 Empirical Application

3.1 Data description

For France, we use a consistent data set for the French distribution utilities for the year 2003. For Germany, only data for 2001 was available on VDEW and VDN reports.[8] Although changes implemented among many German distribution companies between 2001 and 2003 resulted in mergers and restructuring of their activities, for the purposes of this paper we assume the French and German data sets are comparable. We conduct a static efficiency analysis, considering only the technical efficiencies of the utilities (since there is no firm level cost data or input factor price data available for Germany). As mentioned in Section 3.2, we note that consistent and unbiased international cost comparisons require a high level of accounting standards and definitions that until now have not been implemented.[9] The sample statistics for both countries are provided in Tables 1 and 2.

For France, we analyzed 315.000 GWh (excluding distribution losses) and data for 31 million residential customers. For Germany we analyzed 268.000 GWh (again excluding distribution losses), and 13 million customers (out of 40 million total). The two tables show the network length of the two countries: the French distribution companies own 1,200,000 km and the Germans only 440,000 km. However, the number of employees is almost identical (France: 35,000; Germany: 37,000).

3.2 Characteristics of French and German Distribution

National regulators in Europe have grown more interested in cross-country efficiency analysis because it provides them with a more comprehensive view (see Jamasb and Pollit, 2003).[10] Yet international benchmarking studies raise important empirical and methodological concerns. The problems arise from the many practical and technical aspects of the definitions and fields of activities and responsibilities of the national distribution companies. E.g. voltage levels, divisions between transmission and distribution activities, distributors that are not constrained by the same political and regulatory obligations, and variations in standards of

[8] Verband Deutscher Elektrizitätswirtschaft (VDEW) and Verband Deutscher Netzbetreiber (VDN).

[9] Jamasb and Pollit (2003) point out that a major problem of international cost efficiency comparisons is data definition, e.g. regarding accounting rules, depreciation, price deflators, or exchange rates.

[10] In the European context it is particularly important for countries in which only a small number of domestic observations is available; in that context, international benchmarking increases the degrees of freedom and allows a more complete assessment of best practice.

quality. Therefore a closer examination of the French and German distribution structures is necessary. Later, we study technical compatibility using three criteria: distribution structure in general, geographical differences (i.e. population density), and network characteristics.

3.2.1 Structure of distribution

France

The French network is operated by ERDF (95% of French territory). There are 93 local distribution centers (excluding Corsica and overseas territories) aggregated into 8 regional areas that manage and operate the electricity and natural gas distribution networks. At the regional level, the structure is quite homogeneous, while some local units may have more geographical or structural differences (large cities vs. small density areas in rural regions). We limited our data set to electricity activity (number of customers, energy delivered, numbers of employees, etc.).[11]

Germany

In contrast, the German network comprises about 900 different distribution companies, including regional companies and many small, local distributors (Stadtwerke).[12] This structural difference raises the question how to compare consistently the French utilities to the German ones. To realize a coherent benchmarking analysis, we decided to keep only German utilities that have a similar size compared to French local distribution units, that means: Including the largest LDCs (local distribution companies), which have one of the following characteristics: more than 50.000 customers and or 250.000 MWh of electricity delivered.[13]

In addition, the French companies only deliver electricity to final customers (with some exceptions for few companies supplying energy to local independent utilities), and do not operate like the German regional distributors which deliver also part of the power to other local distribution companies. Therefore, the final German sample contains 77 observations including also 31 regional units.

[11] In France, electricity distribution activities cover the following issues: operation and maintenance of the network, meter reading, interventions on meter panels, customer bills and contract managements.
[12] The German data uses 58 regional distribution utilities and 507 local distribution companies with significant size differences.
[13] If we include only the regional distribution companies in Germany which are similar to the French regional size we cannot capture the effect of delivering electricity to the final residential consumers in Germany.

