Deutsches Institut für
Wirtschaftsforschung

DIW BERLIN

Discussion Papers

1118

Michael Zschille • Matthias Walter

The Performance of German Water Utilities: A (Semi)-Parametric Analysis

Berlin, April 2011

IMPRESSUM

DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin

Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
http://www.diw.de

ISSN print edition 1433-0210
ISSN electronic edition 1619-4535

Papers can be downloaded free of charge from the DIW Berlin website:
http://www.diw.de/discussionpapers

Discussion Papers of DIW Berlin are indexed in RePEc and SSRN:
http://ideas.repec.org/s/diw/diwwpp.html
http://www.ssrn.com/link/DIW-Berlin-German-Inst-Econ-Res.html

The Performance of German Water Utilities: A (Semi)-Parametric Analysis

Michael Zschille[1]

DIW Berlin - German Institute for Economic Research

Matthias Walter

Dresden University of Technology

April 2011

Abstract: Germany's water supply industry is characterized by a multitude of utilities and widely diverging prices, possibly resulting from structural differences beyond the control of firms' management, but also from inefficiencies. In this article we use Data Envelopment Analysis and Stochastic Frontier Analysis to determine the utilities' technical efficiency scores based on cross-sectional data from 373 public and private water utilities in 2006. We find large differences in technical efficiency scores even after accounting for significant structural variables like network density, share of groundwater usage and water losses.

Keywords: Water Supply, Technical Efficiency, Data Envelopment Analysis, Stochastic Frontier Analysis, Structural Variables, Bootstrapped Truncated Regression

JEL-Codes: L95, C14, Q25

[1] Corresponding author: Michael Zschille, DIW Berlin – German Institute for Economic Research, Mohrenstrasse 58, D-10117 Berlin, tel.: +49-30-89789-297, fax: +49-30-89789-200, e-mail: mzschille@diw.de.

I. Introduction

The water supply industry typically is dependent on cost-intensive network structures and therefore, by implication, is a candidate for natural monopoly. To ensure efficient production and distribution of good-quality water in sufficient quantity, countries like England, Wales, Australia and Slovenia have established a regulation based on yardstick competition in their water supply industries, but in Germany active price regulation is still in the beginning stage. In the federal state of Hesse a number of trials administered by the Hessian Cartel Office have been undertaken to decrease the prices, primarily because of the wide range of prices observed throughout the country. Currently, prices for residential water customers differ between 0.52 Euro and 3.95 Euro per cubic meter (Bundesverband der Energie- und Wasserwirtschaft, 2008a). In 2009, the German Federal Court of Justice agreed on the proceedings of the Hessian Cartel Office (decision KVR 66/08). This legal decision forced one water supplier to decrease its prices for water by 29.4%.

To identify the causes, structural differences, inefficiency, and to affirm whether the price variations observed are justified, we apply different methods of Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). For the non-parametric DEA, a three-stage approach for efficiency measurement is used. In stage 1, we calculate DEA efficiency scores and determine the returns to scale technology via a test proposed by Simar and Wilson (2002). In stage 2, the efficiency scores are explained by structural variables in a bootstrapped truncated regression framework (Simar and Wilson, 2007). In stage 3, we calculate technical efficiency (TE) scores based on a standard DEA model after including the structural differences through the input adjustment approach proposed by Fried *et al.* (1999). Furthermore, we apply SFA and estimate a cross-sectional cost frontier to compare the results for the structural variables and efficiencies.

Our objective is to encourage in-depth studies of efficiency analysis that could lead the way to the implementation of equitable regulation. Thus, a robust and representative measurement of efficiency is necessary to provide a thorough understanding of Germany's water supply industry, including abstraction, treatment, and distribution.

In Germany groundwater is the most important source, comprising 65.5% of total water production, followed by surface water, including reservoir water (26.4%) and wells/springs (8.1%). In 2006, total water production was about 5.3 billion cubic meters, 20% less than in 1990. Per capita consumption has declined in recent years, from 147 liters per day and per capita in 1990 to 126 liters per day and per capita in 2006 (Bundesverband der Energie- und Wasserwirtschaft, 2008b). In east Germany the decline between 1990 and 2006 is more significant: from 142 to 99 liters per day and per capita.

To ensure stable, safe drinking water quality, utilities have invested about 42 billion Euros in supply infrastructure since 1990, of which almost 60% has been spent on network infrastructure.[2] The breakdown of the industry's cost structure is: 21.5% depreciation, 20.6% personnel costs, 15.4% supply of services, 13.7% administration, 9.6% cost of water purchases and 40.7% other costs[3] (Bundesverband der Energie- und Wasserwirtschaft, 2008b). Water supply companies consist of municipal utilities (*Stadtwerke*) and regional and supra-regional acting special purpose associations known as *Zweckverbände*. The majority of municipal utilities are privately organized but under public control. They often provide additional services such as sewerage, local public transport, and electric and natural gas distribution. Special purpose associations were established to exploit economies of scale, especially in areas of low population density. They benefit from fewer labor input requirements, higher amounts of water sold and possibly from lower wholesale prices if supply by third parties is necessary. Most associations are large in size and often do not deliver drinking water to the end customer, but instead organize water production and purchase. Since including these specific special purpose associations produces inconsistencies in efficiency analysis, we include only the special purpose associations which supply very few communities and deliver drinking water to the end customer.

Efficiency analysis is a key component of incentive regulation for Germany's electricity and gas distribution networks.[4] In combination with the liberalization of energy delivery, incentive regulation has caused most municipal utilities to legally separate ("unbundle") the services they provide and to establish separate accounting. Thus, regulators may have access to operational and financial information. We suggest that a similar regulatory requirement could be applied to the water industry,

[2] This could explain both the low average share of water losses of 6.8% in 2004 in comparison to other countries as well as the high drinking water quality with only a few cases of measurements failing to meet standards (see Deutsche Vereinigung des Gas- und Wasserfaches e.V., 2006).

[3] Other costs include interest payment for debt, material costs and taxes. Additionally, municipalities in some federal states may require licensing fees.

[4] See Agrell *et al*. (2008) for the methods and calculation based on the ordinance for the incentive regulation, *Anreizregulierungsverordnung* (ARegV).

especially if research confirms that the widespread price differences observed are caused by inefficiencies or excessive profit generation.

The article is structured as follows. Section 2 reviews relevant literature with respect to the applied methodologies. Section 3 explains the methodologies applied, and Section 4 discusses the data used. Results are presented in Section 5, and Section 6 concludes.

II. Literature Review

A detailed current survey of the literature on water supply efficiency with respect to Germany is provided by Hirschhausen *et al.* (2009a). There is no comprehensive efficiency analysis of Germany's water supply industry based on a representative and consistent data set. A study of rural water supply by Cantner and Hanusch (1991) determined the technical inefficiencies of only 13 rural utilities using a corrected ordinary least squares (COLS) approach. Sauer and Frohberg (2007) applied SFA to a relatively small sample of 47 water utilities in east and west Germany, using a symmetric generalized McFadden function to compare the technical efficiency levels. They concluded that the utilities should focus on efficient usage of the input chemicals in order to increase allocative efficiency.

Walter *et al.* (2009) surveyed the international literature on water utilities and found three general categories:

1. studies to determine whether private or public services are more efficient. Examples are Bhattacharyya *et al.* (1995), Saal and Parker (2001), Saal *et al.* (2007) and more recently Benito *et al.* (2010). The main conclusion is that the institutional setting and regulation rather than ownership type determine efficiency.

