Efficiency Analysis of East European Electricity Distribution Utilities -
Legacy of the Past?

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ABSTRACT

As the European Union is extending eastwards, there is also an increasing need for comparative efficiency analysis in the EU-member countries. This paper is the first cross-country efficiency analysis of electricity distribution in Central Europe. (Poland, Czech Republic, Slovakia and Hungary). We compare the relative efficiency of East European local distribution companies (LDCs) among themselves, as well as with German (LDCs), using two common benchmarking methods: the non-parametric Data Envelopment Analysis (DEA), and, as a parametric approach, the Stochastic Frontier Analysis (SFA), estimating a translog production function. The comparison of relative efficiency scores is mainly based on a model including technical and geographical data, especially number of customers, inverse density index, total power sales, length of the grid and number of people employed. First results indicate that the Polish distribution companies are inefficiently small. Hungary and Slovakia feature the highest efficiency. The results shed light on the need for further restructuring in Eastern Europe.

Keywords: Efficiency analysis, econometric methods, electricity distribution in Central Eastern Europe

JEL Classification: L51, L43, P31, C1

Not competing for the Young Economist Award

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1. Introduction

After decades of socialist planning, the energy sector in the East European transition countries underwent substantial market-oriented reform during the last decade. Thus, in the early 1990s, these countries were faced with outdated and polluting power plants, one-sided network integration towards the East, a distorted price structure, and inefficient management structures. As a key sector for economic development, but also as a socially sensitive activity, energy sector reform has been particularly difficult, in particular when it came to mergers between companies, and downscaling of employment. Subsequently, the last decade was characterized by a very tough transformation process from socialist structures towards market economies. The price system had to be changed from “social tariffs” to cost-covering, and yet efficient prices. The vertically integrated monopolies had to be unbundled. Even regional units had to be disintegrated due to new political borders (Czechoslovakia, Yugoslavia, Soviet Union). Parts of the unbundled monopolists were privatized. Regulation authorities were established and environmental standards as well as renewable-promotion schemes were implemented. In brief, the CEECs experienced 50 years of gradual reforms of the West European power sector in only 15 years.

On the other hand, all East European countries having joined the EU recently now have to apply recent directives calling for liberalization in particular the Electricity Directive 2003/54 (“Acceleration Directive”) as the key European legislation establishing the internal market of electricity. It requires unbundling of transmission and distribution, non-discriminatory access to the transmission and the distribution networks, and a low market concentration. The merger process in the electricity sector, actively engaged in the EU-15, is therefore likely to spread to Eastern Europe as well. Little is know, however, about the competitiveness of the electricity sector, and whether differences between East and West European companies prevail.

Efficiency analysis has emerged as powerful tool to understand the structure of electricity sectors, and help companies and regulators to understand the drivers of productivity. As the European Union is extending eastwards, there is also an increasing need for comparative efficiency analysis in the EU member countries. However, literature is rare: Kocenda and Cabelka (1999) assessed the liberalization
of the energy sector in the transition countries with respect to its effect on transition and growth. The only quantitative study to date is Fillipini, Hrovatin and Zoric (2003), who analyze the efficiency of electricity distribution companies in Slovenia, using a stochastic frontier analysis. They pointed out that Slovenian distribution companies are cost inefficient and that in a situation of increasing returns to scale most utilities do not achieve the minimum efficient scale. The general lack of analysis on Eastern Europe calls for an international benchmarking of East European electricity companies. Similar comparative work has been carried out by Jamasb and Pollit (2003), evaluating the performance of national utilities within a larger context of six West European Countries, and Estache et al. (2004), who argue in favor of international coordination of electricity regulation in South America.

This paper is the first cross-country efficiency analysis of electricity distribution in Central Europe (Poland, Czech Republic, Slovakia and Hungary). We compare the relative efficiency of East European regional distribution companies (RDCs) among themselves, as well as with German (RDCs), using two common benchmarking methods. First we apply the non-parametric Data Envelopment Analysis (DEA). Further, to examine the effect of the choice of benchmarking methods we use in addition a parametric approach, the Stochastic Frontier Analysis (SFA), estimating a translog production function.

