From Transition to Competition -
Dynamic Efficiency Analysis of Polish Electricity Distribution Companies

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Astrid Cullmann\textsuperscript{1, 2} and Christian von Hirschhausen\textsuperscript{3}

Corresponding Author:
Astrid Cullmann
Dept. of International Economics
DIW Berlin (German Institute for Economic Research)
Koenigin-Luise-Str. 5
D- 14195 Berlin (Germany)
tel.: +49-30-89789-672
chirschausen@diw.de

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\textsuperscript{2}Astrid Cullmann is Project Associate, DIW Berlin.

\textsuperscript{3}Chair of Energy Economics and Public Sector Management, Dresden University of Technology, and Research Professor, DIW Berlin.
Abstract

In this paper we test the hypothesis that the economic transition toward a market economy increases the efficiency of firms. We study 32 Polish electricity distribution companies between 1997-2002. We apply common benchmarking methods to the panel: the nonparametric data envelopment analysis (DEA), the free disposal hull (FDH), and, as a parametric approach, the stochastic frontier analysis (SFA). We then measure and decompose productivity change with Malmquist indices. We find that the technical efficiency of the companies has increased during the transition, while allocative efficiency has deteriorated. We also find significantly increasing returns to scale, suggesting that the regulatory authority should allow companies to merge into larger units.

Keywords: Efficiency analysis, electricity distribution, transition, econometric methods, Poland, DEA, SFA

JEL Classification: P31, L51, L43, C1
1 Introduction

One of the key concerns of the literature on economic transition in Eastern Europe is the link between economic reforms and productivity at the level of firms, sectors, and of national economies. In general, one expects that the move from central planning and state ownership toward market competition and more efficient corporate governance increases the productivity at all levels. Several studies confirm this hypothesis by applying recent methods of productivity analysis such as data envelopment analysis (DEA) and stochastic frontier analysis (SFA). Thus, Halpern and Körösi (2001) show that in the Hungarian corporate sector increasing competition has lead to a gradual improvement in efficiency and a shift from decreasing to increasing returns to scale. Using an unbalanced panel of firms, Funke and Rahn (2002) show that the East German firms undergoing transition were significantly less efficient than firms in Western Germany. Similar studies using advanced quantitative methods include Brada, King and Ma (1997) on Czechoslovakia and Hungary; Jones, Klinedinst and Rock (1998) on Bulgaria; Piesse (2000) on Hungary; and Koop, Osiewalski and Steel (2000) on a comparison between the Polish and Western economies.

However, the past fifteen years have also taught us that not all expectations regarding the virtues of transition have materialized. This is particularly true in the capital-intensive and highly politicized infrastructure sectors, where reforms have sometimes been slow and painful (see EBRD, 1996,
In the last decade energy sector reform has been especially difficult because its mergers have often resulted in significant downsizing and plant closures (see early evidence by Newbery, 1994 and Stern, 1994).

There have been few studies of restructuring’s impact on the electric sector’s productivity or on individual companies in the emerging internal energy markets in Europe. The literature is scarce: Kocenda and Cabelka (1999) studied the liberalization of the energy sector in the transition countries with respect to its effect on transition and growth. Filippini, Hrovatin and Zoric (2004) analyzed the efficiency of electricity distribution companies in Slovenia, using a stochastic frontier analysis. They found that Slovenian distribution companies were cost inefficient and that in a situation of increasing returns to scale most utilities did not achieve the minimum efficient scale. Cullmann, Apfelbeck and Hirschhausen (2006) provide a cross-country efficiency analysis of regional electricity distribution companies (RDCs) in four East European transition countries (Czech Republic, Slovakia, Hungary and Poland). They found that the restructured Czech electricity distribution companies regularly obtained the highest efficiency scores; by contrast, the Polish had the lowest efficiency scores in the region, and were also found to be very heterogeneous amongst themselves. However, this latter study was only based on the cross-section data set for 2001.

In this paper, we provide a dynamic efficiency analysis of Polish regional
electricity distribution companies over a longer period. Our aim is three-fold: first, we want to validate the previous result that Polish RDCs could benefit from merging into larger units; second, we want to quantify how productivity evolves as the transition proceeds; third, we want to contribute to the current discussion in the literature on transition and productivity. We use a unique data set including technical data and cost and price data for six years (1997-2002). We apply a broad range of models to the Polish electricity distribution, such as cost efficiency models to evaluate allocative efficiency, and panel data analysis to estimate efficiency change over time.