2. studies on the estimation of economies of scale, density, and scope using stochastic frontier methods. Examples are Saal and Parker (2000, 2005), Sauer (2003, 2004, 2006) and Filippini *et al.* (2008). Whereas economies of density and scope throughout the water supply chain, and sewerage, electricity and gas activities can be affirmed, economies of scale appear to be exhausted beyond a certain threshold. Saal and Parker (2005) found diseconomies of scale for the UK water sector with a mean output level of 62.89 m m^3. Fraquelli *et al.* (2004) estimated a cost function for a sample of Italian multi-utilities providing gas, water and electricity, and found economies of scope to exist only for smaller utilities while

cost advantages of diversification could not be confirmed for utilities larger than the median output level.

3. studies using DEA and regression analysis to determine whether structural variables influence individual efficiency scores.

We review this third category in more detail, given our similar approach. Table 1 shows four recent DEA studies evaluating the impact of structural and quality variables with the resulting significant variables. Renzetti and Dupont (2009) use the multistage procedure recommended by Fried *et al.* (1999), focusing on the relative efficiency of 64 municipal water suppliers in Ontario, Canada. Inputs and outputs are involved in an application of a variable returns to scale DEA procedure passing through stage 1. Stage 2 examines the role of six external factors upon water agencies by regressing the total input slack values on a vector of variables that are expected to influence efficiency, but are beyond the control of agency managers. The six factors are: differences in elevation between each city's highest point and its water treatment facility, the maximum weekly summer temperature in 1996 in each city, total precipitation in each city, population density, ratio of residential water use to total water agency output, and number of residential dwellings. Due to the censored normal distribution of the error term the authors use a Tobit regression, and to undertake valid hypothesis testing they adopt a bootstrapped truncated regression algorithm as described in Simar and Wilson (2007). In stage 3 another DEA procedure with original output and adjusted input measures is conducted to establish a base equal to the least-favorable external conditions. The adjustment removes the differences in external operating environments that may distort efforts to assess the utilities' relative technical efficiency. DEA mean efficiency scores are absolutely higher in stage 3 than in stage 1 by 6.6% using the Tobit adjustment, and by 28.4% using the truncated regression adjustment.

García-Sánchez (2006) uses a four-stage approach to estimate the technical and scale efficiency of 24 Spanish municipal water supply agencies with staff, treatment plants and network length as the inputs. The outputs are amount of water delivered, number of properties connected and water analyses performed. Stage 1 is the statistical selection of inputs and outputs using Pearson's correlation coefficient to eliminate those which are improperly correlated. Following Roll *et al.* (1989), the DEA model with the best- discriminating characteristics is chosen. To produce a homogeneous analysis of the particular external conditions of each municipality, a three-step process in stage 2 detects the influence of external circumstances on the estimation of levels of efficiency via a Tobit model. The ten circumstances (social variables) are: population, population density, level of income, average temperature, size of municipal area, tourist index, square meters of greenbelts, economic activity, number of houses, and average number of people per house. Stage 3 estimates constant returns to scale (CRS) efficiency scores according to Charnes *et al.* (1978) and variable returns to scale (VRS) efficiency scores according to Banker *et al.* (1984). Stage 4 compares the differences in efficiency indexes caused by the type of ownership using the Mann-Whitney-Test. This methodology produces three best-discriminating DEA models with nearly identical efficiency scores, all of which find that only population density has a statistical significant impact on inefficiencies. García-Sánchez concludes that efficiency scores do not depend on the type of ownership.

Tupper and Resende (2004) determine whether calculated efficiency levels in the Brazilian water sector depend on structural and quality variables by using a second stage Tobit regression. Their results suggest that only water losses have a significant impact on efficiency levels. Looking at 38 Spanish water utilities and comparing DEA efficiency levels with and without the inclusion of quality variables, Picazo-Tadeo *et al.* (2008) also conclude that water losses have a significant impact on efficiency levels, and that the different efficiencies do not influence the utilities' ranking. The mean efficiency score is 0.773 when not accounting for the operating environment and 0.851 for the adjusted efficiency scores. In this study, unaccounted-for water is seen as indicator for service quality.

III. Methodology

DEA approaches

Unlike parametric approaches, DEA approaches can handle zero outputs, assign individual weights to the outputs of each firm so those with low industrial demand are not punished, and they do not require *a priori* assumptions on the functional form.

DEA uses linear programming methods to obtain measures of technical efficiency. A piece-wise surface (frontier) consisting of input and output variables for a sample of firms can be constructed. Firms' efficiency is measured by calculating the distance between each data point and the point on the frontier. The frontier represents the most-efficient firms with technical efficiency equal to one, the so-called peer firms. Under input orientation, the firms produce the same output with fewer inputs. The Banker, Charnes and Cooper (BCC)[5] formulation of DEA is expressed by the following linear programming problem (see Banker *et al.*, 1984):

$$
\begin{aligned}
&\min_{\theta,\lambda}\ \theta \\
&s.t.\quad -q_i + Q\lambda \geq 0 \\
&\qquad\ \ \theta x_i - X\lambda \geq 0 \\
&\qquad\ \ I1'\lambda = 1 \\
&\qquad\ \ \lambda \geq 0
\end{aligned}
$$

with θ as a scalar, X as $N*I$ input matrix for N inputs and I firms, Q as $M*I$ output matrix for M outputs and $I1$ as a $I*1$ vector of ones. Inputs and outputs for the *i*-th firm are represented by the column vectors x_i and q_i, and λ represents a $I*1$ vector of constants. Using the BCC formulation which allows for differences in the sizes of firms, we construct a convex hull enveloping the data points.

DEA models can be either input- or output-oriented. Under input orientation the efficiency scores correspond to the largest feasible proportional reduction in inputs for fixed outputs, and under output orientation to the largest feasible proportional expansion in outputs for fixed inputs. It is common practice to apply input orientation when analyzing network utilities, because the firms are generally required to supply services to a fixed geographical area, and hence the output vector is essentially fixed.

To determine the returns-to-scale technology, we conduct a two-part returns-to-scale test as proposed by Simar and Wilson (2002). Test 1 tests the null hypothesis that the production frontier exhibits global CRS against the alternative test hypothesis that the production frontier exhibits VRS. If the null hypothesis is rejected, test 2 is conducted. It tests the null hypothesis that the production frontier exhibits globally non-increasing returns to scale (NIRS) against the alternative hypothesis of VRS. Following Simar and Wilson (2002), the returns-to-scale test is:

Test 1: H_0: the production frontier is globally CRS

H_1: the production frontier is VRS

Test 2: H_0: the production frontier is globally NIRS

H_1: the production frontier is VRS

[5] The BCC formulation is often referred to as a variable returns to scale formulation.

The ratio of means defined by

$$\hat{S}_n^{CRS} = \sum_{i=1}^{n} \hat{D}_n^{CRS}(x_i, y_i) \Big/ \sum_{i=1}^{n} \hat{D}_n^{VRS}(x_i, y_i)$$

for test 1 is used as a test statistic and measures the distance between the CRS and the VRS frontier, where $\hat{D}$ represents an efficiency estimate. For test 2 the distance between the NIRS and the VRS frontier is measured using this test statistic. For both tests, the null hypothesis is not rejected when the distance between both frontiers is small.

Within a bootstrap procedure, pseudo samples S_{bn}^* with $b = 1,...,B$ bootstrap replications are generated according to the original sample S_n to derive bootstrap estimates $\hat{\omega}_b^*$, with ω denoting a univariate parameter for each testing problem and $\hat{\omega}$ as a consistent estimator of ω. With $\hat{\omega}_{obs}$ denoting the observed value of the test statistic mentioned above, we can derive *p*-values according to the approximation $\hat{p} = \Pr(\hat{\omega}^* \leq \hat{\omega}_{obs} \mid H_0, S_n)$. For both tests, *p*-values higher than the significance level of 5% lead to the rejection of the null hypothesis.

