

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). First results indicate that the Polish distribution companies are inefficiently small. Czech Republic 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

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 Thus, in the early 1990s, these countries were faced with outdated and polluting power plants, one-sided network integration towards the East, a distorted price structure and inefficient management structures.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.²

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 known, 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 point 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. Section 4 presents the empirical results. We find significant differences between the efficiency scores. Polish distribution companies seem to be inefficiently small, whereas Czech and Slovak companies feature the highest efficiency. When compared to the 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 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 RDCs; foreign investors now hold majority stakes in the remaining three RDCs. Since early 1990s, most RDCs 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 RDCs were sold to foreign investors (E.ON, RWE, and EdF) in the mid 1990s already. While this has led 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 RDCs (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 RDCs 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 RDCs, we apply the standard quantitative methodologies that have proven to be very useful in a number of different sectors and applications: data envelopment analysis (DEA) as well as stochastic frontier analysis (SFA), (see Coelli, et al., 1998, for a complete survey). 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 return 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:

$$\begin{aligned} & \min_{\theta, \lambda} \theta \\ & \text{s.t.} \\ & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & \lambda \geq 0. \end{aligned}$$

θ is the efficiency score, and λ 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 . To determine the VRS efficiency scores certain 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 and Coelli, et al., 1998).

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. The underlying assumption to measure the efficiency relative to an efficient production frontier consists in splitting the error term into a stochastic residuum (noise) and an inefficiency-term. Usually, inefficiency terms are assumed to be distributed half-normally. Originally the model was specified for cross-sectional data. Hence, the mathematical expression of the stochastic production process is:

$$Y_i = x_i\beta + (v_i - u_i), \quad i = 1, \dots, N \quad (1)$$

where Y_i is output (or the logarithm of output) of the i -th firm,

x_i is a $k * 1$ vector of input quantities of the i -th firm,

β 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.

We use the maximum likelihood method to estimate the parameters of the stochastic production function defined by equation (1). In the empirical estimation of frontier models two alternative functional forms has been commonly used: The Cobb-Douglas and the Translog functional form. While no imposing restrictions upon returns to scale or substitution possibilities we decide to specify a translog functional form. The model to be estimated is defined by:

$$\ln y_i = \beta_0 + \sum_{j=1}^2 \beta_j \ln x_{ji} + \sum_{j \leq k}^2 \sum_{k=1}^2 \beta_{jk} \ln x_{ji} \ln x_{ki} + v_i - u_i \quad (2)$$

where variables have the preliminary mentioned definitions. We implement model variations in respect to the distribution of the technical inefficiency, including the half-normal and truncated normal distribution. SFA is more complex than DEA in terms of data requirements and handling. In recent productivity analyses econometric distance functions are frequently applied due to the advantage of allowing dealing with multiple-outputs multiple-inputs. The distance function approach was 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 distance function is expressed by:

$$D_i(X, Y) = \max \{ \rho : (X / \rho) \in L(Y) \} \quad (3)$$

These considerations 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 $M (m = 1, 2, \dots, M)$ outputs, $K (k = 1, 2, \dots, K)$ inputs and $I (i = 1, \dots, I)$ firms, can be expressed by (Coelli, 2002):

$$\begin{aligned} -\ln(x_{Ki}) &= \alpha_0 + \sum_{m=1}^M \gamma_m \ln y_{mi} + \frac{1}{2} \sum_{m=1}^M \sum_{n=1}^M \gamma_{mn} \ln y_{mi} \ln y_{ni} + \sum_{k=1}^{K-1} \beta_k \ln \left(\frac{x_{ki}}{x_{Ki}} \right) \\ &+ \frac{1}{2} \sum_{k=1}^{K-1} \sum_{l=1}^{K-1} \beta_{kl} \ln \left(\frac{x_{ki}}{x_{Ki}} \right) \ln \left(\frac{x_{li}}{x_{li}} \right) + \sum_{k=1}^{K-1} \sum_{m=1}^M \beta_{km} \ln \left(\frac{x_{ki}}{x_{Ki}} \right) \ln y_{mi} + v_i - u_i \end{aligned} \quad (4)$$

It can be estimated by a stochastic frontier production function defined as $y = f(x) + v - u$. We included different specification of the distance function approach in our efficiency analysis but realized that it was not the appropriate model for the analysis of the data available on 47 East European Distribution Companies.⁴

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), by means of linear programming, whereas we

apply the econometric estimation maximum likelihood method (ML) to conduct our stochastic frontier analysis (SFA) in a more sophisticated version. Within the translog specification of the SFA, which capture only one dependent variable, 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 ⁵

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 RDCs 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 comparison 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 RDCs, 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 (RDCs) in Poland (33), the Czech Republic (7), Hungary (4) and Slovakia (3), for the year 2003.⁶ In addition, we use data for 36 German RDCs.⁷

The variables are defined in the following way:

- labor input is estimated by the number of workers;⁸
- 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;⁹
- 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.¹⁰

For DEA Models 1 and 2 we have 47 observations. For DEA Models 3 and 4 as well as the SFA Models 1 and 2, we dispose of 84 observations. Summary statistics for the data are presented in Table 2.¹¹

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, followed by the parametric and stochastic SFA Models 1-2. All discussion involves physical quantities and technical relationships. Thus, we exclusively focus on the utilities technology and production process assessing the technical efficiency. 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. With respect to the DEA analysis 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 companies is flexible including that utilities are able to improve productivity not only by increasing technical efficiency but also by exploiting scale economies. When looking at the different market concentration in the countries considered, this is indeed what we expect the East European RDCs 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 Model 1 (Figure 1), and then compare it to 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).¹² Including the Inverse Density Index changes significantly the rank of the individual firms within each country. Companies who operate in a less favourable

environment gain efficiency, so that the average efficiency scores in Model 2 are definitely higher. But the rank between the countries does not change, so that we limit our interpretation to Model 2. The CRS estimates indicate that the Czech RDCs are by far the most efficient, with an average of 90%, and four (out of their 7) RDCs 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 RDCs are characterized by a large heterogeneity in efficiency scores.

When looking at the more generous VRS efficiency values, the picture changes somewhat, whereas the ranking between the utilities is only slightly modified.¹³ The Polish RDCs gain considerably efficiency. Although Poland is the biggest country of the analyzed new member states, it has got incomparable many distribution companies and therefore a significantly higher market concentration. This result, which means the low technical CRS efficiency scores combined with a notable difference to the VRS scores, indicates that the Polish electricity distribution companies are too small to be efficient.¹⁴ We summarize that their inefficiency mainly seems to root in their size which is visualized for Model 1 in Figure 3 by means of a trend line for the estimated technical efficiency scores. In fact this can be confirmed by running an additional DEA problem with non decreasing returns to scale (NIRS) imposed.¹⁵ 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 distribution companies and the first impression is that they do not look to small. This leads us to assume that here it seems that they profit the other way around, which means that the firms operate in an area of decreasing returns to scale. At least the output sales in GWh, confirm this

assumption: 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. Running an additional NIRS DEA confirms this result.¹⁶

Figure 1 Results DEA Model 1, CRS

Figure 2 Results DEA Model 2, CRS

Figure 3 Scale Efficiency for East European Countries, Model 1

DEA Models 3 and 4 (5 countries)

We now enlarge the cope of countries beyond Eastern Europe, and compare the efficiency of these countries with RDCs from Germany. As explained above, we consider Germany to be representative for a traditional market-economy electricity country (even though the East Germany part underwent rapid restructuring in the early 1990s.)¹⁷ Table 3 shows the technical CRS and VRS efficiency estimates for the DEA Model, excluding the inverse density index. 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). Considering Eastern Europe apart in the general estimation, the CRS results are consistent with those obtained in the DEA Models 1 and 2, which means that the relation between the countries has not changed. DEA only provides relative performance measures. For that reason it does not make sense to compare the individual efficiency scores to the preliminary obtained results and one can neglect the fact all East European Countries now features higher efficiency scores. 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 RDCs, 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%), even before Germany (72%), the rest of the pack staying in line. This indicates that, when compared to Germany, the Czech Republic utilities feature higher scale inefficiency. The Polish companies hardly gain in efficiency.

DEA Model 4 includes the inverse density index, and thus can account for structural density differences between the countries. The results of the CRS- and VRS-specification are depicted in Figure 3. Here we find that among the East European countries, Poland and Slovak Republic gain due to their lower population density. But one can see that this effect is particularly strong in the case of Germany which represents a surprising result. The VRS-specification, also indicated in Figure 2, point out much more variation. The effect is, once again, particularly strong for the Czech Republic, which confirms the previous result: the Czech Republic utilities feature higher scale inefficiency. The overall trend remains valid, however: the Polish companies still are less efficient than the companies of the other countries. Considering the pure technical efficiency, the companies of the Czech Republic do best among the analyzed new member states, followed by Hungary, but that we found a high potential in both countries to improve productivity by exploiting scale efficiencies. The same hold for Poland. 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 4: Results Model 4, DEA, CRS

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).¹⁸ We calculated the predicted technical efficiency according to Coelli (1996).¹⁹ The results of this approach lead to lower gaps between the firms of each country. This can be explained econometrically: in contrary to the non parametric DEA approach, stochastic frontiers do not assume all deviations from the frontier are due to inefficiency. If any noise is present, the influence on the DEA frontier and hence the measurement of technical efficiencies is higher in comparison to the stochastic frontier approach. No company can achieve values higher than 0.9. The differences between the average of Poland and the other countries have also decreased.²⁰