3.2.2 *Population density and geographical differences*

The French population is disseminated more throughout the country, involving more long, medium and low voltage lines. German population density is on average twice the French (228 inhabitant/km² vs.106 inhabitant/km²). The entire surface of France is greater than Germany, and with more rural areas. In addition, the location of customers within a distribution area differs. German inhabitants are concentrated around large cities with high load levels involving a stronger network with high transmission capacity (but smaller line lengths). This paper uses the criteria of the inverse density to capture the nature of the distribution area for customer density, noting that the index can only reflect the effect of average density within the distribution area and not the different location of the customers within it. The inverse density index is defined as the number of km² per inhabitant.[14]

We classified the companies as urban or rural to analyze the effect on efficiency. For French companies the classification criteria includes the length of medium voltage feeders, the number of customers connected to a MV/LV substation, and the number of customers living in agglomerations of less than 10,000 inhabitants. The French distribution units are split in 71 rural units and 22 urban ones. However, we classified the German distribution utilities without applying an explicit index. Companies operating in cities with more than 200,000 habitants were classified in the urban group; the rest were assigned to the rural sample.

3.2.3 *Network and voltage differences*

A major difference is the voltage levels of the networks. French distribution companies use less than 20 kV lines; higher voltage lines are operated by the transmission companies. German distribution uses up to 110 kV.[15] Because the data for Germany is not divided between voltage levels, we consider the entire activity.

A further difference between French and German distribution networks is the ratio of underground cables. As shown in Tables 1 and 2 German companies have invested more in underground technology, even in low density areas. In France only 38% of the distribution network of our sample is underground whereas 85% of the German distribution lines are

[14] For French companies, there was only information about the number of customers supplied. Thus we assume a mean number of 1.77 inhabitants per electricity customer to calculate the inverse density index for each French distribution company.

[15] More precisely, we assume that operating a 20 kV network in France is the same as operating a 110 kV network in Germany in terms of labor input. We are aware that the differences may involve extra resources for German companies concerned, and therefore additional distribution costs.

cables. Therefore one model extension (COLS Model 3.3) attempts to capture the effect by including the network length of cables and aerial lines separately.

3.3 *Model Specification*

Availability of data is the major constraint for the choice of input and output variables to describe the technology of the firms. We note that until 2006, when the German regulator began to operate, German firms were not legally obliged to collect and to provide their data and even than the data is not published outside the regulatory authority. Thus, we turned to the models used to derive efficiency measures in electricity distribution described in the literature, while noting the ongoing discussion about the variables to be used as inputs and outputs (e.g. a survey by Jamasb and Pollit, 2001).

Table 3 shows the list of models that have been tested. We chose a traditional model which has been applied for similar sector studies (see Hirschhausen et al., 2006, 2008a and 2008b). The inputs for the base model are labor, estimated by the number of employees and[16] length of the grid (capital). The outputs are total sales (in GWh) and the number of customers. We conduct three different model variations:

1. To account for differences in the regions, we include a structural variable, the inverse density index (IDI, measured in km^2 per inhabitant). Utilities with a dense customer structure obviously have a natural cost advantage. When taken as output, the IDI improves the performance of sparsely inhabited distribution areas.
2. We defined the network length as an output, assuming that the companies are unable to control the network length.
3. We test the effect of the share of cable lines (underground investment) on the companies' output and technical efficiency by dividing the sum of network length into aerial and cable lines.

[16] We have in mind for example, the potentially distorting effects of outsourcing: a utility can improve its efficiency simply by switching from in-house production to outsourcing. For that reason we sorted eliminated out utilities with an abnormal low number of employees. In addition, employment data in Germany includes all workers in the electricity utility including generation responsibilities; we subtract one employee for each 20 GWh produced for the large regional companies managing generation (see Hirschhausen et al., 2006).

It is important to note that the Cobb-Douglas production function is only defined for one output. Since there are multiple outputs, we aggregate customers and electricity sold to one index. The different weights are shown in Table 5.[17]

4 Interpretation and Discussion of Results

We focus exclusively on the utilities' technology and production processes to assess technical efficiency.[18] We then show the empirical results for our different model extensions, analyzing the impact of the customer density (including the difference between rural and urban companies), network size, and percentage share of cable lines.