A three-stage approach including bootstrapping

This article applies a three-stage DEA approach to obtain valid results for technical efficiency scores. Our stage 1 includes outlier detection, in which the partial indicator *revenues divided by total water output* is used to detect extreme observations. We also apply the super-efficiency approach proposed by Banker and Gifford (1988), noting that some observations may have efficiency scores greater than one, i.e. lie above the constructed frontier.[6] We apply the super-efficiency criterion repeatedly until no clear outliers remain. Therefore, we set the maximum attainable efficiency score on a level of 1.2 due to a dense distribution of technical efficiency scores up to this level, as suggested by Banker and Chang (2006). Above the level of 1.2, technical efficiency scores are less densely distributed and show higher dispersion. Finally, we use a standard DEA approach to obtain first technical efficiency scores.

Stage 2 regresses the efficiency scores obtained by the standard DEA approach on several explanatory variables such as output density or the location of the utility in

[6] Within a super-efficiency reference, observations for the evaluation of an observation *i* are constructed by only using all observations other than *i*. See Banker and Gifford (1988) or Banker and Chang (2006).

east or west Germany. Studies calculating efficiency scores using the non-parametric DEA approach often conduct a regression analysis (most often Tobit) for the inclusion of parametric components. However, Simar and Wilson (2007) argue that the use of a Tobit regression in a two-stage analysis is inappropriate, because it fails to account for serial correlation in DEA efficiency estimates and the results can be invalid and lead to incorrect inference. Similarly, Grosskopf (1996) argues that problems may arise through the distribution of the error terms due to a possible correlation between the explanatory variables used in regression analysis and the variables used for calculating the DEA efficiency scores. To sidestep this controversial issue, we apply a bootstrapped truncated regression as proposed by Simar and Wilson (2007) with two different possible algorithms. While the goal of algorithm 1 is only to improve on inference, algorithm 2 considers bias correction. Unfortunately, the application of bias correction can introduce additional noise, which we find to be the case, and therefore we use algorithm 1 without bias correction. In a first step, we derive coefficient estimates $\hat{\beta}$ and an estimate of the standard deviation of the error term $\hat{\sigma}_\varepsilon$ from the truncated regression of the efficiency values $\hat{\theta}_i > 1$ on the explanatory variables using the maximum likelihood method. Therefore, we use the reciprocal values of the DEA technical efficiency scores resulting from stage 1. Next, we conduct a bootstrap algorithm with *B* bootstrap replications based on those coefficient estimates and on the estimated standard deviation of the error term.

Within the bootstrap algorithm, the error term ε_i for each observation *i* is drawn from a $N(0,\hat{\sigma}_\varepsilon^2)$ distribution, for which we assume a left-truncation at $(1 - z_i\hat{\beta})$. Based on the error terms ε_i, we can calculate new efficiency estimates $\theta_i^* = z_i\hat{\beta} + \varepsilon_i$, which can be regressed again on explanatory variables using maximum likelihood estimation with left truncation at one. As follows, the bootstrap algorithm yields *B* estimates for each coefficient. Using this set of coefficient estimates, confidence intervals can be constructed following Simar and Wilson (2000).

Stage 3 of our approach includes the regression results within the calculation of new DEA efficiency scores; we adjust inputs for the influence of exogenous variables following Fried *et al.* (1999), who recommend regressing total input slacks defined as $(1-TE)*x_j^k$ for the *j=1,…,* N firms and *k* inputs on explanatory variables to derive coefficient estimates and an estimate of the error term.[7] We then predict input slacks based on the estimated coefficients and use them to adjust inputs according to

$$x_j^{adj} = x_j + [Max\{I\hat{T}S_j\} - I\hat{T}S_j]$$

for the one-input case with $I\hat{T}S_j$ denoting the predicted input slacks. For all observations $j=1,...,N$ input *x* is proportionally adjusted by the difference between the maximum predicted input slack $Max\{I\hat{T}S_j\}$ of all observations and the predicted input slack of the unit under consideration. For the unit operating under the least-favorable circumstances and thus exhibiting the highest input slack the difference in parentheses is equal to zero and the inputs are not increased. For all other observations the difference is positive and the inputs are increased while output is held constant so that the efficiency scores are adjusted for external influences. According to Fried *et al.* (1999), the new efficiency scores incorporate the operating environment directly into the production process. Thus, having adjusted the inputs for the operating environment, we conclude that firms' management causes the remaining inefficiency.

SFA approach

In comparison to DEA, SFA can reduce the impact of statistical noise and measurement errors to produce results that are more robust against outliers. SFA uses econometric techniques for the estimation of a stochastic frontier that can be used for the determination of efficiency scores. It is also possible to estimate production functions, cost functions and input and output distance functions.

Aigner *et al.* (1977) develop a normal/half-normal model for SFA with a composed error term. They propose the decomposition of the error term into a noise term v_i and an inefficiency term u_i. The noise term v_i aims to capture statistical noise and measurement errors and is assumed to be normally distributed with $v_i \sim iid\ N(0,\sigma_v^2)$. The half-normally distributed error term u_i with $u_i \sim iid\ N^+(0,\sigma_u^2)$ captures inefficiency effects. For a total cost function, the Aigner *et al.* model (ALS model) has the form

[7] We focus only on the radial portion of total input slacks, hence on the pure inefficiency, because we want to evaluate the impact of structural differences on efficiency scores.

$$\ln TC_i = \beta_0 + x_i^{'}\beta + v_i + u_i$$

where *TC* denotes total costs, x_i the vector of explanatory variables and v_i and u_i the error terms as described above for all firms *i* with *i=1,…, N*. The parameters to be estimated are represented by β_0 for the intercept and β for the vector of coefficients. Only the realizations of the composed error $\varepsilon_i = u_i + v_i$ are observable. Jondrow *et al.* (1982) propose to predict the inefficiency term u_i by the conditional expectation of u_i given the realizations of ε_i:

$$u_i = E[u_i \mid u_i + v_i]$$

Using the estimates of u_i, a measure of technical efficiency (TE) is then derived as $TE_i = \exp(-u_i)$.

As mentioned earlier, for the application of SFA it is necessary to assume a functional form. The most common functional forms used are the Cobb-Douglas function and the Translog function. In this article we apply both types of functional relationships and we choose the more suitable frontier based on information criteria and a Likelihood-Ratio test. All variables included in the function are divided by their means as the point of approximation. To obtain linearity in the parameters, we take the natural logarithm of all variables.[8]

For the specification of our SFA cost model, we consider the same input, outputs and structural variables used in the DEA model to ensure comparability of the results. Since our dataset lacks information on input prices, it is not possible to estimate a cost function including input prices and output quantities as required by standard microeconomic theory (see Chambers, 1988). Therefore, we can only include total costs as the dependent variable and different output measures as explanatory variables. Due to the omission of input prices in the cost function, we can only consider technical efficiency rather than technical and allocative efficiency. Input prices usually capture regional price differences. Similar to our approach, Martins *et al.* (2006) estimate a cubic cost function for the Portuguese water industry while omitting input prices. They argue that regional differences in prices are small in a small country like Portugal. We assume that the costs of materials, capital and energy input are similar throughout Germany. In fact, there can be significant regional differences with respect to the price of labor between east and west Germany since

[8] When necessary, zero-values were replaced by 10^{-6}. This approach is in line with Fraquelli *et al.* (2004).

the average wage level in east Germany is still lower than in the western part. We therefore include a dummy variable for east German water utilities to account for differences between east and west Germany.