This paper is structured in the following way: Section 2 describes the reform process in Poland since the beginning of economic transition, particularly the difficulties in restructuring this politically and socially sensitive sector. Section 3 introduces the data set, model specifications, and inputs and outputs used in the efficiency analysis. We apply a series of traditional and some innovative approaches in nonparametric and parametric estimation. Section 4 presents the nonparametric approaches including usual data envelopment analysis (DEA), an ex ante descriptive statistical method for outlier detection, the stochastic DEA using the order-m efficiency estimates, and the free disposal hull (FDH) estimator. Section 5 presents results of the parametric approaches: output stochastic frontier analysis and different panel data models. We interpret and compare the results obtained. We find that overall transition did not have a significant positive effect on efficiency: while
the technical efficiency increases during the observation period, the allocative efficiency decreases. Section 6 offers our conclusions and suggestions for further research, and discusses several policy implications.

2 Electricity Restructuring Since Transition Began

Electricity sector-restructuring has proven to be one of the more difficult exercises in the process of economic transition and therefore has taken more effort and more time than initially expected. In socialist countries the electricity sector was assigned a prominent political and ideological role, (“Lenin’s communism is Soviet power plus electrification”). Subsequently, reforms towards more market-oriented structures were challenging: the price system was changed from “social tariffs” to cost-covering prices; vertically integrated monopolies were unbundled while some portions became privatized; regulatory authorities were established; environmental standards and renewable-promotion schemes were implemented. In brief, the East European transition countries undertook reforms within a decade that had occupied their West European counterparts for almost half a century.

Newbery (1994), Stern (1994) and Stern and Davis (1998) have provided evidence on the economic regulatory and political challenges of restructuring the electricity sector; many of their observations are still valid. More recent
evidence by EBRD (2004) and Hirschhausen and Zachmann (forthcoming) confirms that the electricity sector is still one of the unresolved legacies of transition in many countries.

Together with high voltage transport and low voltage distribution of electricity, regional electricity distribution retains many of the characteristics typical of a natural monopoly (subadditive cost function). This implies that contrary to electricity production and electricity retail, there can be no competition in electricity distribution. It also gives the electricity sector an important role both in socialist systems and in market economies. Electricity distribution is perhaps the most complicated element in restructuring, where industrial demand has collapsed at the same time residential use is rising. Distribution is a political issue when pricing or security becomes most sensitive for industrial and residential users. When added to the natural monopolistic character of the sector, electricity companies may discover they hold the upper hand in negotiations with state and federal regulators during the time of transition.

Poland, by far the largest electricity producer and distributor among the East European transition countries still has substantial problems to resolve before it can completely reform its electricity sector. Its historical dependence on coal – a supply source that suffers from chronic over-employment, centralized bureaucratic structure, and a high degree of politicized decision-making – has weakened modernization efforts. For example, to preserve
employment in several mines, Poland was forced to buy its own expensive coal. In socialist times, the electricity sector was organized by a Central Ministry which delegated operational powers to one electricity company in each of the 33 regions (voivody). The structure remained unchanged during the first decade of transition; by international comparison, 33 distribution companies is a large number for total sales of only about 90 TWh of electricity.

The country’s capital stock also remained largely unchanged, and few investments occurred. To date, privatization of the distribution companies in Poland has been largely unsuccessful thus far, with only 3 of the 33 companies being bought by (foreign) private investors. By international comparison, the Polish electricity sector has clearly lost attractiveness vis-a-vis more active transition countries, such as the Czech Republic and Hungary.

Recently, however, the reform process has picked up speed, with attempts to merge the existing regional structures into seven large distribution companies (2004) and therefore benefit from the assumed economies of scale. This consolidation plan also includes the creation of a few large holding companies for electricity generation ("national champions"). In the first round of consolidation, 14 regional companies were created out of the initial 33 distributors. From an economic perspective, such concentration is justified if the size of the units can be shown to be too small. This is a major concern
of this paper and the following quantitative analysis.