The paper is structured in the following way: the next section describes the state of reforms in electricity distribution in Eastern Europe. We identify general trends, such as privatization and changes of electricity demand; however, our main focus is on the development in the core countries Poland, the Czech Republic, Slovakia, and Hungary. Section 3 defines models for a comparative efficiency analysis, and describes the data. We develop various models to compare the efficiency between the East European countries, and also with a representative benchmark from West European country, Germany. We devise two quantitative approaches: i) the traditional data envelopment analysis (DEA), and ii) a stochastic frontier analysis (SFA), including the multi-output multi-input version of the distance function. Section 4 presents the empirical results. We find significant differences between the efficiency scores. Polish distribution companies seem to be inefficiently small, whereas Hungarian and Slovak companies feature the highest efficiency. When compared to the

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German companies, all East European distributors seem to be inefficient; however, this effect is softened when we correct for different consumer densities. In Section 5, we derive some conclusions and identify future research topics.

2. Reform of the Electricity Sector in Eastern Europe

To analyze the value chain of the electricity sector it is common to differentiate between electricity generation, transmission, distribution, and the retail market. Regional electricity distribution covers purchases from high-voltage electricity and supplies of low-voltage electricity to final customers (householders, small and medium size industries, communal services, some large industries) through a grid of electric cables and transformer stations. Distribution is perhaps the most complicated element in the energy chain to restructure: demand has collapsed in the industrial sector, whereas it is rising in the residential sector. The capital stock had not been renewed for quite some time. Also, electricity distribution is the most politicized of all activities, having to do directly with sensitive pricing issues and security of supply.

Over the last decade, all East European countries have made attempts to modernize and privatize their electricity distribution, with different degrees of success (see EBRD, 2004, Chapter 4 for a detailed survey). Poland is by far the largest electricity producer and distributor in the region, and it had also had the hardest time to restructure its energy sector. In socialist times, the country had set up one distribution company per region (voivody), e.g. a total of 33; this is quite a lot for a distribution of only about 100 TWh of electricity. But the corporate structures were hardly modified in the transition period, as one would have expected. Also, privatization has been largely unsuccessful thus far, with only 3 of the 33 companies being bought by (foreign) private investors. Plans to reorganize the 33 existing regional structures into 7 new, larger distribution companies have been discussed intensively, but not yet implemented.

The Czech Republic and Hungary are structurally quite similar, with electricity distribution capacity of around 10 GW, and eight and six regional distribution companies, respectively. The Czech Republic has pursued a conservative policy, keeping a state owned generation company (CEZ) as the dominant owner of five RDC’s; foreign investors now hold majority stakes in the remaining three RDC’s. Since early 1990s, most RDC’s have massively invested into the renovation and the strengthening of their distribution facilities, so that by today, the technical state is satisfactory. Hungary has certainly
pursued the most consequent strategy of divestiture and privatization: all of the six RDC’s were sold to foreign investors (E.ON, RWE, and EdF) in the mid 1990s already. While this has lead to high privatization proceeds and new capital investments, it has certainly not favoured the emergence of a competitive electricity market, as all three investors belong to the large European oligopolists eager to extend their market power to Eastern Europe.

Slovakia is the smallest country in the region by size and by number of RDC’s (only 3), but its electricity generation and distribution (about 30 TWh) reaches the level of its neighbour Hungary. This is due to the relatively high electricity intensity of the countries industry, and rising household demand. Reforms of the three RDC’s were delayed for quite some time: the companies were transformed into state-owned corporations only in 2001, and separated from their generation facilities. Privatization began in 2002, with 49% of each RDC put up for tender, and majority stakes at a later point in time. Market liberalization in Slovakia is also somewhat behind schedule: as of 2005, only one third of electricity consumption was liberalized, the remainder being scheduled for July 2007, the latest date permitted by European directives. Thus, in general, the East European countries found a difficult point of inception for electricity sector reforms.

3. Methodology and data

3.1. METHODOLOGY

In order to measure the efficiency of the East European RDC’s, we apply the standard quantitative methodologies that have proven to be very useful in a number of different sectors and applications (see Coelli, et al., 1998, for a complete survey): data envelopment analysis (DEA) as well as stochastic frontier analysis (SFA), including the multi-output multi-input version of the distance function. DEA is a non-parametric approach determining a piecewise linear efficiency frontier along the most efficient utilities to derive relative efficiency measures of all other utilities. The efficiency scores can be obtained either within a constant returns to scale (CRS) approach or a less restrictive variable returns to scale (VRS) approach. The VRS approach compares companies only within similar sample sizes; this approach is appropriate if the utilities are not free to choose or adapt their size. We argue that the CRS approach is more relevant for our analysis. It assumes that companies are flexible to adjust their size to the one optimal firm size. However, we also calculate the VRS model in order to
report scale efficiency information, which is delivered by the difference between the CRS and VRS scores.