According to the ALS model, we specify our model as

$$\ln TC_i = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{k,i} + \sum_{j=1}^{M} \theta_j \ln z_{j,i} + v_i + u_i$$

with *TC* denoting total costs, x_k representing the vector of the *k* explanatory variables and v_i and u_i as the two error terms as shown above. We include a set of $j=1,\ldots, M$ structural variables denoted by z_j to account for the operating environment. The *z* variables are included in the function since they are assumed to directly influence the production process such that each utility in our dataset faces an individual frontier. We thus follow the methodology chosen for DEA, where the input adjustment approach is assumed to change the production process: "The new radial efficiency measures incorporate the influences of the external variables on the production process, and isolate the managerial component of inefficiency" (Fried *et al.*, 1999). For DEA and SFA, final efficiency scores are thus net of structural influences and represent managerial inefficiencies (Coelli *et al.*, 1999). In the SFA framework, it would also be possible to let the operating environment influence the inefficiency term u_i by allowing for a non-zero mean according to $u_i \sim iid\ N^+(\mu, \sigma_u^2)$ as proposed by Stevenson (1980). Using such an approach, the operating environment would have an impact on the distance between each observation and the estimated common frontier. The operating environment would still have an impact on the resulting efficiency scores (Coelli *et al.*, 1999). Thus, we include the *z* variables directly in our function to be in line with the methodology chosen for DEA.

Further assumptions on the error terms are necessary. Hadri (1999) and Hadri *et al.* (2003) argue that size-related heteroscedasticity is likely to occur in the two-sided noise term v_i when using cross-section data. Heteroscedasticity can also occur due to considerable differences in the size of firms included in a dataset. Not accounting for heteroscedasticity might lead to biased parameter estimates and efficiency estimates. We therefore let the standard deviation of the two-sided noise term vary with water intake as a proxy variable for firm size. The standard deviation of v_i is $\sigma_{v,i} = \exp(W_i \gamma)$, with W_i representing the set of explanatory variables assumed to influence the standard deviation of v_i and γ representing the vector of parameters to be estimated (see Hadri, 1999).

IV. Data Description

This article is based on cross-sectional data in 2006 with an original dataset of 1096 water utilities. Full data availability is given for 373 observations. The data is taken from the statistical publication published by the German Association for Energy and Water Industries (Bundesverband der Energie- und Wasserwirtschaft, 2008c) and the utilities' annual financial statements. Topographical maps provide elevation differences. The descriptive statistics for the variables are shown in Table 2 and the correlation matrix is shown in Table 3.

The utilities deliver drinking water to about 32 million people (approximately 39% of the total population) and are located in all federal states except Bremen. Although the dataset includes only a fraction of the industry's 6500 firms, it can be characterized as representative, considering the population served and the type of utility.

There are both large and small utilities, the latter with only 199 000 cubic meters water delivered to households. Total water deliveries are 1.98 billion cubic meters. Some supply private customers at higher cost due to the need for more water connections, while those serving primarily industrial customers or re-distributors can often deliver at lower cost since fewer water connections are needed. This relationship can also be justified by the higher correlation of water deliveries to private customers than deliveries to non-households. We treat *private consumption* and *industrial/other consumption* as separate outputs. Total *water meters* is an output variable to avoid discriminating against utilities that serve low-consumption customers. This is also justified by the relatively low correlation between the number of meters and private consumption. Similar model specifications were recommended by Thanassoulis (2000a, b) and applied e.g., by García-Valiñas and Muñiz (2007). In contrast to the model specifications used in their studies, we do not include network length in our model.

We use total revenues from water supply in 2006 as the proxy for *total costs*. We assume revenues to be equal to the costs of supply following the European water framework directive (Directive 2000/60/EC, Article 9) which states that revenues must cover all material costs, depreciation and labor costs.[9] In addition, efficiency can be measured by the amounts that customers pay for water supply, so our results

[9] This cost recovery principle for water supply appears in the legislation for local public authorities in all German federal states.

can be interpreted as "consumer-perceived efficiency". Brunner and Riechmann (2004) recommend this approach to determine whether tariffs for water deliveries are reasonable, and if not, by how much they can be reduced. A regulator is mainly concerned with the protection of consumer interests so that water tariffs are of more interest than, e.g., the capital structure of a water utility. Under perfect competition, firms cannot charge different prices due to different capital structures. The advantage of this revenue yardstick approach is that there is no need to measure capital and capital costs. Hence, we treat revenues as a reasonable alternative input variable with interpretative possibilities. However, issues like public transfers to municipal companies could bias results. Moreover, despite the use of monetary data, we consider only technical efficiency and not allocative efficiency.

The variable *network length* shows large differences in firm and area sizes. We omit this as an input variable, because costs for network infrastructure and investments are already included within the total cost block represented by total revenues. However, we include *network length* when calculating the structural variable *output density*.

Stages 2 and 3 of our DEA and the SFA also consider other explanatory variables, such as *total population* and *output density,* when we compare the possible differences between water utilities in rural and urban areas. On the one hand, higher density might lead to efficiency advantages since fewer capital input, i.e. network infrastructure, is required to distribute a certain amount of water. But high density can also lead to efficiency disadvantages e.g., when laying pipes in densely settled downtowns. The assumption of efficiency advantages of higher density is confirmed by Renzetti and Dupont (2008) and García-Sánchez (2006). *Output density* is computed as total amount of water delivered to households and non-households per kilometer of network length (*Metermengenwert*).[10] We omit *population* in the regression analysis due to its very high correlation with the output variable *water delivered to households*.

We consider the *share of groundwater input* per utility, because groundwater requires less treatment than surface water. While pumping costs tend to be higher for groundwater (see Filippini *et al.*, 2008; Garcia and Thomas, 2001), the capital costs are normally lower than for the use of storage water (Coelli and Walding, 2006). Hence, utilities using more groundwater tend to achieve higher efficiency scores. We assume that the type of water extracted is given exogenously, since only available

[10] This variable serves as a key indicator in the regulation of water utilities in Hesse (see Hirschhausen *et al.*, 2009b).

water sources can be used in a utility's service territory. The water utilities in our dataset extract 75.1% of the raw water input from groundwater resources, while 20.8% are surface water and 4.1% well-spring sources. Thus, they use slightly more groundwater than is typical for the entire German water supply industry.

The variable *leak ratio* is defined as water losses between extraction and end-user consumption divided by total water input. While water losses depend on exogenous circumstances such as the type of soil, they can also be influenced by management via better maintenance or replacement investments. Furthermore, water losses can also be a proxy for the age of the infrastructure. Older networks usually are characterized by an increased pipe bursts resulting in higher water losses. Thus, in the short run it is arguable that water losses are exogenously determined since the replacement of the infrastructure is only possible within a longer time horizon.

We also consider *elevation differences* within utility service territory, e.g., water distribution in hilly regions requires higher pumping costs. The variable measures the difference between the highest settlement in a service area and the lowest point. We assume that higher elevation differences will have a negative impact on firms' performance.

Yet another variable is *operational differences in east and west Germany.* After German reunification, significant investments were made to modernize eastern water networks and treatment plants. Regional differences show up in price differentials, where prices for drinking water in the east are usually higher than in western Germany. A closer look at the differences in the efficiency scores of the utilities in each geographical area is thus of interest. We include a dummy variable with a value of one when the utility is situated in the eastern part of Germany.

The water utilities are also characterized by different governance modes and ownership structures. We include a dummy variable with value of one for water utilities with a *private governance mode* and zero otherwise. Even under a private governance mode, ownership can be public, private or a mixture of both.

We include the *per-capita debt* of each municipality since municipalities usually require water utilities to pay concession fees or to earn a particular rate of return such that the municipalities can balance their budgets with the additional earnings. We assume that higher per-capita debt might lead to higher prices for water and corresponding higher inefficiency values.

Finally, we include a dummy variable for possible *scope effects with sewage services*.

Total water intake of the utilities in our dataset is 2.21 billion cubic meters. Water intake consist of both own water abstraction and water purchases from other utilities, e.g., bulk water suppliers. The variable *water intake* is a measure for firm size and included as a heteroscedastic variable in the standard deviation of the two-sided noise term in SFA to account for size-related heteroscedasticity as described earlier.