4.1 Base Model

We begin with the deterministic COLS models. The results for all different specifications are shown in Table 5. COLS Model 1 calculates the efficiency for the French and German distributors without any structural variable. The outputs are aggregated to create a joint index for total sales and the number of customers, in a first step 50/50 each (COLS Model 1.1). A similar approach with different weights is used in COLS Model 1.2 (number of customers: 70%, total sales: 30%). We are aware that the construction of this composite index can be criticized.[19] In this paper, we test the sensitivity of the results with regard to different weights.

We obtain an average efficiency of 34%. We note that the German utilities (32%) are on average less efficient than the French (37%) given our data set and model specification. With regard to the aggregation index one can observe that models using a higher weight for number of customers (70%) vs. the total sales of energy (30%) (COLS Model 1.2) lead to better average efficiency scores (37%), confirming our hypothesis that the total number of a distribution utility's employees depends mainly on the total number and location of the

[17] We weight the number of customers more than the total sales in GWh. Our rationale is that the number of connections determines the need for input factors more than the energy demanded. Within certain limits the maintenance for a customer is quite cheap by using thicker wires and cables, for example, without increasing costs significantly. The weights are based on those used by the UK regulator OFGEM.

[18] We are aware that our empirical results cannot provide an overall economic efficiency measure, including the allocative efficiency of the firms due to the limited data availability of factor prices and costs.

[19] OFGEM's definition of an index has caused much debate. Naturally, weights are debatable; a detailed cost driver analysis must be conducted considering the influence on costs of the two different outputs. This paper shows the variation in the production function and the related efficiency scores when defining other weights.

customers.[20] Figure 1 shows the results for COLS Model 1.2. In all of the following graphs the firms are ordered by size (size defined as the annual amount of electricity sold). Thus we observe that the small French utilities are on average less efficient than the larger ones. This would suggest scale inefficiency of the smaller firms. We do not observe such results for German companies. However, our database does not include the small German distributors; therefore we cannot conclude anything about the return to scale.[21]

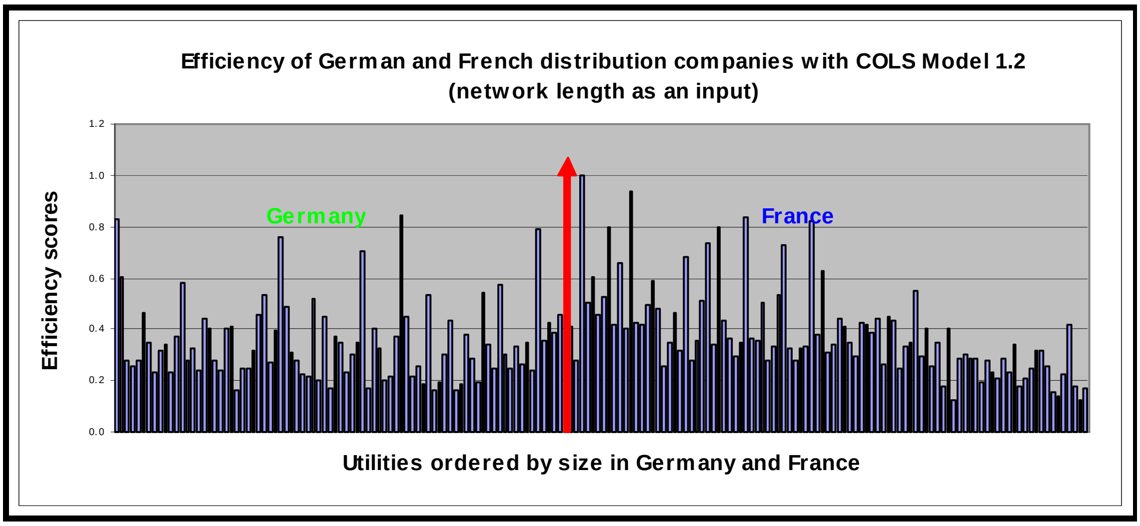

Figure 1: Comparison of France and Germany with the basic COLS Model

The results are confirmed with SFA estimation (SFA model 1.1). To achieve robust, reliable results we conduct model variations of the distributional form of the inefficiency effects (half normal versus truncated normal).[22] As described above we calculate the predicted technical efficiency according to Battese and Coelli (1995). Although the tendency of the deterministic COLS results can be confirmed, this approach leads to smaller gaps between the French and German companies. We offer an econometric explanation: in contrast to the deterministic COLS approach, stochastic frontiers do not assume that all deviations from the frontier are due to inefficiency. SFA allows for statistical noise in the data; therefore, the calculated SFA technical efficiency scores are somewhat higher than COLS.