3 Data, Variables, and Model Specifications

3.1 Data

Our analysis is based on a panel data set for 32 Polish regional distribution companies for the period between 1997 and 2002.\footnote{Data for one company (Gornoslaski Zaklad Elektroenergetyczny SA) was completely missing.} Both technical and cost data is available from the utilities’ annual reports from 1997 onwards; before that year, companies were not obliged to report this data systematically. In 2003, the merger process set in, and it became more difficult to compare the companies.

The electricity distribution companies operate under very similar technical and institutional conditions. As natural monopolies, their tariff setting is subject to supervision by the national Polish regulatory authority. Table 1 provides a summary of the main data of the companies. The size, in terms of km$^2$ distribution area, is quite similar among the 32 companies.\footnote{In that respect, the Polish distribution companies are more homogeneous, than for instance in Germany. The two exceptions which are smaller than the average are STOEN, the Warsaw distribution company, and Lodzki Zaklad Energetyczny SA.} On the other hand, there are considerable differences in consumer density, in particular between the more densely settled regions in the Center and the South of the country and the less densely settled regions in the North and East.
Partial productivity indicators vary somewhat among the 32 companies.

The average labor productivity has increased from 1765 Mwh per employee in 1997 to 2152 in 2002. The firms feature different labor productivity, such as Zamojska Korporacja Energetyczna SA (1097 MWh per employee) and Zakład Energetyczny Plock SA (12199 MWh per employee). This is partly due to variations in outsourcing (for which no data is available).  

Another partial performance measure, the number of customers per employee, also increased on average from 270 in 1997 to 364 in 2002. Capital productivity is approximated by the ratio of electricity sold in Mwh divided by network length. The average capital productivity is rather constant over the period, ranging from 101 Mwh per km network to 106 Mwh per km of network. This indicates that input factor adaptation largely relies on labor, but that there is some flexibility regarding the capital input (∼ network length) as well.

### 3.2 Variable definition

The available data allows for an analysis of both the technical and the cost efficiency.  

For estimating the technical efficiency, we use a traditional model which has been applied for similar sector studies (Hirschhausen et al., forthcoming, and Cullmann, et al., 2006): labor and capital are used as inputs,  

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6Labour productivity is particularly high for Zakład Energetyczny Plock SA, which supposedly has a very high degree of outsourcing.

7A broad range of models is used to derive efficiency measures in electricity distribution. For a survey, see Jamasb and Pollit (2001).
electricity distribution and the number of customers are the output.

Labor input is estimated by the number of workers. The descriptive statistics (Table 1) show that total employment in the Polish electricity distribution has decreased over the years. Capital input is approximated by the length of the existing electricity cables. Investments in grid extension were insignificant in the period under observation, and the cable length has remained almost constant. We differentiate between voltage levels (high, medium, and low) by introducing a cost factor for each type of line.  

We use the amount of electricity distributed to end users (units sold) and the total number of customers as output variables. The amount of electricity distributed somewhat declined from 89.2 GWh (1997) to 86.7 GWh (2002); this trend is representative for the transition period, as rising electricity prices and increased energy efficiency dampen consumption. The number of customers increased mainly due to the rising number of residential households. On the output side, we also include an inverse density index (settled area in km\(^2\) per inhabitant) to account for the structural differences: this index (IDI) favors the efficiency scores of less densely inhabited regions. The descriptive statistics show significant differences among the firms in terms of population density.

Our cost model includes total cost (Totex), capital costs, and labor costs.  

\(^8\)The factors are 1, 1.6, and 5 for low, medium and high voltage respectively. They are adopted from Verband Deutscher Elektrizitätswirtschaft’s (2001) estimates for Germany’s electricity distribution.
Totex and labor costs are available for all companies in Polish Zloty (Plz). The average wages and the input factor price for labor, are calculated as the ratio of labor expenditures divided by the number of employees. Following Filippini, et al. (2004), we define capital costs as the difference between total cost and labor costs. The capital stock is approximated by network length. We can thus derive the "price" of capital as the ratio of (residual) capital cost and the capital stock (∼ network length).