V. Results

DEA efficiency scores and regression on structural variables

We apply a three-stage procedure to obtain valid results for DEA technical efficiency scores.[11] In stage 1, the ratio of revenues and total water output is used as a partial indicator for outlier detection. Here, 11 observations are deleted. For the application of the super-efficiency approach, variable returns-to-scale and input orientation are assumed.[12] The assumption of VRS is confirmed by the returns-to-scale test at a significance level of 1% conducting 1000 bootstrap replications. In the following application of the super-efficiency criterion, 22 additional observations are deleted due to technical efficiency scores greater than the critical value of 1.2. The detected outliers do not belong to a specific group of water utilities. We observe no systematic scheme when looking at characteristics like firm size measured by total water output, eastern or western location, output densities, etc. Municipal utilities as well as some special purpose associations are excluded.

Table 4 summarizes the efficiency scores obtained in stage 1. Efficiency scores show high dispersion and a relatively low mean level of 64.24%, possibly due to the large difference in prices and hence revenue disparities.[13]

In stage 2, the input slacks are regressed on several explanatory variables. We apply a bootstrapped truncated regression with 2000 replications as proposed by Simar and Wilson (2007) to check for structural reasons for efficiency differences. The estimated coefficients and significance levels are shown in Table 5. The signs of the

[11] Some authors even refer to the approach chosen here as a four-stage approach.

[12] DEA and the bootstrapped truncated regression are conducted using Software R with the package FEAR by P. W. Wilson.

[13] We also apply DEA with bias-corrections (bootstrapping). Due to the application of bias-corrections, the mean efficiency level is 0.5881 and is thus lower than under the standard DEA approach (0.6424). Regression results in stage 2 are similar to the results using standard DEA. For simplicity we focus on the results of standard DEA in the following sections.

coefficients show that higher share of groundwater input has a negative impact on input slacks (i.e. a positive impact on efficiency), thus confirming our assumption of the efficiency-enhancing effect of a higher groundwater usage compared to the use of surface water. A higher *share of water losses*, higher *output density*, higher *elevation differences*, higher *per-capita debt* in the municipality, *eastern location*, *private governance* and *provision of sewage services* have a positive impact on input slacks. The positive sign of the coefficient for the *output density* indicates that the disadvantages of a higher density overcome the possible efficiency gains of supplying water with less capital input. Water utilities under a private governance mode show higher input slacks compared to publicly managed utilities. A possible explanation is the greater revenues attained by privately organized water utilities since they are unregulated natural monopolies that aim to maximize profits. The assumption of possible scope effects between water and sewage services is not confirmed.

Factoring our variables into the calculation of technical efficiency scores using the input adjustments approach proposed by Fried *et al.* (1999) requires us to predict inefficiencies via regression analysis. Using this approach, only variables that cannot be influenced by management are included. Arguably, management can change the governance mode and the provision of sewage services. However, since only cross-sectional data is available, we assume that in the short run given by our dataset, those variables are not influenceable. While water losses can at least partially be influenced by better maintenance efforts, they also depend on exogenous factors and on the age of infrastructure. The age of infrastructure can also be evaluated as more or less exogenously given due to the longevity of network infrastructure investments. We thus use the regression results described above and shown in Table 5 to adjust inputs for the operating environment.

Using the standard DEA approach in stage 3 again allows us to obtain the final technical efficiency scores as shown in Table 4. In comparison to the results of stage 1 before accounting for structural variables, the mean efficiency score increases substantially from 0.6424 to 0.7351. The minimum efficiency score obtained is now 0.5219 compared to 0.2983 before input adjustment. However, additional influencing exogenous factors, e.g., climatic conditions or aspects of economic geography could be considered, given extended data availability. As expected, the correlation between the efficiency scores in stages 1 and 3 is low. The *Spearman correlation coefficient* has a value of 0.1305. Similarly, the *Pearson rank correlation coefficient* between the efficiency scores is 0.1817, and the *Kendall rank correlation coefficient* is 0.0889. The significant change in efficiency scores after input adjustment is also shown in Fig. 1 for the 10% of utilities with the most significant changes in efficiency scores. While efficiency scores increase for most utilities after taking the operating environment into account, efficiency scores also considerably decrease for others.

An illustration of efficiency scores obtained in stage 3 appears in the Salter diagram depicted in Fig. 2. On the y-axis, the utilities are sorted according to their efficiency scores. On the x-axis, the width of a bar represents a utility's total water deliveries. The highest efficiency scores are obtained by small and larger water utilities representing the VRS approach of our DEA specification. The lowest efficiency scores are represented by the smaller utilities, but this requires careful interpretation. By using a VRS approach, these inefficiencies cannot be scale-inefficiency; however, there appears to be a cost disadvantage for smaller firms. Further research is needed to identify the actual saving potentials resulting from mergers and acquisitions.[14]

Assuming that all residual inefficiency after stage 3 cannot be assigned to structural differences, the free area in the upper left area of the graph (above the inefficient utilities) represents the potential for price decreases. The inefficiency is therefore equal to the price decrease, whereas the x-axis represents the quantity that could benefit from this decrease.

SFA efficiency scores and interpretation

Coefficient estimates for both the Cobb-Douglas model and the Translog Stochastic Frontier model are given in Table 6.[15] We include the same inputs, outputs and structural variables as in the DEA model. We only use the 340 observations remaining after the application of the DEA super-efficiency approach to ensure comparability of the results. In the Cobb-Douglas framework, all output coefficients are positive and highly significant. Thus, the property of a cost function to be non-decreasing in outputs is fulfilled (see Coelli *et al.*, 2005, p. 23). In the Translog model, the linear output coefficients remain positive but the coefficient of the water meters is no longer significantly different from zero. However, the Akaike

[14] The high efficiencies for the largest utilities can also be due to missing peers.
[15] Estimations are conducted using the STATA 11.1 statistical software.

information criterion (AIC) and the Bayesian information criterion (BIC) both recommend using the Translog function. This is confirmed by a Likelihood-Ratio test (LR-test). The value of the test statistic is 76.10 and is thus higher than the χ^2 value of 12.59 with 6 degrees of freedom for a confidence level of 95%.

Looking at the influence of the structural variables, *water losses*, the *share of groundwater input, elevation differences* and the *location in east Germany* have a significant impact on total costs in the Cobb-Douglas and Translog models. The signs of the estimated coefficients are in line with the bootstrapped truncated regression. The coefficient of the *output density* is only significant in the Cobb-Douglas model and has a positive impact on total costs. It shows a positive impact on input slacks as seen in the bootstrapped truncated regression. The coefficients for *per-capita debt, private governance mode,* and *scope effects with sewage services* are not significant in the SFA models and hence not further compared with bootstrapped truncated regression results. The coefficient of the volume of water intake, included as heteroscedastic variable in the standard deviation of the two-sided noise term v_i, is negative and highly significant in both models, confirming the assumption of size-related heteroscedasticity.[16]

Efficiency scores for both SFA models together with the results of the DEA approaches are shown in Table 4. At the mean and the median, the SFA efficiency scores are significantly higher than the DEA efficiency scores. The rank correlation between the DEA and SFA efficiency scores is quite low. Comparing the DEA efficiency scores and the results of the Cobb-Douglas model, the *Spearman rank correlation coefficient* has a value of only 0.0381 and 0.0300 in the Translog model. The DEA and SFA results can thus be regarded as independent. The minimum efficiency scores of both approaches are similar, with 52.2% for DEA and 54.4% for SFA under the Cobb-Douglas model. For the Translog model, the minimum efficiency score is 63.6%.