The French distribution utilities still feature on average a higher technical efficiency score (France 0.74; Germany 0.71) which confirms the results found in the previous deterministic

[20] The German distribution companies still seem to be less efficient (35% vs. 30%).

[21] Note that even for the French market, we only compare the efficiency of small and larger distributors and do not test return to scale. For the German market, Hirschhausen et al., 2006 demonstrated that some returns to scale exist.

[22] Note that the SFA technical efficiency scores rely on the distributional assumptions chosen by the modeller.

parametric approaches. In addition, this approach reveals that smaller French utilities are on average less efficient than the larger companies. Again, this indicates a certain tendency of scale inefficiency in the smaller French companies.

We now turn to the econometric output of our ML estimation for SFA estimation. Table 4 shows that all of the variables included in the Cobb-Douglas production function are significant. Since the coefficients do not differ much across the model variations, the function appears to be well specified: both inputs have a positive and approximately the same impact on the aggregated output. In addition, the summary statistics show the relative importance of statistical noise, v_i (with normal distribution) and inefficiency u_i (with truncated normal distribution) in estimation of the stochastic frontier (see Jamasb and Pollit, 2003 and Coelli et al., 2005). The sigma squared σ^2 is the sum of variances of statistical noise $\sigma_v{}^2$ and inefficiency $\sigma_u{}^2$. The relative importance of inefficiency (gamma) is defined by $\gamma = \sigma_u{}^2 / (\sigma_v{}^2 + \sigma_u{}^2)$. All of our different model runs obtain a gamma different from 1. We can conclude that noise has an influence in the estimated function and it is appropriate to apply SFA in addition to COLS to validate the results and observe if the results change significantly while allowing for statistical noise.

4.2 Model extension with regard to customer density

We first introduce the inverse density index into the COLS Models 3.1 and 3.2, defining it as an output to capture the nature of a structural variable on which the distributors do not have an influence.[23] Results may largely depend on the choice of the different weights to aggregate the outputs to a joint index. To achieve robust, reliable results, we also employ different variations as outlined in Table 3.

[23] We are aware of the criticism that in COLS Models 3.1 and 3.2, the variable inverse density index has been added to the outputs to account for the differences between urban and rural supplied areas; actually, it is not strictly correct to use this data as an output because density is a structural factor that is independent of distribution activity. Population density may explain the differences in efficiency between companies, but should not be linked in the production function of the electricity distribution activity.