All input prices and costs were deflated by means of the price index of sold production of industry (1995=100) available from the statistical information center in Poland. Average costs varied significantly between the companies with a difference of up to 50 Plz/MWh, and there was a general upward trend. Although there were major labor reductions during our study period, total labor costs increased because of rising wages. Capital costs and output prices also rose.

### 3.3 Model specification

Frequently the choice of variables is constrained by data availability, and this held true for the transition countries of Eastern Europe. In essence, choices must be made using the following criteria: i) nonparametric vs. parametric
approaches; ii) technical efficiency models vs. allocative efficiency models; iii) deterministic vs. stochastic approaches (see Coelli et al., 2005, for a survey).

Based on the available data and our own modeling experience, we chose the following models: a DEA Model 1 which uses the traditional choice of technical efficiency analysis: the inputs are the number of employees (labor), and the length of the electricity grid (capital); the outputs are total sales (in GWh) and the number of customers. In the extended version of the model (DEA Model 2), we include a structural variable to account for structural differences among regions: the inverse density index (IDI, measured in km² per inhabitant). To obtain robust and reliable results, we then estimate the extended DEA Model 2 also by the FDH-approach (free disposal hull, FDH Model 1) and the stochastic DEA, the so-called order-m Estimator (Order-m Model 1). For the stochastic approach to technical efficiency analysis, the SFA Model 1 uses the basic set of two inputs and two outputs, to which we add the structural inverse density index (IDI) in SFA Model 2. We apply two different panel data specifications, Battese and Coelli (1992), called SFA Model 1, and Battese and Coelli (1995), called SFA Model 2, which we discuss in Section 5.1. Table 2 summarizes the models for estimating technical efficiency.

With regard to estimating allocative efficiency (see Table 3), we estimated nonparametric approaches and parametric cost functions: DEA Model 3
uses total cost as a dependent variable, whereas DEA Model 4 uses the physical output "electricity sold" (in MWh) and the number of customers. DEA Model 5 uses total costs as input, and the amount of electricity sold and the number of customers as output. SFA Model 3 defines the total costs as the dependent variable and both outputs (electricity sold and number of customers) and the input factor prices as regressors. In addition we apply fixed and random effects panel models developed by Greene (2005). In SFA Model 4 and 5 we define the input as the sum of the monetized input factors, the total costs, and the aggregated output index as the dependent variable.

4 Nonparametric Approaches and Results

4.1 Basic DEA, FDH, and stochastic DEA

Common nonparametric estimators are the data envelopment analysis (DEA) and the free disposal hull (FDH) estimator, proposed by Deprins et al. (1984). As we dispose of panel data we take into account both efficiency and technical changes. In addition to traditional benchmarking, we apply recently developed approaches, such as the stochastic DEA, the so-called order-m estimator, proposed by Cazals, Florens and Simar (2002).

In a first step, the discussion involves physical quantities and technical relationships. Thus, we focus exclusively on the utilities’ technology and production process to assess the technical efficiency. Next we provide an overall
economic efficiency measure, with allocative efficiency of the firms, by including cost and price data. With respect to the DEA analysis we emphasize on the constant returns to scale approach (CRS), because we expect the Polish RDCs to adapt towards an optimal firm size. We also check the correlations to test for the consistency results and to exhibit the overall trends we observe within the companies.

The idea of estimating production efficiency scores in a deterministic nonparametric framework was originally proposed by Farrell (1957) who defines a measure of firm efficiency relative to a given technology (the production frontier) which can be estimated by envelopment techniques, such as DEA and FDH. DEA involves the use of linear programming methods to construct a piecewise linear surface or frontier over the data and measures the efficiency for a given unit relative to the boundary of the convex hull of \( X = \{(x_i, y_i), i = 1...n\} \), where \( x_i \) defines the input vector and \( y_i \) the output vector of the \( i \)th out of \( n \) firms.

\[
\hat{\theta}_k = \min \{\theta | y_k \leq \sum_{i=1}^{n} \gamma_i y_i; \theta x_k \geq \sum_{i=1}^{n} \gamma_i x_i; \theta > 0; \gamma_i \geq 0, i = 1, ... n\} \quad (1)
\]

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. Calculations can be done using an input-orientation or an output-orientation. Traditionally, efficiency analysis in the electricity sector assumes the output fixed in a market with the legal duty to serve all customers in a predefined service territory.
Following Simar and Wilson (1998), $\theta_k$ measures the radial distance between the observation $x_k, y_k$ and the point on the frontier characterized by the level of inputs that should be reached to be efficient. A value of one $\theta_k = 1$ indicates that a firm is fully efficient and thus is located on the efficiency frontier. The DEA estimates may depend heavily on the assumption that the production frontier is convex. The FDH estimator, in contrast, relaxes the assumption of convexity.