Since DEA and SFA are different approaches, a direct comparison of their resulting efficiency scores might be misleading. Efficiency levels in DEA also depend on the number of variables and observations. Indeed, the error term of the employed SFA captures statistical noise and measurement errors, but the availability of panel data

[16] We also estimate a model without heteroscedasticity in v_i. While parameter estimates remained similar, a LR-test suggested using the model which corrects for heteroscedasticity (p-value of 0.0028 in the Translog model). This is emphasized by the high significance of the estimated parameter for *volume of water intake*.

would allow for the application of sophisticated SFA models considering unobserved firm-specific heterogeneity. Given the lack of input prices and the occurrence of zero values for some of the variables, our dataset is imperfectly suited for stochastic frontier models. However, the comparisons with the DEA results are a satisfying cross-check and nicely illustrate the dependence on the applied methodology.

VI. Conclusions

This article has provided the first efficiency analysis of water utilities throughout Germany. To avoid distortions in DEA efficiency scores we employed the super-efficiency approach for outlier detection. The application of a bootstrapped truncated regression identified the factors that significantly influenced the technical efficiency scores. *Output density*, *water losses*, *groundwater ratio*, *elevation differences*, *location in east Germany*, *governance mode*, *joint provision of water and sewage services* and *per-capita debt of a municipality* were included to account for structural differences in water supply. The significance of a density measure confirmed other international studies. The leak ratio showed a significant positive impact on input slacks. We observed that the significance indicates possible underinvestment for companies with high leak ratios. DEA efficiency scores showed a relatively low mean level, although we chose a VRS approach based on a returns-to-scale test. In addition to the DEA approach, we estimated a cross-sectional cost frontier using SFA and included the same variables in the estimated frontier as in the DEA approach. The signs of the significant coefficients for the structural variables were in line with the regression results for the DEA input slacks. Efficiency levels under SFA were substantially higher than under DEA, which might be explained by the methodological differences between DEA and SFA.

In summary, we found large differences in efficiency, an indication of the potential for cost savings and consumer price decreases. Further, the striking inefficiency of small water utilities introduces the issue of the adequacy of such firms' supply structures.

We propose that future research should examine: other possible exogenous factors; the use of panel data and sophisticated stochastic frontier models; and the determination of economies of scale, scope and density. We suggest that the regulatory policies currently under discussion should be based upon solid analyses of firms' performance and the prudent selection of variables in addition to considering exogenous circumstances.

Acknowledgements

This article is a product of the research programs on ‘‘efficiency analysis in network industries’’ and ‘‘water economics and management’’ administered by the Chair of Energy Economics and Public Sector Management (EE^2) at Dresden University of Technology, the German Institute for Economic Research in Berlin and partner institutions. It is based on an earlier version co-authored by Jörn Guder, Barnabas Kittlaus and Robert Moll. Earlier versions were presented at the Conference on Communal Infrastructure Management 2009 in Berlin, the European Workshop on Efficiency and Productivity Analysis (EWEPA) 2009 in Pisa, the Annual Conference of the European Association for Research in Industrial Economics (EARIE) 2009 in Ljubljana, and the Annual Congress of the German Economic Association (*Verein für Socialpolitik*) 2009 in Magdeburg. We thank the participants, in particular Astrid Cullmann, Christian von Hirschhausen, Maria Nieswand and David Saal for support, criticism, and methodological hints, and Felix Zschoge for his assistance with data collection.

References

Agrell, P., Bogetoft, P., Cullmann, A., Hirschhausen, Cv., Neumann, A. and Walter, M. (2008) Projekt GERNER IV Ergebnisdokumentation: Bestimmung der Effizienzwerte Verteilernetzbetreiber Gas. Available at: http://www.bundesnetzagentur.de/media/archive/14563.pdf (accessed 05 June 2009).

Aigner, D., Lovell, C.A.K. and Schmidt, P. (1977) Formulation and Estimation of Stochastic Frontier Production Function Models, *Journal of Econometrics*, **6**, 21-37.

Banker, R.D. and Chang, H. (2006) The Super-Efficiency Procedure for Outlier Identification, not for Ranking Efficient Units, *European Journal of Operational Research*, **175**, 1311-20.

Banker, R.D., Charnes, A. and Cooper, W.W. (1984) Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science*, **30**, 1078-92.

Banker, R.D. and Gifford, J.L. (1988) A Relative Efficiency Model for the Evaluation of Public Health Nurse Productivity, mimeo, Carnegie Mellon University.

Benito, B., Bastida, F. and García, J. (2010) Explaining Differences in Efficiency: An Application to Spanish Municipalities, *Applied Economics*, **42**, 515-28.

Bhattacharyya, A., Harris, T.R., Narayanan, R. and Raffiee, K. (1995) Specification and Estimation of the Effect of Ownership on the Economic Efficiency of the Water Utilities, *Regional Science and Urban Economics*, **25**, 759-84.

Brunner, U. and Riechmann, C. (2004) Wettbewerbsgerechte Preisbildung in der Wasserwirtschaft, *Journal for Public and Nonprofit Services*, **27**, 115-30.

Bundesverband der Energie- und Wasserwirtschaft (2008a) *Wasserpreise – Fragen & Antworten*. BDEW, Berlin.

Bundesverband der Energie- und Wasserwirtschaft (2008b) *Branchenbild der Deutschen Wasserwirtschaft*, wvgw Wirtschafts- und Verlagsgesellschaft Gas und Wasser mbH, Bonn.

Bundesverband der Energie- und Wasserwirtschaft (2008c) *118. Wasserstatistik Bundesrepublik Deutschland 2006*, wvgw Wirtschafts- und Verlagsgesellschaft Gas und Wasser mbH, Bonn.

Chambers, R. (1988) *Applied Production Analysis: A Dual Approach*, 4. edn, Cambridge University Press, Cambridge, Massachusetts.

Charnes, A., Cooper, W.W. and Rhodes, E. (1978) Measuring the Efficiency of Decision-Making Units, *European Journal of Operational Research*, **2**, 429-44.

Coelli, T., Perelman, S. and Romano, E. (1999) Accounting for Environmental Influences in Stochastic Frontier Models: With Application to International Airlines, *Journal of Productivity Analysis*, **11**, 251-73.

Coelli, T., Rao, D., O'Donnell, C. and Battese, G. (2005) *An Introduction to Efficiency and Productivity Analysis*, 2. edn. Springer Science+Business Media, Inc., New York.

Coelli, T. and Walding, S. (2006) Performance Measurement in the Australian Water Supply Industry, in *Performance Measurement and Regulation of Network Utilities* (Eds) T. Coelli and D. Lawrence, Edward Elgar Publishing, Cheltenham, pp. 29-61.

Deutsche Vereinigung des Gas- und Wasserfaches e.V. (2006) Trinkwasserqualität in Deutschland einwandfrei, *Energie Wasser-Praxis*, **10**, 46.

Filippini, M., Hrovatin, N. and Zorić, J. (2008) Cost Efficiency of Slovenian Water Distribution Utilities: An Application of Stochastic Frontier Methods, *Journal of Productivity Analysis*, **29**, 169-82.

Fraquelli, G., Piacenza, M. and Vannoni, D. (2004) Scope and Scale Economies in Multi-Utilities: Evidence from Gas, Water and Electricity Combinations, *Applied Economics*, **36**, 2045-57.

Fried, H.O., Schmidt, S.S. and Yaisawarng, S. (1999) Incorporating the Operating Environment into a Nonparametric Measure of Technical Efficiency, *Journal of Productivity Analysis*, **12**, 249-67.

Garcia, S. and Thomas, A. (2001) The Structure of Municipal Water Supply Costs: Application to a Panel of French Local Communities, *Journal of Productivity Analysis*, **16**, 5-29.

García-Sánchez, I.M. (2006) Efficiency Measurement in Spanish Local Government: The Case of Municipal Water Services, *Review of Policy Research*, **23**, 355-71.