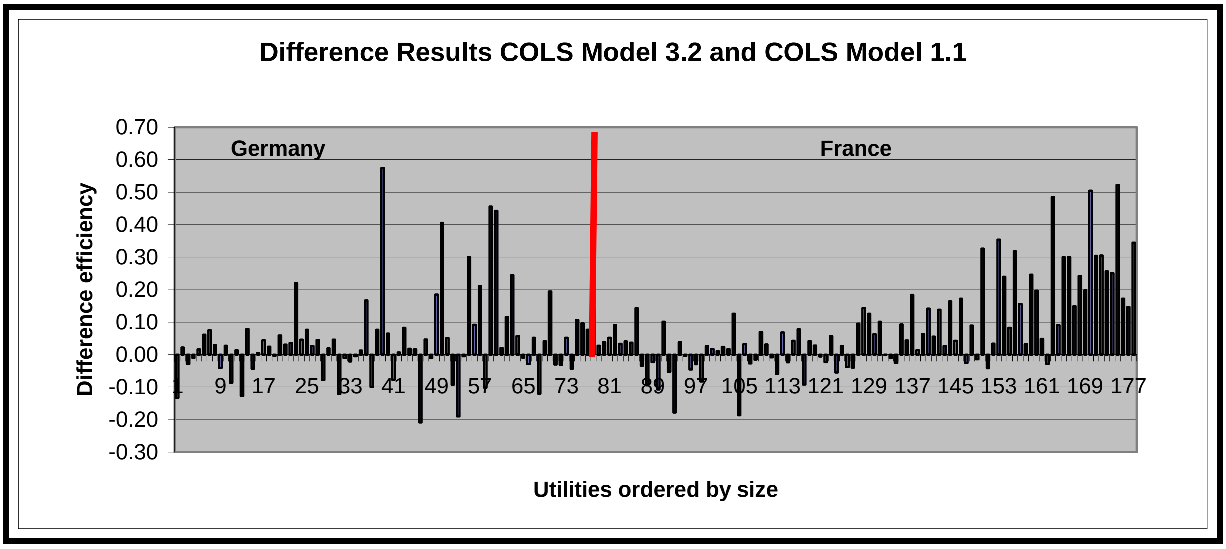

Figure 2: Impact of the inverse density index on the efficiency scores

Figure 2 shows that adding the inverse density index as an output produces better results for nearly all companies, especially for the French (as mentioned, France is more rural and less densely populated than Germany). There is also a different impact of the inverse density index in both countries. The situation in Germany appears to be more heterogeneous and some distributors benefit from the inclusion. In France, the small firms mainly increase their technical efficiency via compensation. The gap between rural and urban companies decreases while considering inverse density population.

To find the impact of the inverse density index using SFA (SFA Model 2.1 and 2.2), we define the index as a structural variable directly influencing the inefficiency distribution (see Coelli et al., 2005) (to discuss further methodological issues, see Battese and Coelli, 1995).
There is an econometric explanation for why Figure 3 shows that the small German companies are compensated in the SFA specification. Recall that in contrast to the parametric COLS where we compensate the firms by considering the structural variable as an output the stochastic frontier models specify the index as an explanatory variable of the efficiency differences. Within this specification we do not compensate the firms and estimate a significant relation coefficient of 0.48. Simply put, when the inverse density index increases, the inefficiency effect increases. From this we can conclude that the French distribution utilities are operating in even less favorable distribution areas compared to Germany.

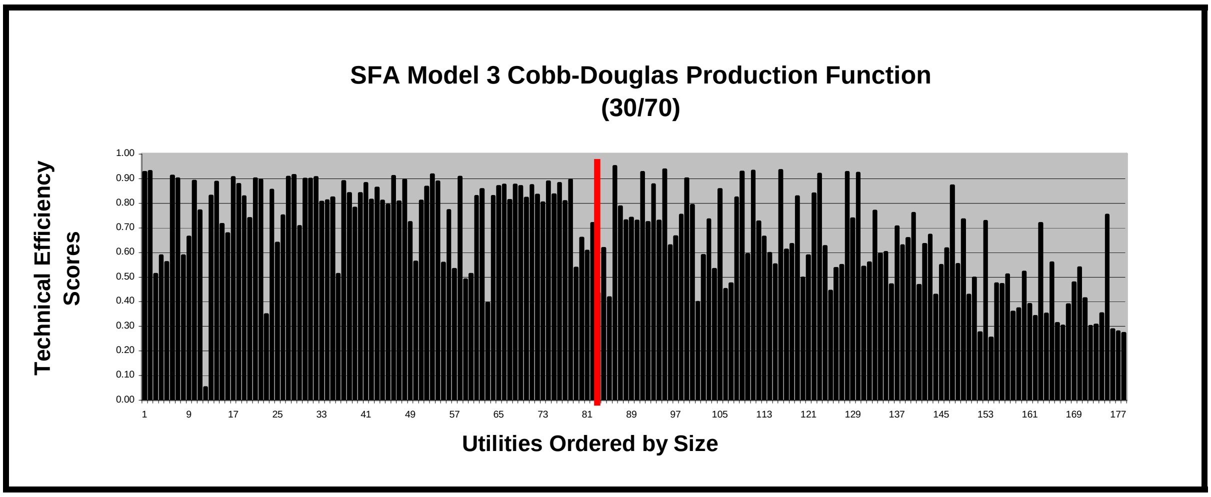

Figure 3: SFA efficiency scores with the inverse density index as an explanatory variable for inefficiency