If price data is available and one assumes a behavioral objective, such as cost minimization, it is possible to consider allocative efficiency and relate it to technical efficiency to measure the overall efficiency of the firms (see Coelli 2005, p. 183).

Cazals et al. (2002) propose the nonparametric order-m estimator as an alternative, which is based on the expected minimum input frontier. This type of estimator is more robust since it permits noise in input measures, and consequently individual observations including extreme outliers have much less influence on the efficiency frontier.\footnote{For details see Cazals et al. (2002) and Wheelock and Wilson (2003).}

\subsection*{4.2 Empirical results: technical efficiency}

In DEA Model 1 the Polish companies achieve an average technical efficiency of 0.59 under a CRS assumption.\footnote{In DEA Model 1 and 2 we estimate a pooled DEA that is we estimate one frontier for the entire observation period (1997-2002) without accounting for the technical changes in each year.} The correlation analysis of the
efficiency estimates for each year ranges around 0.9, implying that there is no significant change between the different years on the company level. When applying the less constraining VRS approach, the Polish RDCs considerably gain in efficiency, reaching an average efficiency level of 0.75. In comparison to other Central European new EU member states, Poland is relatively large but it has got incomparably and overproportionally many distribution companies. The low technical CRS efficiency scores combined with a notable difference in the VRS scores indicate that the Polish electricity distribution companies are “too small to be efficient”.\textsuperscript{14} We postulate that their inefficiency chiefly originates in their size; Figure 1 shows the differences of DEA Model 1 under a CRS assumption and DEA Model 1 under a VRS assumption.\textsuperscript{15}

Including the inverse density index in DEA Model 2 changes the rank of the individual firms (see Figure 2). Companies which operate in a less favorable environment, particularly the smaller companies, significantly gain efficiency in all years. The average efficiency increases to 0.72 under CRS and 0.79 under VRS. In both models we observe that the average efficiency increases slightly over the years.\textsuperscript{16}

Our result can be confirmed by Malmquist indices which measure the change

\textsuperscript{14}In all years, 50 per cent of the larger companies are on average more efficient than the smaller ones, which also indicates that there are increasing returns to scale.

\textsuperscript{15}In the following graphs the firms are ordered by size, defined in our analysis by electricity sold in Mwh, beginning with the largest company in each year at the left.

\textsuperscript{16}In DEA Model 1 from 0.56 to 0.59 under CRS, and 0.71 to 0.75 under VRS, and in DEA Model 2 from 69.7 to 73.1 under CRS and from 77.3 to 80.2 under VRS.
of total factor productivity for a particular firm between two periods. The index is constructed by measuring the radial distance of the observed output and input vectors in periods $s$ and $t$ relative to the reference technologies $S^*$ and $S^t$. By means of the Malmquist indices one can decompose efficiency change into technical, efficiency and total factor productivity components (for more details see Coelli, 2005, p. 67).

The empirical results indicate a technical change of 1.026 on average during the observation period. This implies that the technical efficiency increase found in our DEA Model 1 and DEA Model 2 results from technical progress.

In addition, we note the sensitivity of the results from a different set of production assumptions by estimating the technical efficiencies using the FDH Model 1. Only 13 enterprises out of our sample are not classified as fully efficient. This finding suggests that the DEA results are not robust with respect to non trivial changes in the production assumption. However, we also note that in every period the same utilities are classified as inefficient which indicates a certain validation of the inefficiencies of these firms. All of the firms classified as inefficient are medium-sized or smaller when size is defined as the annual amount of electricity sold. Thus, the inefficiency of these companies can be seen as robust while any conclusion with regard to the efficient firms cannot be easily drawn.