The determination of the efficiency score of the \( i \)-th firm in a sample of \( N \) firms in the CRS model is equivalent to the following optimization:

\[
\min \theta, \lambda \theta \\
\text{s.t.} \\
- y_i + Y \lambda \geq 0, \\
0 x_i - X \lambda \geq 0, \\
\lambda \geq 0.
\]

\( \theta \) is the efficiency score, and \( \lambda \) a \( N \times 1 \) vector of constants. Assuming that the firms use \( E \) inputs and \( M \) outputs, \( X \) and \( Y \) represent \( E \times N \) input and \( M \times N \) output matrices, respectively. The input and output column vectors for the \( i \)-th firm are represented by \( x_i \) and \( y_i \). The constraints ensure that the \( i \)-th firm is compared to a linear combination of firms similar in size.\(^3\) The system is solved once for each firm (for details, see Jamasb and Pollitt, 2003, 1612, and Coelli, et al., 1998, Chapter 6).

DEA is a relatively uncomplicated approach. The determination of an explicit production function is not required. However, since DEA is a non-parametric approach the impact of the respective input factors on the efficiency cannot be determined. Furthermore, DEA does not account for possible noise in the data and outliers can have a large effect on the result. We therefore introduce a second methodology, the stochastic frontier analysis (SFA), which is a parametric approach to efficiency benchmarking. The theory of stochastic frontier production functions was originally proposed by Aigner, Lovell and Schmidt (1977) as well as Meeusen and van den Broeck (1977). This approach requires the definition of an explicit production or cost function. Based on the usual OLS regression a parallel shift of the original production function yields the efficiency frontier. This is caused by an underlying assumption splitting the error term into a stochastic residuum (noise) and an inefficiency-

\(^3\) To determine efficiency measures under the VRS assumption a further convexity constraint \( \sum \lambda = 1 \) has to be considered.
term. Usually, stochastic errors are assumed to be distributed half-normally. Originally the model was specified for cross-sectional data. Hence, the mathematical expression of the production process is:

\[ Y_i = x_i \beta + (v_i - u_i), \quad i = 1, ..., N \]  

(1)

where \( Y_i \) is output (or the logarithm of output) of the \( i \)-th firm,
\( x_i \) is a \( k \times 1 \) vector of input quantities of the \( i \)-th firm,
\( \beta \) is a vector of parameters to be estimated,
\( v_i \) are random variables which are assumed to be iid. \( N(0, \sigma_v^2) \), independent of \( u_i \).
\( u_i \) are non-negative random variables usually assumed to be half normal distributed (iid. \( |N(0, \sigma_U^2)| \)), thereby accounting for individual technical inefficiency.

SFA is more complex than DEA in terms of data requirements and handling, but has the advantage of allowing to deal with multiple-outputs multiple-inputs in the form of a distance function, originally proposed by Shephard (1970). The basic idea is that in the case of a given production possibility frontier, for every producer the distance from the production frontier is a function of the vector of inputs used, \( X \), and the level of outputs produced, \( Y \). The input orientated approach is defined on the input set \( L(Y) \) and considers, by holding the output vector fixed, how much the input vector may be proportionally contracted. The input distance function is expressed by:

\[ D_i(X, Y) = \max \{ \rho : (X / \rho) \in L(Y) \} \]  

(2)

\( D_i(X, Y) \) is non-decreasing, positively linearly homogeneous and concave in \( X \), and increasing in \( Y \). \( \rho \) is the scalar distance by which the input vector can be deflated. If \( D_i(X, Y) = \rho = 1 \), \( X \) is located on the inner boundary of the input set and the utility is 100% efficient. The first step is to estimate the distance from the frontier. Therefore both the efficiency frontier as well as the relationship between inputs and outputs have to be determined. These considerations also include the
case of multi-output production functions which can not be estimated with conventional SFA techniques. The estimating form of the translog input distance function in its normalized parametric form with \( M \) \((m = 1, 2, ..., M)\) outputs, \( K \) \((k = 1, 2, ..., K)\) inputs and \( I \) \((i = 1, ..., I)\) firms, can be expressed by (Coelli, 2002):