García-Valiñas, M.A. and Muñiz, M.A. (2007) Is DEA Useful in the Regulation of Water Utilities? A Dynamic Efficiency Evaluation (A Dynamic Efficiency Evaluation of Water Utilities), *Applied Economics*, **39**, 245-52.

Grosskopf, S. (1996) Statistical Inference and Nonparametric Efficiency: A Selective Survey, *Journal of Productivity Analysis*, **7**, 161-76.

Hadri, K. (1999) Estimation of a Doubly Heteroscedastic Stochastic Frontier Cost Function, *Journal of Business & Economic Statistics*, **17**, 359-63.

Hadri, K., Guermat, C. and Whittaker, J. (2003) Estimating Farm Efficiency in the presence of Double Heteroscedasticity using Panel Data, *Journal of Applied Economics*, **6**, 255-68.

Hanusch, H. and Cantner, U. (1991) Produktion öffentlicher Leistungen – Effizienz und technischer Fortschritt, *Jahrbücher für Nationalökonomie und Statistik*, **208**, 369-84.

Hirschhausen, C.v., Walter, M. and Zschille, M. (2009a) Effizienzanalyse in der Wasserversorgung – Internationale Erfahrungen und Schlussfolgerungen für Deutschland, *GWF Wasser Abwasse*r, **2-3 2009**, 170-5.

Hirschhausen, C.v., Cullmann, A., Walter, M. and Zschille, M. (2009b) Fallende Preise in der Wasserwirtschaft Hessen auf dem Vormarsch, *DIW Wochenbericht*, **76,** 150-5.

Jondrow, J., Lovell, C.A.K., Materov, I.S. and Schmidt, P. (1982) On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model, *Journal of Econometrics*, **19**, 233-8.

Martins, R., Fortunato, A. and Coelho, F. (2006) Cost Structure of the Portuguese Water Industry: A Cubic Cost Function Approach, University of Coimbra, Faculty of Economics, Group of Monetary and Fiscal Studies (GEMF), Working Paper No. 9 (2006), University of Coimbra, Portugal.

Picazo-Tadeo, A.J., Sáez-Fernández, F.J. and González-Gómez, F. (2008) Does Service Quality Matter in Measuring the Performance of Water Utilities? *Utilities Policy*, **16**, 30-8.

Renzetti, S. and Dupont, D. (2009) Measuring the Technical Efficiency of Municipal Water Suppliers: the Role of Environmental Factors, *Working Papers 0901*, Brock University, Department of Economics.

Roll, Y., Golany, B. and Seroussy, D. (1989) Measuring the Efficiency of Maintenance Units in the Israeli Air Force, *European Journal of Operational Research*, **43**, 136-42.

Saal, D.S. and Parker, D. (2000) The Impact of Privatization and Regulation on the Water and Sewerage Industry in England and Wales: A Translog Cost Function Model, *Managerial and Decision Economics*, **21**, 253-68.

Saal, D.S. and Parker, D. (2001) Productivity and Price Performance in the Privatized Water and Sewerage Companies of England and Wales, *Journal of Regulatory Economics*, **20**, 61-90.

Saal, D.S. and Parker, D. (2005) Assessing the Performance of Water Operations in the English and Welsh Water Industry: A Panel Input Distance Function Approach, *Aston Business School Research Papers* ***RP 0502***, Aston University.

Saal, D.S., Parker, D. and Weyman-Jones, T. (2007) Determining the Contribution of Technical Change, Efficiency Change and Scale Change to Productivity Growth in the Privatized English and Welsh Water and Sewerage Industry: 1985–2000, *Journal of Productivity Analysis*, **28**, 127-39.

Sauer, J. (2003) The Efficiency of Rural Infrastructure – Water Supply in Rural Areas of Transition, *ERSA 2003 Congress*, **Paper 463**.

Sauer, J. (2004) Rural Water Suppliers and Efficiency – Empirical Evidence From East and West Germany, *Discussion Paper* ***No. 63***, Institute of Agricultural Development in Central and Eastern Europe.

Sauer, J. (2005) Economies of Scale and Firm Size Optimum in Rural Water Supply, *Water Resources Research*, **41**, W11418, doi:10.1029/2005WR004127.

Sauer, J. (2006) Economic Theory and Econometric Practice: Parametric Efficiency Analysis, *Empirical Economics*, **31**, 1061-87.

Sauer, J. and Frohberg, K. (2007) Allocative Efficiency of Rural Water Supply – A Globally Flexible SGM Cost Frontier, *Journal of Productivity Analysis*, **27**, 31-40.

Simar, L. and Wilson, P.W. (1998) Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models, *Management Science*, **44**, 49-61.

Simar, L. and Wilson, P.W. (2000) Statistical Inference in Nonparametric Frontier Models: The State of the Art, *Journal of Productivity Analysis*, **13**, 49-78.

Simar, L. and Wilson, P.W. (2002) Nonparametric Tests of Returns to Scale, *European Journal of Operational Research*, **139**, 115-132.

Simar, L. and Wilson, P.W. (2007) Estimation and Inference in Two-Stage, Semi-Parametric Models of Production Processes, *Journal of Econometrics*, **136**, 31-64.

Statistisches Bundesamt (2008) Umwelt: Wasserabgabe der Öffentlichen Wasserversorgung, Tabelle 514-32. Available at http://www.statistikportal.de/Statistik-Portal/de_jb10_jahrtabu2.asp (accessed 15 December 2008).

Stevenson, R. (1980) likelihood Functions for generalized Stochastic Frontier Estimation, *Journal of Econometrics*, **13**, 57-66.

Tupper, H.C. and Resende, M. (2004) Efficiency and Regulatory Issues in the Brazilian Water and Sewage Sector: An Empirical Study, *Utilities Policy*, **12**, 29-40.

Walter, M., Cullmann, A., Hirschhausen, C.v., Wand, R. and Zschille, M. (2009) Quo Vadis Efficiency Analysis of Water Distribution? A Comparative Literature Review, *Utilities Policy*, **17**, 225-32.

Table 1: Studies evaluating the impact of structural and quality variables with focus on DEA (Walter *et al.*, 2009)

Author(s)	Data sample	DEA specification	Inputs	Outputs	Results for structural and quality variables
Renzetti and Dupont (2009)	64 Canadian water utilities in 1996	Input orientation; VRS	Labor costs, materials costs, delivery network	Water delivered	Elevation differences, population density, ratio of residential water and number of private dwellings with significant impact on efficiency
García-Sánchez (2006)	24 Spanish water utilities in 1999	Input orientation; CRS	Staff, treatment plants, delivery network	Water delivered, number of connections, chemical analyses performed	Network density with significant influence on efficiency
Tupper and Resende (2004)	20 Brazilian water and sewerage utilities from 1996-2000	Output orientation; VRS	Labor costs, operational costs, capital costs	Water produced, treated sewage, population served-water, population served-treated sewage	Network densities and accounted-for water ratio with significant influence on efficiency
Picazo-Tadeo *et al.* (2008)	38 Spanish water utilities (with 20 also providing sewerage services) in 2001	Output orientation; CRS	Delivery network, sewer network, labor, operational costs	Population served, water delivered, treated sewage	Accounted-for water does not influence the ranking of utilities