We now enlarge our analysis to the stochastic nonparametric approach, the
order-m estimation.\textsuperscript{17} We note that technical efficiency also increases during the observation period from 0.93 to 0.97. Thus the results from the DEA Models 1 and 2 can be confirmed.

4.3 Empirical results: allocative efficiency

In DEA Model 3 we estimated the relative cost efficiency of the firms by relating the inputs to the respective factor prices. We find that while the technical efficiency increases, from 0.76 in 1997 to 0.81 in 2002, the allocative efficiency decreases moderately, from 0.87 in 1997 to 0.84 in 2002. This implies that the cost efficiency or the overall efficiency of the firms, calculated as the product of technical and allocative efficiency, remains at a similar level. Thus we observe two trends: first, over the years, the utilities learned to improve the technical aspect of the production process; second, they were unable allocate the inputs more efficiently. This result can be confirmed by using DEA Model 5, where we include the total costs as input instead of the physical input factors. With this specification the average efficiency score for the entire industry decreases from 0.86 to 0.70 during the observation period. Again we note that the companies failed to utilize the input factors more cost effectively.

\textsuperscript{17}We consider the order-m results as a verification and validation method rather than as a method to predict the real relative efficiency estimate because the order-m relaxes the convexity constraint. Like the FDH estimator, it implies a larger number of companies on the efficiency frontier and a small range of efficiency differences. If m is infinite, the order-m converges toward the free disposal hull estimation (see Cazals, 2002.)
Across all model specifications, STOEN was the most efficient. This can be explained by its customer structure, both with regard to density and to specific electricity consumption patterns; there is a high degree of industrial demand, for example. The results remains valid when we compensate other regions for their structural disadvantage, by using the inverse density index. Other metropolitan distributors, like Lodz, Krakow, or Wroclaw do not achieve the same technical efficiency, but their efficiency scores are also above average.

5 Parametric Approaches and Results

5.1 Stochastic frontier model and panel data models

The stochastic frontier approaches\(^{18}\) provide a parametrization of the input-output relationship. Contrary to the ordinary least squares (OLS), the stochastic frontier model decomposes the residuals into a symmetric component \(\nu_i\) representing statistical noise, and an asymmetric component representing inefficiency \(u_i\).\(^{19}\) Referring to the translog functional form yields

\(^{18}\)The theory of stochastic frontier production functions was originally proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977).

\(^{19}\)See also Coelli (2005, p. 243). For the noise components \(\nu_i\) it is assumed that they are independently and identically distributed normal random variables with zero mean and variance \(\sigma^2_{\nu_i} \sim iidN(0, \sigma^2_{\nu_i})\). Alternatives for the distributional specifications of the \(u_i\)'s as well as the likelihood functions for the different models are summarized in Kumbhakar and Lovell (2000). The above measures of technical efficiency rely on the value of the unobservable \(u_i\) being predicted (see Coelli, 2005, p. 8).
the stochastic frontier production function in the following form

$$\ln y_i = \beta_0 + \sum_{n=1}^{N} \beta_n \ln x_{ni} + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} \beta_{nmi} \ln x_{ni} \ln x_{mi} + \nu_i - u_i$$

(2)

where $i$ is the index for firm $i$. Cost frontiers apply instead of $\nu_i - u_i, \nu_i + u_i$.

Finally we apply two types of panel analysis based on Battese and Coelli (1992, 1995) and Greene (2005), respectively. Battese and Coelli (1992) proposed a random effects model with a varying technical inefficiency over time as follows.\textsuperscript{20}

$$u_i t = f(t) \cdot u_i$$

(3)

where

$$f(t) = \exp[\eta(t - T)]$$

(4)

$\eta$ is an unknown parameters to be estimated.

The Battese and Coelli Specification (1995) accounts explicitly for environmental non-stochastic factors such as the inverse density index, that are observable once the production decisions are made. The inefficiency effects $u_i$ are expressed as an explicit function of a vector of firm specific variables

\textsuperscript{20}See Coelli (2005), p. 278. They use the same parameterizations used in the cross sectional models. The log likelihood function is presented in the original paper of Battese and Coelli (1992).
and a random error (see Coelli, 1996, p. 5)

\[ u_i \sim N^+(z_{it}'\gamma, \sigma_u^2) \]  

(5)

where \( z_{it} \) is a vector of environmental variables which may influence the inefficiency effects \( u_i \), and \( \gamma \) is a vector of parameters to be estimated. The other variables are defined as above.