\[
-\ln \left( \frac{X_{ki}}{y_{mi}} \right) = \alpha_0 + \sum_{m=1}^{M} \gamma_{mv} \ln y_{mi} + \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \gamma_{mn} \ln y_{mi} \ln \gamma_{ni} + \sum_{k=1}^{K-1} \beta_{k} \ln \left( \frac{X_{ki}}{X_{Kk}} \right) + \frac{1}{2} \sum_{k=1}^{K-1} \sum_{i=1}^{I} \beta_{ki} \ln \left( \frac{X_{ki}}{X_{Kk}} \right) \ln \gamma_{mi} + v_i - u_i
\]

(3)

It can be estimated by a stochastic frontier production function defined as \( y = f(x) + v - u \). Most common assumptions are, once again, the normal distribution, \( u_i \sim N(\mu, \sigma^2) \) and the half-normal distribution truncated at zero, \( u_i \sim N(0, \sigma^2) \). Further, the inefficiency can also be assumed to be constant over time resulting in \( u_i = \eta(T-t) \) (Battese and Coelli, 1992).

3.2. MODEL SPECIFICATION AND CHOICE OF VARIABLES

A difficult task in efficiency analysis is the choice of appropriate model. The literature is rather heterogeneous on which variables are used as inputs and outputs; the choice of variables is also constrained by data availability. In this respect, East European countries are still among the least developed countries, in particular when compared with Anglo-Saxon countries (such as the UK or Australia), where ample data is collected and made publicly available.

We have three criteria for differentiating among different models:

- **scope of countries**: in the base model, we compare the efficiency of the four East European countries among themselves. In addition, we add a comparison between these countries and Germany, a traditional electricity that has not gone through the socialist period and 15 years of transition (at least for the largest part of its electricity sector);

- **choice of input and output parameters**: in the base model, we use the traditional choice of parameters: the number of employees (labor), and the length of the electricity grid (capital), are taken as inputs; as outputs we define total sales (in GWh) and the number of customers. In the
extended version of the model, we include a structural variable to account for differences among regions: the inverse density index (measured in km² per inhabitant);

- the estimation method: the base models are estimated using the data envelopment analysis (DEA), whereas we also use stochastic frontier analysis (SFA) in the more sophisticated version. Within the SFA, a choice has to be made on how to weight the outputs (sales and no of customers): we use a 50:50 weighting in one model, and 30:70 in another.

Combining all model specifications give us a total of 16 estimation runs. We limit the presentation of results to six models, as summarized in Table 1.

In what we call the base model (DEA Model 1), we perform a “plain vanilla” efficiency analysis using two inputs and two outputs. The number of customers and the total sales are treated as output variables, and we use a variable for labour and capital input, respectively. In the extension of the base model (DEA Model 2), we add the inverse density index (IDI) as an output variable. The IDI is defined by the reciprocal value of the population density. This structure variable should secure that companies get compensation if the structure of their supplied area tends to be unfavorable. In DEA Model 3, we add German RDC’s to the sample to check for differences in efficiency scores between East European transition countries and a “traditional” electricity sector. There is no inverse density, which is changed in DEA Model 4, where the East European countries and Germany are compared using the inverse density index as an output parameter. We thus have direct comparism between DEA Models 1 and 3, and DEA Models 2 and 4, respectively. SFA Models 1 and 2 use the full set of data for East European and Germany RDC’s, using different weights for the output.

Table 1: Model Specifications

3.3 DATA

The data used in this paper includes information on the regional electricity distribution. Companies (RDC's) in Poland (33), the Czech Republic (70), Hungary (4) and Slovakia (3), for the year 2003. In addition, we use data for 36 German RDCs. The variables are defined in the following way:

4 Results from other models are available upon request.
- **Labor** input is estimated by the number of workers;⁷
- **capital** input is approximated by the length of the existing electricity cables. We differentiate between voltage levels (high, medium and low voltage) by introducing a cost factor for each type of line;⁸
- the amount of electricity distributed to end users (units sold) and the total number of customers are used as output variables (due to data limitations, we cannot differentiate between operating costs (OPEX) and capital costs (CAPEX));
- the use of the **inverse density index** (settled area in kilometers per customers supplied) in the base model specification is motivated by the argument that utilities with a dense customer structure have a natural cost advantage over those with a weak customer density. When taken as an output, the inverse density index improves the performance of sparsely inhabited distribution areas.⁹