A similar approach, with different weights, was used in SFA Model 2 (number of customers: 70%, total sales: 30%).²¹ Results are shown in Figure 5: The “small” East European countries (Slovakia: 75%, Czech Republic: 74% and Hungary: 73%) still have a clearly efficiency advantage over the large one (Poland: 65%). Germany (74%) is located now on the same rank as the Czech Republic. The average values of the countries, especially without considering Poland, tend to differ less than in the previous SFA Model 1. In contrary to this, the values for single firms tend to differ stronger. Slovakia, Czech Republic, Hungary and Germany all vary around an average efficiency of 74%, therefore can be seen surprisingly as countries featuring the same technical efficiency in the electricity distribution. Contrarily to the DEA results Germany has lost its overall leader position. The results for Poland are again

similar: although the efficiency difference has decreased like in SFA Model 1, the Polish distribution companies still have the lowest efficiency scores. Slovak Republic, as the smallest New Member State, features in both parametric SFA estimations the highest efficiency score.

Figure 5: Results SFA Model 1

Figure 6: Results SFA 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 4 provides an overview of the results obtained from the models with all 5 countries, thus DEA Model 3-4 and SFA Model 1-2. At first sight, the results appear to be robust, with regard to the ranking of the countries, especially for Poland: Polish distribution companies tend to obtain the lowest efficiency scores in all models and with all estimation techniques. With respect to the DEA analysis approach, Czech Republic consistently features a leader position among the East European Countries.

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 Kruskal 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 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.²²

Table 3: Comparison of Efficiency measures across different methods, all country case

5. Conclusions

In this paper, we have compared the efficiency of regional distribution companies (RDCs) 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.

Our results indicated marked differences between the efficiency scores, both within the countries, and between the countries. The Polish RDCs 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 RDCs 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 difference 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 from 1995-2004 (data permitting).

The use of monetized cost data would also allow more reliable conclusions regarding scale efficiencies (e.g. Farsi and Filippini 2004) ; it might also inverse the 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.

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² See Newbery (1994), Stern (1998), Kocenda and Cabelka (1999) and Hirschhausen (2002, Chapter 9) for a general presentation of the transition process in the electricity sector.

³ To determine efficiency measures under the VRS assumption a further convexity constraint $\sum \lambda = 1$ has to be considered.

⁴ Like for the basic translog production function we used the computer program Frontier Version 4.1, involving a three step estimation procedure, to obtain the ML estimates for the parameters of the distance function model. (see Coelli 1996). But for our data sample it was not possible, by means of a Davidon-Fletcher-Powell iterative maximisation routine, to attain the global maximum of the likelihood function.

⁵ Results from other models are available upon request.

⁶ One Czech and two Hungarian companies are missing due to data availability (number of customers lacking), in some cases, data is for 2002.

⁷ 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.

⁸ We are aware of the criticism of this choice of variable due to the potentially distorting effect of outsourcing: a utility can improve its efficiency simply by switching from in-house production to outsourcing.

⁹ Following standard practice: factor 5 for high voltage, 1.6 for medium voltage and 1 for low voltage cables.

¹⁰ We define the inverse density index as an output due to the assumption of an input orientated approach: we have to keep in mind that the utilities cannot influence the structure of their supplied area. Density is also one of the structural variables defined in the German association agreements.

¹¹ The data for Eastern Europe was collected from company reports and national statistics, the data for Germany was taken from VDEW (Verband Deutscher Elektrizitätswirtschaft). For Hungary the data inhabitants and supplied area were not raised. For calculating the inverse density index the national average was taken. (This does not allow a comparison between the different distribution companies, but still makes sense in a comparison with the other countries).

¹² The average scale efficiency can be calculated by the quotient of CRS and VRS scores and indicates to which extent the companies are close to the optimal size, i.e. the one where the highest productivity level is reached.

¹³ Recall that the VRS approach compares only companies of similar size (or other characteristics), and thus yields higher scores than the CRS approach.

¹⁴ Recall that the difference in the CRS and VRS technical efficiency scores for a particular firm indicates scale inefficiency due to increasing or decreasing returns to scale. Thus CRS scores can be decomposed in pure technical efficiency and scale efficiency

¹⁵ To determine the nature of scale inefficiencies the DEA model has to be altered. We have to substitute the VRS convexity constraint $\sum \lambda = 1$ by $\sum \lambda \leq 1$ to ensure that the i th firm will be benchmarked against firms smaller than it. When the NIRS TE scores are unequal to the VRS TE scores, than increasing returns to scale apply. For the polish companies this was consistently the case. For more details see Coelli (1998).

¹⁶ 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.

¹⁷ For efficiency analysis of German electricity distribution, including a comparison between East and West Germany, see Hirschhausen and Kappeler (2004).

¹⁸ 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.

¹⁹ We applied the Battese and Coelli (1995) Specification, who propose a stochastic frontier model in which the inefficiency effects are expressed as an explicit function of a vector of firm specific variables, in our case the inverse density index, and a random error. See Coelli (1996) p. 5 for more detail.