Next we examine the differences and characteristics of urban and rural companies. We sort the different efficiency averages in four groups: urban French, urban German, rural French and rural German. Companies in urban areas feature on average higher average efficiency scores than their counterparts in rural areas in both countries. We observe that the French urban companies operate more efficiently than their German counterparts. Within the German rural companies, there is a high variation in the technical efficiency scores. In France we observe clearly that the small utilities are on average less efficient. Thus the rural French companies feature scale inefficiency. For all models, urban companies feature on average higher efficiency scores than rural ones. Indeed, the number of employees is less important in city areas; since the customer distances are smaller and the network is mainly underground (i.e. less maintenance and repair).

4.3 Model extension considering network length

In the previous models the network length is considered as an input, meaning that the distribution companies can control and optimize the volume of their network by using network planning. On the other hand, distribution companies are obligated to deliver electricity to any customer and at any locale, making it impossible to fully optimize the network's topography. Therefore network length is also an output. We note that the gap between the French and German utilities increases in favor of French companies when network length is defined as an output. This implies that French companies must manage a longer network since their customers live throughout the service are and are not concentrated around larger cities (Germany).

The difference between overhead aerial and underground cable lines is also a factor. We can determine if ceteris paribus a greater share of cables lines has a positive or negative effect on the produced output and the relative technical efficiency of the companies. COLS Model 3.3 considers an aggregated output variable from energy sold, number of customers, and total area covered. Network length is an input variable, as well as total number of employees, but now we divide it into overhead and underground lines. It appears that underground lines have ceteris paribus a greater impact on the production process since it is necessary to have nearly three times fewer underground lines than overhead to produce a certain term of output with the same number of employees. This is shown by the estimated coefficients of the separated network length inputs (0.16 aerial vs. 0.52 cables) in the Cobb-Douglas production function specification. Both estimated coefficients are significant at the 5% level. This result confirms the current assumption which asserts that less labor works are required for operating underground networks than overhead lines (no tree-cutting, less preventive maintenance).
For efficiency scores, the gap between German and French companies increase greatly (mean in Germany is equal to 40.9% vs. mean in France is equal to 48.9%).

5 Conclusion

This paper has compared the technical efficiency of distribution companies in two of the largest European countries: France and Germany. Our results indicate marked differences in the efficiency scores both within the countries and between the countries, and between different model specifications. On average, the French distribution companies appear to be more efficient which we confirmed across all model specifications. However, these results cannot be used in the “real world” of regulatory process. As mentioned our paper concerns the application of different methods and model specifications within a technical and physical framework and therefore reveals only some of the trends.

By comparing urban and rural distribution areas we find that for all models companies in urban areas showed higher efficiency scores. Including the inverse density index into the econometric models on the output side compensate utilities that operate in less densely settled areas meaning that they gain technical efficiencies. The Battese and Coelli Model in the SFA framework helps to quantify the impact which the inverse density index has on the technical inefficiencies.

This study represents a starting point for further analysis and research. We note that every cross-country efficiency analysis encounters problems concerning the availability and especially the heterogeneity of the operation processes in the countries under study. It is especially important that additional research employs the most recent data samples (especially for Germany where the electricity sector underwent structural reforms after 2001). The use of monetized cost data would also support more reliable conclusions about allocative efficiency and scale efficiencies of the distribution utilities.

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Appendix

Table 1: Summary Statistics Germany

	Electricity Sold in MwH	Number of Customers	Network Length in km	Labor, Number of Employees	Inverse Density Index in km2/inhabitants	Surface total in km2	Underground rate
Mean	3478514	194752	5705	486	2996	1112	0,85
Min	249591	71	446	16	101	16	0
Max	61845700	1800000	75223	4692	24200	13190	1
St. Error	9568855	280635	10310	736	4277	2524	0,18
Median	866870	94792	2268	200	1150	221,5	0,92
Sum	267845576	14995929	439270	37422		84509	