For DEA Models 1 and 2 we have 47 observations. For DEA Models 1 and 2, and the SFA Models 1 and 2, we have 84 observations. Summary statistics for the data are presented in Table 2.¹⁰

**Table 2: Summary Statistics**

4. Results and Interpretation

This section presents the empirical results for the six model runs. First we discuss the non-parametric DEA Models 1-4, then followed by the parametric SFA models 1-2. We have estimated both the constant and the variable returns to scale approach (CRS and VRS), but we insist mainly on the CRS results. This seems to be more appropriate in the current setting: it assumes that the size of the

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⁵ One Czech and two Hungarian companies are missing due to data availability (number of customers lacking), in some cases, data is for 2002.
⁶ German distribution companies for which no inverse density index was available, or which had an output of less than 10 GWh or less than 10 customers were sorted out. In addition, Mitteldeutsche Energieversorgung AG was sorted out because of their abnormal high inverse density index.
⁷ We are aware of the criticism of this choice of variable due to the potentially distorting effect of outsourcing: an utility can improve its efficiency simply by switching from in-house production to outsourcing.
⁸ Following standard practice: factor 5 for high voltage, 1.6 for medium voltage, and 1 for low voltage cables.
⁹ Density is also one of the structural variables defined in the German association agreements.
¹⁰ The data for Eastern Europe was collected from company reports and national statistics, the data for Germany was taken from VDEW (Industrial Organization).
companies is flexible, and this is indeed what we expect the East European RDC's to be, searching to adapt towards an optimal firm size. We also check the correlations and rank-correlations to test for the consistency of results.

4.1 RESULTS FROM THE DEA MODELS

DEA Models 1 and 2 (4 East European countries)

We start with estimation of the base model DEA 1 (Figure 1), and then compare it with the extended DEA Model 2, where we include the structural variable (inverse density index, IDI) in order to correct for regional differences concerning the customer density. Results for the extended DEA Model 2 are presented in Figure 2, together with the mean technical efficiency values for the four countries (CRS and VRS), and the average scale efficiency.\footnote{The scale efficiency indicates to which extent the companies are close to the optimal size, i.e. the one where the highest productivity level is reached.} In the CRS estimates, the Czech RDC's are by far the most efficient, with an average of 90%, and four (out of their 7) RDC's on the efficiency frontier (i.e. belonging to the 100% efficient companies). Hungary (74%), and Slovakia (69%) follow suit. Poland obtains the lowest average score (65%), even though, contrary to Hungary and Slovakia, it has one company on the efficiency line. A possible interpretation could be that whereas the Slovak and the Hungarian companies are rather homogenous, the Czech and, in particular, the Polish RDC's are characterized by a large heterogeneity in efficiency scores.

When looking at the more generous VRS efficiency values, the pictures changes somewhat, whereas the ranking between the utilities is only slightly modified.\footnote{Recall that the VRS approach compares only companies of similar size (or other characteristics), and thus yields higher scores than the CRS approach.} The Polish RDC's gain considerably in efficiency. Although Poland is the biggest country of the analyzed new member states it has got incomparable many distribution companies. These results indicate that the Polish electricity distribution companies are too small to be efficient. Their inefficiency seems to root in their size. The rise of efficiency is even more marked for Slovakia (from 69% to 95%), which may seem illogical. Even though Slovakia is the smallest of the analyzed countries it has only got three local distribution companies and the first impression is that they do not look to small. Here it seems that they profit the other way around: at least concerning the output sales in GWh the Slovakian electricity distribution
companies are far above the average. They seem to benefit from the slope regression of the piecewise linear production function that is generated by the program in DEA-VRS.\textsuperscript{13}