The major shortcoming of the above specified and estimated panel data models is that any unobserved time-invariant, firm-specific heterogeneity is considered as inefficiency. To overcome this problem, we estimated in a second step the fixed and random effects models derived by Greene (2005), who extended the stochastic frontier model in its original form to panel data models by adding a fixed or random effect in the model.\(^{21}\)

The true fixed effects model can be expressed by

\[ y_{it} = \alpha_i + x_{it}'\beta + v_{it} - u_{it} \]  

(6)

In fact, one can interpret the model as if a full set of firm dummy variables were added to the stochastic frontier model capturing the unmeasured heterogeneity directly in the production function, (Greene, 2005).

\(^{21}\)The two are called the true fixed effects model and the true random effects model, respectively. The two sets of maximum likelihood estimates as well as the inefficiency predictions were obtained using LIMDEP (Greene, 2002).
The true random effects frontier model can be expressed by

\[ y_{it} = (\alpha + w_i) + x_{it}'\beta + v_{it} - u_{it} \]  

(7)

where \( w_i \), a random (across firms) constant term, represents the cross section heterogeneity.

5.2 Empirical results: static analysis

For the SFA models the outputs were aggregated\(^{22}\) to create a joint index for total sales and the number of customers. We calculated the predicted technical efficiency according to Coelli (1996), assuming a truncated normal distribution for the technical inefficiencies. In order to compare the SFA results to the pooled DEA, we assumed for the moment no technical change and no variation of the inefficiencies in time. Therefore the results indicate the average technical efficiency of the firms across the observation period.

The results of this approach lead to the same trend seen in the nonparametric DEA Model 1: large utilities are on average more efficient (the 50 per cent of the largest equal 0.74, in contrast to the 50 per cent of the smallest equal to 0.56). In a second step, we also model the variation of the inefficiencies over time according to Coelli (1992). Surprisingly, the results indicate that the technical efficiency of the firms does not change significantly over the years.

\(^{22}\)For the SFA run the outputs were logged and each weighted fifty percent each.
Applying the SFA Model 2 we find that the structural variable which is the inverse density index has a significant influence on the inefficiency scores. Within this model specification, we find a lower average efficiency of the firms (ranging around 46 per cent) because the average value of the truncated normal distribution is now directly estimated by the structural variables. However, we confirm our finding that the larger utilities are on average more efficient. When we model the variance of the inefficiencies over time, the results indicate a slight increase in average technical efficiency from 0.45 to 0.48, confirming the results of the nonparametric DEA and the order- \( m \) analysis. In both stochastic frontier specifications we find evidence that STOEN is relatively more efficient than the other companies.

5.3 Empirical results: accounting for technical change

We conduct model variation for both SFA Model 1, and SFA Model 2, first assuming a constant trend, and then extending the analysis by allowing the technological change to increase or decrease with time. The nonparametric analysis already demonstrated that the industry-specific technological development is positive for the electricity distribution in Poland. The estimates of the technical change parameters indicate a technological progress which decreases over the sample period since the sign of the squared time trend is negative. More precisely, we estimate that output increased at a ratio of
approximately 2.4 per cent per annum due to technological change.\footnote{Note, however, that the parameters lack statistical significance, and therefore one must be careful in making a detailed interpretation.}

We can summarize that the SFA results are similar to the DEA results. We observe some technological change in the electricity distribution industry.

### 5.4 Cost efficiency

The stochastic cost frontier specification (SFA Model 3) identifies the minimum costs at a given output level, the input factor prices, and the existing production technology. The specification of the cost frontier is similar to Filippini (2004).\footnote{A Cobb Douglas functional form has been adapted, because we want to avoid the potential risk of multicollinearity among second order terms due to the large number of parameters in a translog model, and the strong correlation between output characteristics, (see Filippini 2004 p.13).} Linear homogeneity in input prices is imposed by dividing the monetized values by the price of the capital. We observe an increase in the annual average cost inefficiency over the years from 30 per cent in 1997 to 41 per cent in 2002. The DEA results suggested that the allocative efficiency decreased over time whereas the technical efficiency increased. Consequently the overall cost efficiency remained the same, because cost efficiency decreased. In our cost model the latter trend is not reflected. The SFA Model 3 is only coherent with decreasing allocative efficiency in time. From 1997-2002 50 per cent of the largest companies operated on the same cost efficiency level as the smaller utilities. This changed in the last two years of our observation panel when the small utilities become slightly more
inefficient than the larger ones. This result reinforces support for continuing the consolidation process now underway in Poland’s electricity distribution sector.