²⁰ Note, however, that some of the parameters lack statistical significance.

²¹ The explanation for this approach is that the number of connections determines the need for input factors more than the demanded energy. Within certain limits the maintenance 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.

²² 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).

Table 1: Model Specifications

Model	Countries included	Variables	Description
DEA Model 1	Only East European Countries	All variables included without Inverse Density Index	Input orientation CRS, VRS, TE
DEA Model 2	Only East European Countries	All Variables with Inverse Density Index	Input orientation CRS, VRS, TE
DEA Model 3	All Countries	All Variables without Inverse Density Index	Input orientation CRS, VRS, TE
DEA Model 4	All Countries	All Variables with Inverse Density Index	Input orientation CRS, VRS, TE
SFA Model 1	All Countries	All Variables included	Translog Output weighted 50/50
SFA Model 2	All Countries	All Variables included	Translog Output weighted, customers 0,7/ sales 0,3

Table 2: Summary Statistics

Variable	Employment	No. of Customers in thd.	Area of supplied region in sqkm	Inhabitants in supplied area in thd.	Low Voltage lines, length in km	Medium voltage lines, length in km	High Voltage lines, length in km	Sales in GWh
Poland (33 observ.)								
Mean	1615	453	9478,2	1173	11712,1	8300,9	972,4	3027,67
Standard Deviation	597,9	222	5894	542	6079	4221	390,6	1964,30
Minimum	779	156	486	428	3479	3340	378	818,24
Maximum	3500	1115	27229	2421	22199	17820	1798	11444,59
Slovak Rep (3 observ.)								
Mean	2170	766	16235,3	1793	16445	10083,3	1412,7	6195,33
Standard Deviation	271	196	1556,8	369	5180,8	2343,9	1235,1	1981,12
Minimum	1988	619	14982	1550	10465	7921	264	4083,00
Maximum	2482	990	17978	2219	19574	12574	2719	8012,00
Czech Rep (7 observ.)								
Mean	2622	686	9677,8	1355	16410,4	9185,1	1656,9	6010,8
Standard Deviation	3779	218	4547	557	6102,5	3346,9	770,2	2055,9
Minimum	665	406	497	700	7353,5	3632	194	3580,6
Maximum	11163	1014	15028	2205	23849	13848	2545	8840
Hungary (4 observ.)								
Mean	1494	657			14427,8	11291,8	1205,8	4416,6
Standard Deviation	164	308			2534,8	657	384	1560,9
Minimum	1404	220			12090	10344	1005	3380,7
Maximum	1740	943			17519	11862	1782	6737,2
Germany (37 observ.)								
			Inverse Density Index					
Mean	639	207	0,01		5294,3	2572	316,1	2320,5
Standard Deviation	837	260	0,01		9452,1	4176,5	686,4	3256,8
Minimum	6	0.073	0,00		0,00	0,00	0,00	29
Maximum	4125	1060	0,02		54651	20528	2847	14229

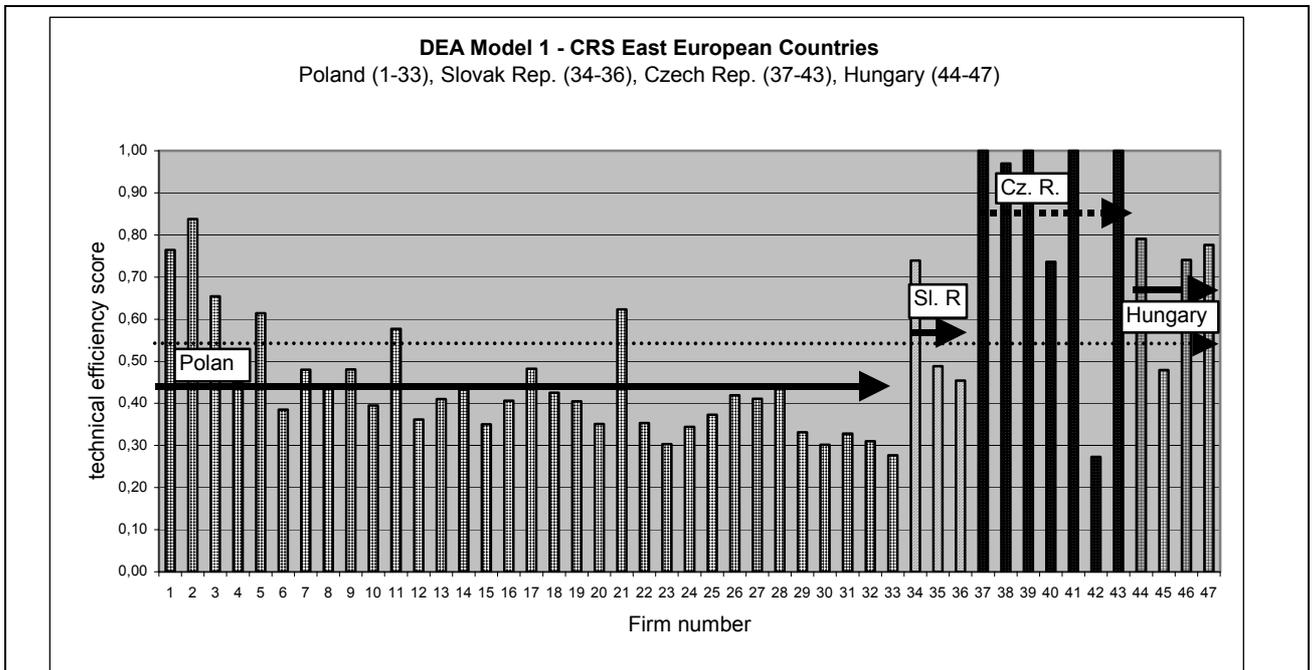
Table 3: Results Model 3; DEA, CRS, VRS and Scale Efficiency