Table 2: Summary Statistics France for the 93 ERDF local distribution units

	Electricity Sold in MwH	Number of Customers	Network Length in km	Labor, Number of Employees	Inverse Density Index in km2/inhabitants	Surface total in km2	Underground rate
Mean	3393068	331660	13231	381	21254	5473	0,39,
Min	909468	109720	4060	189	69	107	0,13
Max	13735300	1539592	32303	1252	59750	13871	1
St. Error	1731424	181521	6112	158	15277	3169	0,21
Median	3196215	302766	12650	352	18572	5602	0,32
Sum	315555286	30844342	1230454	35433		509032	

Table 3 List of different model specifications

Table 3a) For deterministic COLS Models

	COLS Model 1.1:	**COLS Model 1.2:**	**COLS Model 2.1:**	**COLS Model 2.2:**	**COLS Model 3.1:**	**COLS Model 3.2:**	**COLS Model 3.3:**
INPUTS							
Number of workers,	*	*	*	*	*	*	*
Network length	*	*			*	*	* (cable and aerial separated)
OUTPUTS							
Electricity sold (50%)	*		* (40%)	* (20%)	* (40%)	* (20%)	* (20%)
Number of customers (50%),	*		* (40%)	* (60%)	* (40%)	* (60%)	* (60%)
Electricity sold (30%)		*					
Number of customers (70%)		*					
Inverse density index					* (20%)	* (20%)	
Network length			* (20%)	* (20%)			
Surfqce							* (20%)
FUNCTIONAL FORM	Cobb Douglas productio n function	Cobb Douglas productio n function	Cobb Douglas productio n function	Cobb Douglas productio n function	Cobb Douglas productio n function	Cobb Douglas productio n function	Cobb Douglas productio n function

Table 3b) For stochastic SFA Models

	SFA Model 1.1:	**SFA Model 1.2:**	**SFA Model 2.1:**	**SFA Model 2.2:**
INPUTS				
Number of workers,	*	*	*	*
Network length	*	*	*	*
OUTPUTS				
Electricity sold (50%)	*		*	
Number of customers (50%),	*		*	
Electricity sold (30%)		*		*
Number of customers (70%)		*		*
STRUCTURAL VARIABLE				
Inverse density index			*	*
FUNCTIONAL FORM	Cobb Douglas productio n function	Cobb Douglas productio n function	Cobb Douglas productio n function	Cobb Douglas productio n function

Table 4 Estimated variable parameters and statistics for the SFA models (t statistics in parentheses)

	SFA Model 1.1 half normal distribution	SFA Model 1.2 half normal distribution	SFA Model 1.1 truncated normal distribution	SFA Model 1.2 truncated normal distribution
$ß_0$	-0.84 (6.0)	-0.71 (5.2)	-0.88 (8.1)	-0.79 (6.7)
$ß_1$	0.5 (10.8)	0.5 (9.6)	0.47 (10.8)	0.47 (13.0)
$ß_2$	0.47 (8.6)	0.45 (7.8)	0.49 (9.3)	0.48 (10.4)
Log likelihood	-115	-129	-112	-121
Sigma squared	0.36	0.55	0.77	0.13
Gamma	0.65	0.81	0.83	0.9

Table 5: Comparison between urban and rural distribution companies

	COLS Model 1.1	COLS Model 1.2	COLS Model 2.1	COLS Model 2.2	COLS Model 3.1	COLS Model 3.2	Mean
Mean Total	0.34	0.37	0.37	0.36	0.33	0.41	0.46
Mean Germany	0.32	0.35	0.26	0.25	0.30	0.37	0.41
Mean France (Center)	0.36	0.39	0.45	0.44	0.35	0.44	0.50
Mean France (Regions)	0.37	0.43	0.49	0.51	0.32	0.43	0.55
Mean Germany urban	0.39	0.43	0.28	0.27	0.34	0.42	0.46
Mean Germany rural	0.29	0.31	0.25	0.24	0.29	0.35	0.40
Mean France (Center) urban	0.57	0.64	0.50	0.50	0.45	0.58	0.63
Mean France (Center) rural	0.29	0.32	0.43	0.42	0.32	0.40	0.47
Mean France (Regions) urban	0.69	0.79	0.60	0.63	0.62	0.83	0.79
Mean France (Regions) rural	0.33	0.37	0.47	0.49	0.28	0.37	0.53