5.4.1 Distinguishing firm specific heterogeneity from inefficiency

We now turn to the estimation results of SFA Models 4 and 5. Considering the performance in time, we note that in both models the average efficiency (where we define total costs as regressor) decreases from 1997-2002 (see Figure 3). This effect is stronger in the last two years. In 2002 the average efficiency dropped almost 3 per cent in the fixed effects specification and 4 per cent in the random effects specification in comparison to a higher cost input in 2002 (see Figure 3). The overall trend exhibited in the other models remains valid: there is an increase in the cost inefficient use of the input factors in the Polish distributors. Factors that may account for the inefficiency include a decreasing amount of electricity sold to end users in the last two years combined with higher costs induced by new customers and new interconnections on the grid.

In comparison to the technical efficiency SFA Models 1 and 2 and the cost efficiency SFA Model 3, the inefficiency estimates obtained from the fixed effects and the random parameter specification are 30 per cent lower on average. We observe that the inefficiency estimates are sensitive to the specification of unobserved firm specific heterogeneity and therefore, the inefficiency
scores obtained from the traditional specifications (including unobserved
environmental factors), most likely overstate the inefficiency of the Polish
companies.

6 Conclusions and Outlook

In this paper we have provided an efficiency analysis of electricity distribu-
tion companies in Poland - one of the more advanced transition countries
that has recently joined the EU. We have observed that the reform pro-
cess in this sector is heavily influenced by the legacy of decades of socialist
energy policies and by attempts to modernize the sector in the wake of EU-
accession. We take as the point of inception the results from Cullmann et al.
(2006) of a rather low efficiency of Polish companies and a large dispersion
within our sample. The extensive dataset assembled for the current study
contains technical and cost/price data for 1997-2002, thus allowing for a
range of model specifications and simulation analyses. We also conducted a
dynamic analysis to reveal the efficiency change throughout the time period
and verified if transition enhances technical and/or allocative efficiency.

We discovered that while technical efficiency increased during the transition
period for the distribution companies, allocative efficiency did not. This in-
dicates that the companies were able to adapt their physical ratio of outputs
to inputs, i.e. ceteris paribus to deliver the same level of services using less
inputs, but that price developments during the transition were not properly
accounted for. We also found that input factors were not allocated in a
cost-efficient way.

We demonstrated that there were marked differences between the efficiency
scores of larger companies in comparison to the smaller ones (size being de-
dined by the amount of electricity sold). The results indicate that the smaller
utilities are on average less efficient, largely due to scale inefficiency. This
effect is neutralized when we introduce the inverse density index. The lack of
scale efficiency does not change over our observation period. It can be con-
cluded that the process of merging 33 distribution utilities into a handful of
larger groups is an appropriate policy. The distribution company STOEN,
which serves Warsaw, regularly achieves the highest efficiency scores; this
can be explained by the favorable structural parameters.

From a methodological perspective, we find that the results derived by non-
parametric and parametric analysis are consistent and largely robust with
respect to the model specification. Correlation matrices generally yield rel-
etively high values, whereas rank-order correlations are less robust.

Further research should focus on the effects of the merger effort that began
in 2003 and the implications for the efficiency scores. We suggest conducting
a dynamic comparative analysis with neighboring transition countries, such
as the Czech Republic, Slovakia and Hungary and with traditional West
European countries such as Germany or France.
7 References


Table 1: Descriptive Statistics

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<th>Labor Sold in MWh</th>
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Table 2: Model Specification - Technical Efficiency

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Figure 1: Difference Results DEA Model 1 (VRS - CRS)
Figure 2: Difference Results DEA Model 2 - DEA Model 1

Companies ordered by size and year
Figure 3: Average Annual Efficiency - Fixed and Random Effects Model