Mean technical efficiency, Model 3	CRS	VRS	SE
all countries	0,52	0,60	0,90
Poland	0,37	0,41	0,94
Slovak Republic	0,47	0,63	0,81
Czech Republic	0,54	0,76	0,73
Hungary	0,51	0,68	0,79
Germany	0,64	0,72	0,91

Table 4: Comparison of Efficiency measures across different methods, all country case

Approach	DEA 3 CRS	DEA 4 CRS	SFA 1	SFA 2
Mean	0,52	0,53	0,61	0,69
Median	0,45	0,48	0,62	0,74
Deviation	0,22	0,22	0,15	0,17
Maximum	1,00	1,00	0,85	0,92
Minimum	0,19	0,20	0,05	0,00
Sample	84	84	84	84

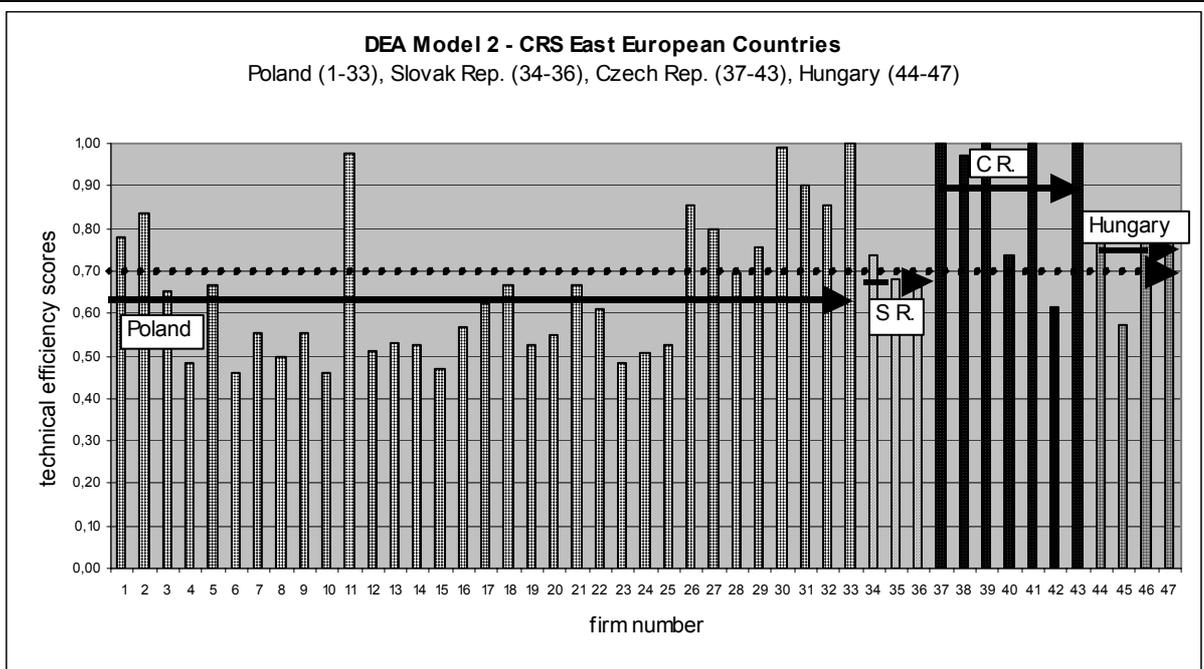
Figure 1: Results DEA, Model 1, CRS



DEA, Model 1, CRS,
without Inverse Density Index
mean efficiency: 53 %
Poland: 44%, Slovak Republic 56%
Czech Republic 85%, Hungary 67%

DEA, Model 1, VRS
without Inverse density Index
mean efficiency (72%)
Poland (68%), Slovak Republic (66%)
Czech Republic (88%), Hungary (78%)