\textbf{Figure 1 Results DEA Model 1, CRS}

\textbf{Figure 2 Results DEA Model 2, CRS}

\textbf{DEA Models 3 and 4 (5 countries)}

We now enlarge the scope of countries beyond Eastern Europe, and compare the efficiency of these countries with RDC's from Germany. As explained above, we consider Germany to be representative for a traditional market-economy electricity country (even through the East Germany partake underwent rapid restructuring in the early 1990s.)\textsuperscript{14} Figure 3 shows the estimates for the DEA Model 3 (VRS) and the statistics for the CRS estimation. In the CRS-specification, one clearly sees a difference between the average efficiency in Germany (64\%) and in the East European countries (between 54\% for the Czech Republic, and 37\% for Poland). For Eastern Europe, these results are consistent with those obtained in the DEA. Models 1 and 2. It seems as if the East European transition economies suffer from a structural lack of efficiency when compared to its Western neighbour. Reasons for this might be the more consistent development of the grid infrastructure in Germany; the drop of industrial electricity demand in Eastern Europe, leading to over dimensioned distribution companies, or an inappropriate territorial structure of most East European RDC's, mainly the Polish ones. Note, however, that the VRS results are, once again, significantly better and that they also modify the ranking of the countries averages: the Czech Republic now features the highest average (76\%), before Germany (72\%), the rest of the pack staying in line. The Polish companies hardly gain in efficiency.

\textsuperscript{13} However to draw the conclusion that the Slovakian electricity distribution companies are to big to be efficient would be drawn to fast. One has to take the special structure of the Slovakian electricity sector into account. Since Slovakia exports a lot of energy and assuming the distribution companies bear at least some of the brunt, some of their input factors serve solving this task, without generating output according to the used model. That would be one possible explanation for their inefficiency in the DEA-CRS model in relation to the electricity distribution of the other countries.
DEA Model 4 includes the inverse density index, and thus can account for structural density differences between the countries. Here we find that the East European countries gain significantly, due to their lower population density. This effect is particularly strong in the case of Poland. The overall trend remains valid, however: the Polish companies still are less efficient than the companies of the other countries. The companies of the Czech Republic do best among the analyzed new member states followed by Hungary. The introduction of the inverse density index causes the firms of the analyzed new member states to gain even more, so that they can even partially outperform the German companies.

**Figure 3: Results Model 4, DEA, CRS**

**Table 3: Results DEA Model 2**

**Table 4: Results DEA Model 3**

4.2 RESULTS FROM THE SFA MODELS 1 AND 2

We now turn to the results of the parametric analysis. The SFA Model 1 calculates the efficiency for all countries (including Germany) and all variables (including the inverse density index). The outputs were aggregated to create a joint index for total sales and the number of customers (Figure 4). We calculated the technical efficiency according to Coelli (1996). The results of this approach lead to lower gaps between the firms of each country. No company can achieve values higher than 0.9. The differences between the average of Poland and the other countries have also decreased.

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14 For efficiency analysis of Germany electricity distribution, including a comparison between East and West Germany, see Hirschhausen and Kappeler (2004).
15 The largest value available among the chosen data set was set to one. The output of each company was divided by the largest values so that for each output every company has now got a value between zero and one. For the first SFA run the outputs were logged and weighted fifty percent each.
16 Note, however, that some of the parameters lack statistical significance.
A similar approach, with different weights, was used in SFA Model 2 (no of customers: 70%, total sales: 30%). Results are shown in Figure 5: the “small” countries (Slovakia: 80%, Czech Republic: 76% and Hungary: 75%) now clearly have an efficiency advantage over the large ones (Poland: 65% and Germany: 63%). The average values of the countries tend to differ less than in the previous SFA Model 1. In contrary to this the values for single firms tend to differ stronger. The overall results are again similar. The Polish distribution companies still have the lowest efficiency scores. Between the German distribution companies and the other electricity distribution companies there is hardly any difference. However the differences between single companies have increased.

Figure 4: Results SFA Model 1

Figure 5: Results SFA Model 2

Table 5: SFA Results Model 2

4.3 CORRELATION AMONG THE RESULTS

We also want to know how robust our analysis is against the model specification and against various estimation techniques. Table 6 provides an overview of the results obtained from the models with all 5 countries. At first sight, the results appear to be robust, with regard to the ranking. Thus, Polish distribution companies tend to obtain the lowest efficiency scores in all models and with all estimation techniques.