Figure 2: Results DEA, Model 2, CRS



DEA, Model 2, CRS,
with Inverse Density Index
mean efficiency: 70%
Poland: 65%, Slovak Republic 69%
Czech Republic 90%, Hungary 74%

DEA, Model 2, VRS
with Inverse Density Index
mean efficiency: 80%
Poland: 74%, Slovak Republic 95%
Czech Republic 96%, Hungary 87%

Figure 3: Regression for the Polish Efficiency technical efficiency scores

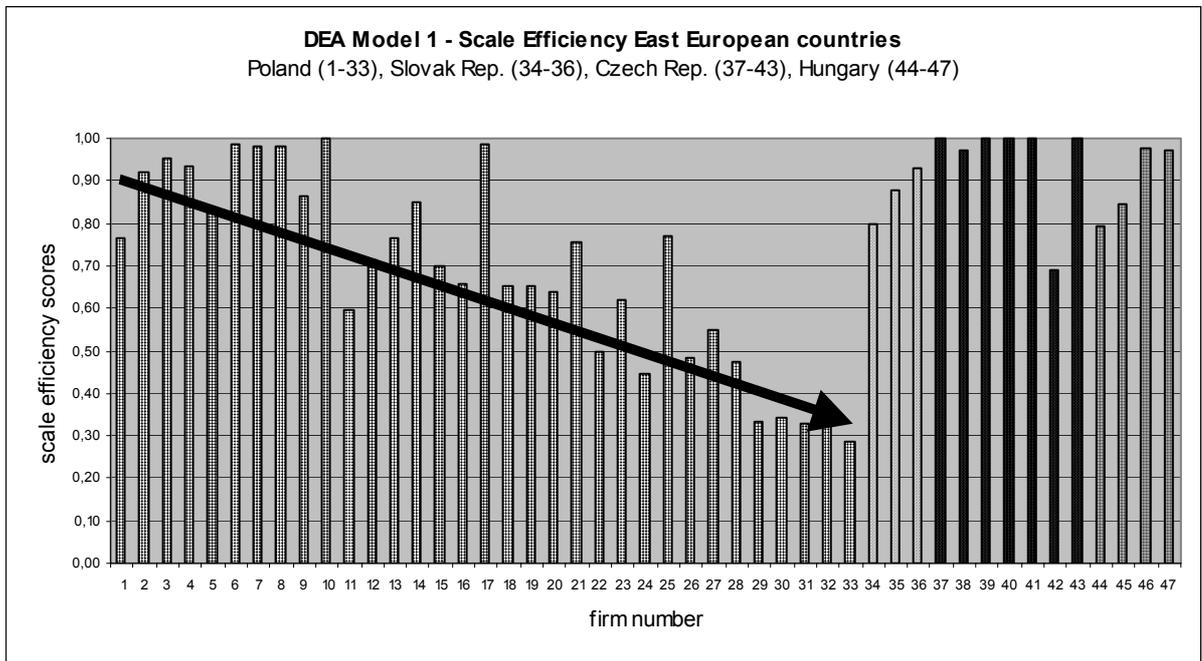
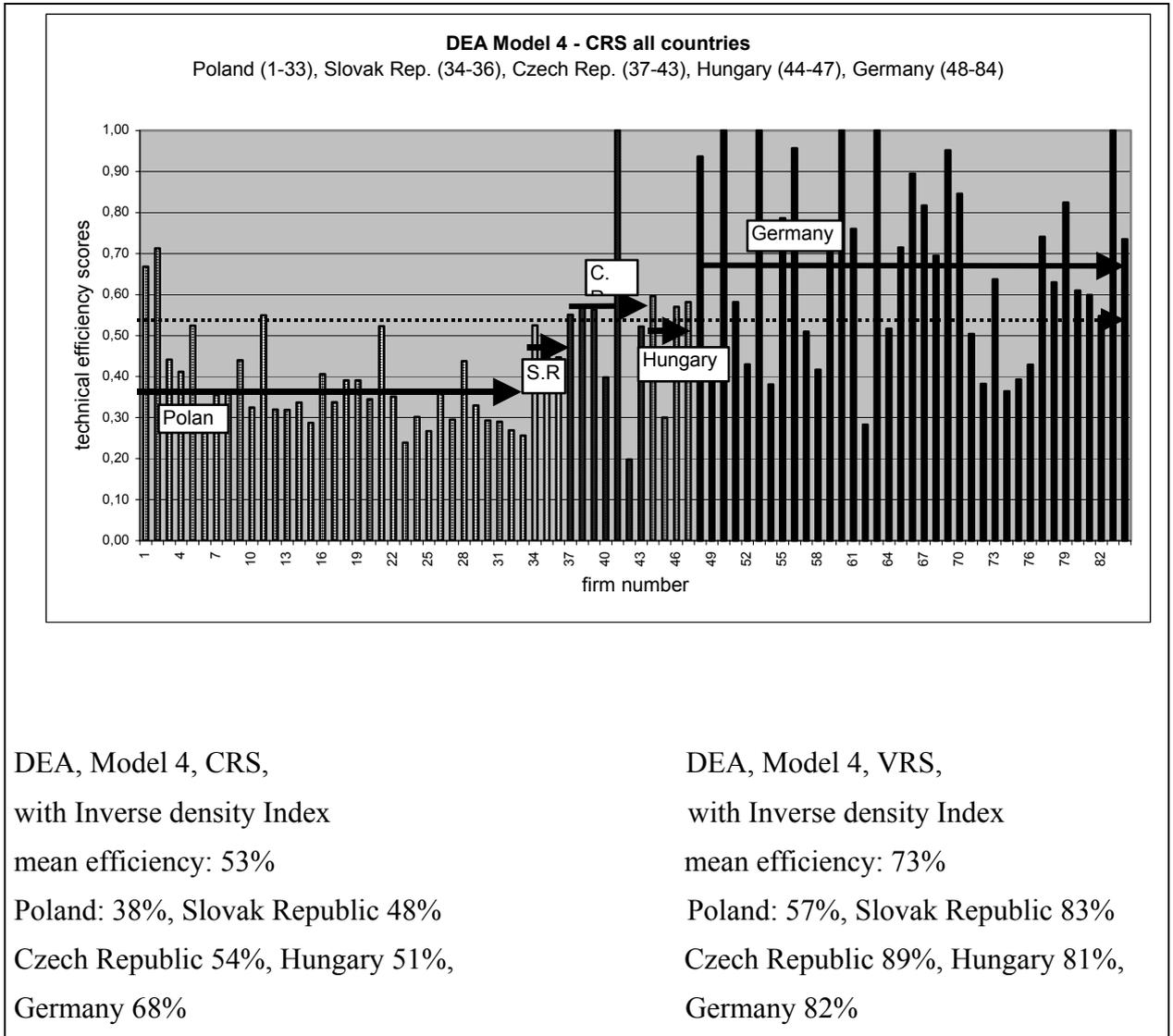


Figure 4: Results: DEA, Model 4, CRS



DEA, Model 4, CRS,
 with Inverse density Index
 mean efficiency: 53%
 Poland: 38%, Slovak Republic 48%
 Czech Republic 54%, Hungary 51%,
 Germany 68%

DEA, Model 4, VRS,
 with Inverse density Index
 mean efficiency: 73%
 Poland: 57%, Slovak Republic 83%
 Czech Republic 89%, Hungary 81%,
 Germany 82%

Figure 5: Results, SFA Model1

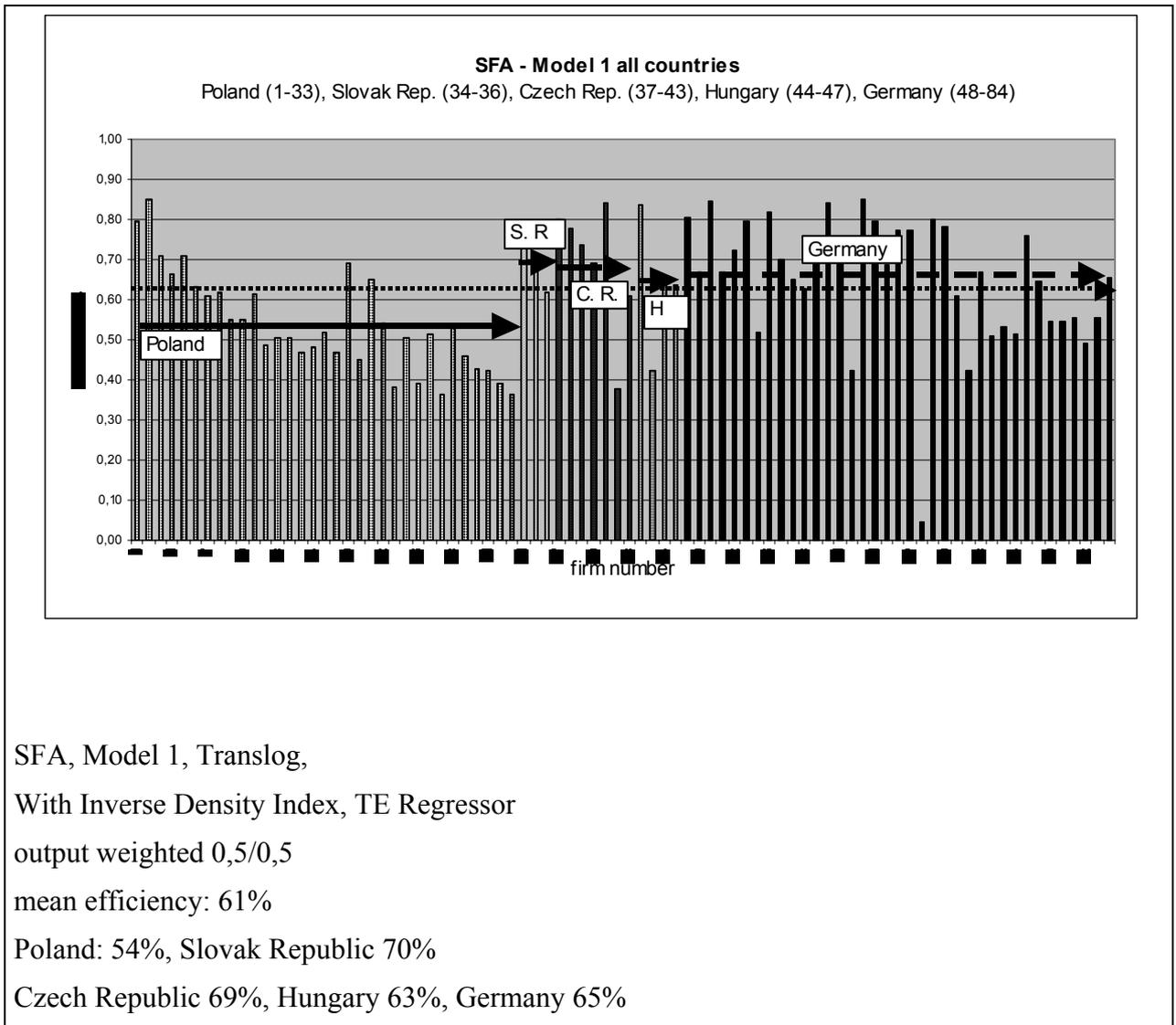
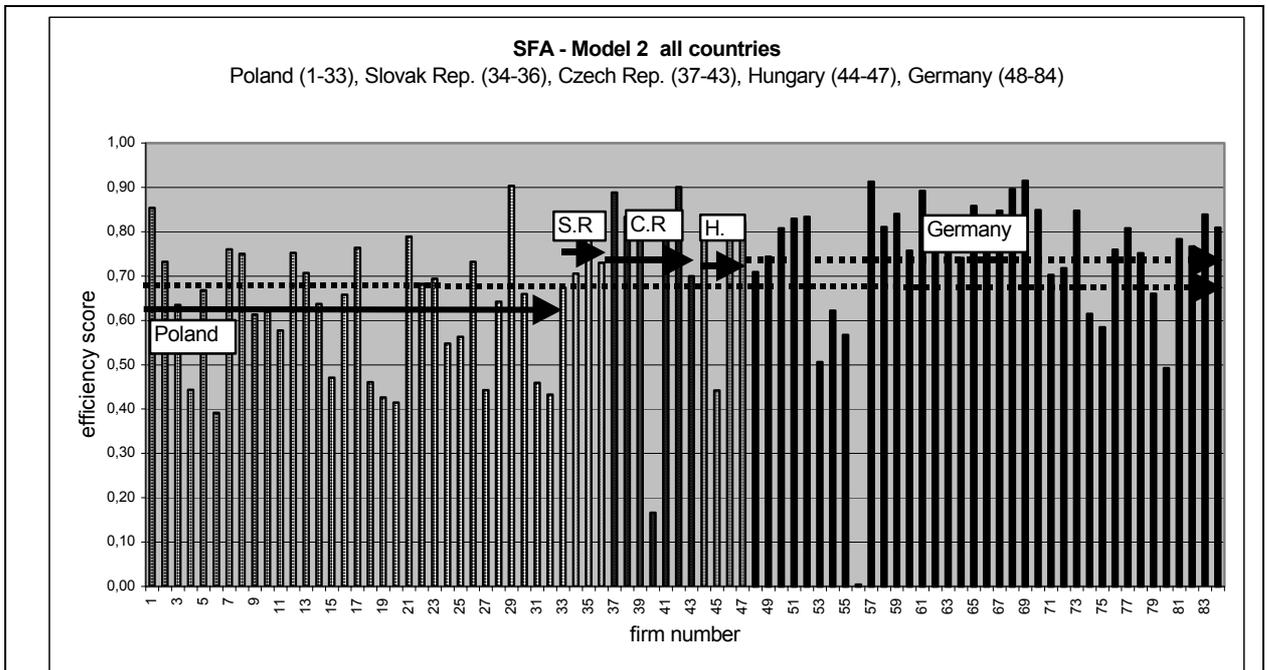


Figure 6: Results, SFA, Model 2



SEA, Model 2, Translog,

with Inverse Density Index, TE Regressor

Output weighted, customers 0,7/ sales 0,3

mean efficiency: 69%

Poland: 62%, Slovak Republic: 75%

Czech Republic 74%, Hungary 73%, Germany 74%