Correlation tests tend to support the hypothesis of robust results: the correlations between pairs of models are positive and always higher than 0.5. With regard to the individual rankings, a Kruskall Wallis Rank Sum test was carried out. The null hypotheses had to be rejected at a significance level of 1% in the case of all methods. This indicates that the efficiency levels are not consistent across our

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17 The explanation for this approach is that the number of connections determine the need for input factors more than the demanded energy. Within certain limits the capacity that has to be installed and maintained for a customer is quite cheap by using thicker wires and cables for example without increasing costs significantly. This has led to the Model 2 to weight the number of customers more than the total sales in GWh.
parametric and non-parametric methods selected. This confirms earlier results, such as Estache et al. (2004), warning against the direct use of these parameters for regulatory purposes.\(^{18}\)

**Table 6: Comparison of Efficiency measures across different methods, all country case**

5. **Conclusions**

In this paper, we have compared the efficiency of regional distribution companies (RDC’s) in the transition countries of Eastern Europe. The reform process in this sector is influenced by the legacy of several decades of socialist energy policy, and by attempts to modernize the sector in the wake of EU-accession. We assess the *technical* efficiency of firms (only), since data on costs and prices is not easily available, and if it was, would be difficult to compare.\(^{19}\)

Our results indicated marked differences between the efficiency scores, both within the countries, and between the countries. The Polish RDC’s regularly have the lowest efficiency scores, and they seem to suffer from a lack of scale efficiency. Recent discussions of merging the 33 companies into 7 or so may therefore be well founded. Companies in the Czech Republic regularly come up with the highest efficiency scores, which may be explained by the substantial restructuring efforts undertaken in the mid 1990s. We also indicate the importance of structural variables in the models.

When comparing the East European RDC’s with their German counterparts, most of the CRS models indicate lower efficiency values in Eastern Europe. We have tried to explain this phenomenon with the more coherent network development in the market economy, and perhaps it is also due to structural variables, such as the population density. The differences in efficiency diminishes when using VRS and SFA models; in fact, German RDCs are no longer leading in several models.

Further research should focus on a more dynamic comparative analysis of efficiency measures in the region, e.g. time series analysis between 1995-2004 (data permitting). The use of monetized cost data would also allow more reliable conclusions regarding scale efficiencies; it might also inverse the

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\(^{18}\) Rather these efficiency scores have to serve as basis for discussion in more detail between firms and regulator, for consistency condition in more detail Bauer et al. (1998).

\(^{19}\) Already in national country studies the data availability is very moderate, but in international comparisons it still seems impossible to obtain accurate measures of operating and capital costs, so that the regulatory process still have to deal with the physical data approach. On the other hand the different benchmark methodologies generate different results.
efficiency relation between Eastern Europe and Germany, as Germany has by far higher labour cost.

Last but not least, a look at the development of individual companies might be useful in explaining the reform trajectory of East European electricity distribution in transition.

6. References


Table 1: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Employment</th>
<th>No. of Customers in thd.</th>
<th>Area of supplied region in sqkm</th>
<th>Inhabitants in supplied area in thd.</th>
<th>Low Voltage lines, length in km</th>
<th>Medium voltage lines, length in km</th>
<th>High Voltage lines, length in km</th>
<th>Sales in GWh</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Poland (33 observations)</strong></td>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td>Mean</td>
<td>1615</td>
<td>453</td>
<td>9478,2</td>
<td>1173</td>
<td>11712,1</td>
<td>8300,9</td>
<td>972,4</td>
<td>3027,67</td>
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Table 3: Results DEA, Model 2

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Table 4: Results DEA, Model 3

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Table 6: Comparison of Efficiency measures across different methods, all country case

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DEA, Model 1, CRS, without Inverse Density Index

mean efficiency: 53%

Poland: 44%, Slovak Republic 56%
Czech Republic 85%, Hungary 67%
DEA, Model 2, CRS, with Inverse Density Index
mean efficiency: 70%
Poland: 65%, Slovak Republic 69%
Czech Republic 90%, Hungary 74%
Figure 3: Results: DEA, Model 4, CRS

DEA, Model 4, CRS, with Inverse density Index
mean efficiency: 53%
Poland: 38%, Slovak Republic 48%
Czech Republic 54%, Hungary 51%, Germany 68%
SFA, Model 1, Translog, With Inverse Density Index, TE Regressor
mean efficiency: 61%
Poland: 54%, Slovak Republic 70%
Czech Republic 69%, Hungary 63%, Germany 65%
Figure 5: Results, SFA, Model 2

SEA, Model 2, Translog, Output weighted, customers 0.7/ sales 0.3
mean efficiency: 69%
Poland: 62%, Slovak Republic: 75%
Czech Republic 74%, Hungary 73%, Germany 74%