Notes: CRS = constant returns to scale, VRS = variable returns to scale

Table 2: Descriptive statistics

Variable Description	Abbr.	Classification	Sum	Min.	Mean	Median	Max.	Std. Dev.
Revenues [1000 Euro]	cost	Input	3 563 312	466	9843	3382	424 000	27 878
Water meters [number]	meters	Output	6 850 857	1653	18 925	9074	1 008 732	57 152
Water delivered to households [1000 m³]	wdelhh	Output	1 490 046	199	4116	1520	142 700	10 873
Water delivered to non-households [1000 m³]	wdelnh	Output	487 598	0.00	1347	354	58 800	4 000
Network length [km]	net	-*	156 834	39	433	225	7858	675
Population [1000]	pop	-**	32 373	5	89	35	3400	233
Output density [1000 m³ per km of network]	dens	Structural var.	-	1.02	10.46	9.25	52.94	5.61
Leak ratio	leak	Structural var.	-	0.01	0.10	0.09	0.30	0.06
Groundwater ratio	ground	Structural var.	-	0.00	0.57	0.71	1.00	0.42
Volume of water intake [1000 m³]	intake	-***	2 205 111	271	6091	2191	217 890	15 775
Elevation difference [m]	elev	Structural var.	-	0.00	53.82	40.00	240.00	47.36
Debt per capita	debt	Structural var.	-	0	1017.12	1024.58	17 253.90	1202.81
Dummy for east Germany	deast	Structural var.	65	0.00	0.18	0.00	1.00	0.38
Dummy for private governance	dpriv	Structural var.	285	0	0.79	1	1	0.41
Dummy for sewage services	dsew	Structural var.	78	0.00	0.22	0.00	1.00	0.41

Notes: *Used to calculate the structural variable *output density*, **Omitted for correlation reasons (see correlation matrix), *** Included as heteroscedastic variable in SFA.

Table 3: Correlation matrix

	cost	meters	net	wdelhh	wdelnh	pop	dens	leak	ground	intake	elev	deast	dpriv	debt	dsew
cost	1.000														
meters	0.644	1.000													
net	0.883	0.704	1.000												
wdelhh	0.976	0.753	0.883	1.000											
wdelnh	0.907	0.456	0.812	0.845	1.000										
pop	0.991	0.716	0.900	0.988	0.875	1.000									
dens	0.410	0.247	0.246	0.435	0.438	0.394	1.000								
leak	-0.001	-0.011	0.068	-0.018	-0.045	-0.002	-0.210	1.000							
ground	-0.050	0.011	-0.027	-0.041	-0.012	-0.038	-0.187	-0.030	1.000						
intake	0.988	0.695	0.896	0.990	0.910	0.988	0.449	-0.005	-0.041	1.000					
elev	0.178	0.134	0.188	0.178	0.148	0.169	0.216	0.260	-0.324	0.186	1.000				
deast	-0.017	-0.013	0.107	-0.044	-0.004	-0.004	-0.217	0.235	-0.015	-0.025	-0.031	1.000			
dpriv	0.019	0.061	0.034	0.036	-0.022	0.027	0.214	-0.042	-0.157	0.025	0.096	-0.038	1.000		
debt	0.798	0.665	0.699	0.793	0.677	0.819	0.238	-0.013	0.011	0.780	0.108	-0.067	-0.012	1.000	
dsew	0.064	0.001	0.095	0.040	0.036	0.065	-0.182	0.106	0.132	0.043	-0.124	0.368	-0.237	0.015	1.000

Table 4: Descriptive statistics for efficiency scores

		Mean	Median	Std. Dev.	Min.	Max.
DEA - Stage 1	TE score	0.6424	0.6050	0.1834	0.2983	1.0000
	Inefficiency	0.3576	0.3950	0.1834	0.0000	0.7000
DEA - Stage 3	TE score	0.7351	0.7210	0.1024	0.5219	1.0000
	Inefficiency	0.2649	0.2790	0.1024	0.0000	0.4781
SFA	Cobb-Douglas	0.8353	0.8497	0.0639	0.5443	0.9471
	Translog	0.8607	0.8707	0.0515	0.6356	0.9512

Table 5: Results for regression analysis of input slacks

Par.	Variable	Regression
β_0	constant	-38.5914*** (10.1156)
β_1	dens	0.9622*** (0.2213)
β_2	leak	30.7805** (13.3956)
β_3	ground	-4.0238* (2.1853)
β_4	elev	0.0752*** (0.0199)
β_5	debt	0.0029** (0.0014)
β_6	deast	4.3098* (2.2449)
β_7	dpriv	8.3446** (3.4429)
β_8	dsew	7.2748*** (2.1798)

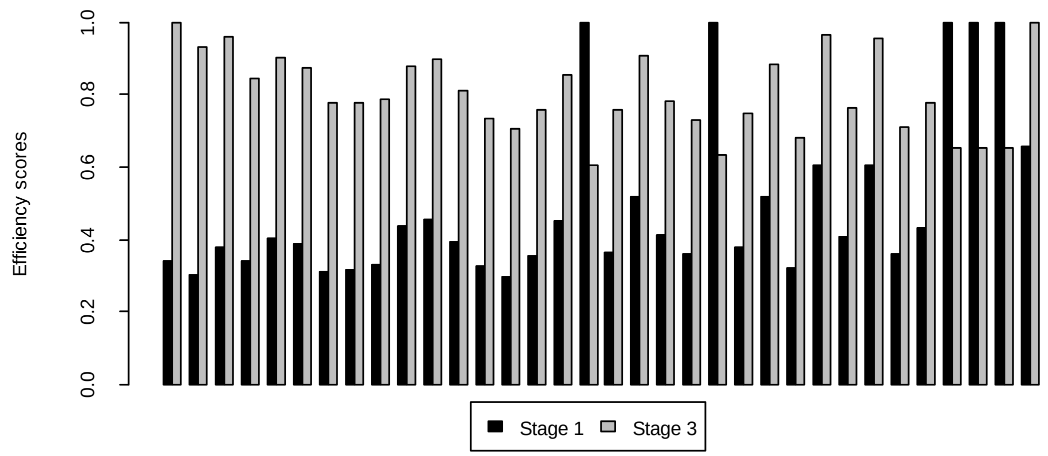
Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. The dependent variable is scaled down by 10^{-3} for representation purposes.

Table 6: Coefficient estimates for SFA

	Parameters	Cobb-Douglas	Translog
β_0	constant	16.1875*** (0.0691)	16.1470*** (0.0705)
β_1	ln *wdelhh*	0.8136*** (0.0594)	0.8565*** (0.0583)
β_2	ln *wdelnh*	0.0088*** (0.0028)	0.1440*** (0.0161)
β_3	ln *meters*	0.1866*** (0.0631)	0.0121 (0.0690)
β_{11}	(ln *wdelhh*)²	-	0.2478 (0.1804)
β_{22}	(ln *wdelnh*)²	-	0.0089*** (0.0011)
β_{33}	(ln *meters*)²	-	0.1982 (0.2195)
β_{12}	ln *wdelhh**ln *wdelnh*	-	-0.0011 (0.0104)
β_{13}	ln *wdelhh**ln *meters*	-	-0.2275 (0.2004)
β_{23}	ln *wdelnh**ln *meters*	-	-0.0014 (0.0120)
θ_1	ln *dens*	0.0928** (0.0438)	-0.0482 (0.0433)
θ_2	ln *leak*	0.0659*** (0.0218)	0.0652*** (0.0198)
θ_3	ln *ground*	-0.0031* (0.0016)	-0.0044*** (0.0015)
θ_4	ln *elev*	0.0050* (0.0029)	0.0052* (0.0029)
θ_5	ln *debt*	-0.0050 (0.0057)	-0.0041 (0.0052)
θ_6	*deast*	0.1681*** (0.0410)	0.0971** (0.0389)
θ_7	*dpriv*	-0.0090 (0.0388)	-0.0380 (0.0354)
θ_8	*dsew*	-0.0365 (0.0379)	-0.0367 (0.0340)
γ_0	constant	-3.2400*** (0.2557)	-3.5093*** (0.3024)
γ_1	ln *intake*	-0.2048* (0.1116)	-0.3256*** (0.1213)
σ_u		0.2384	0.1968
	AIC	74.0660	9.9701
	BIC	131.5002	90.3779
	Log-Likelihood	-22.0330	16.0150

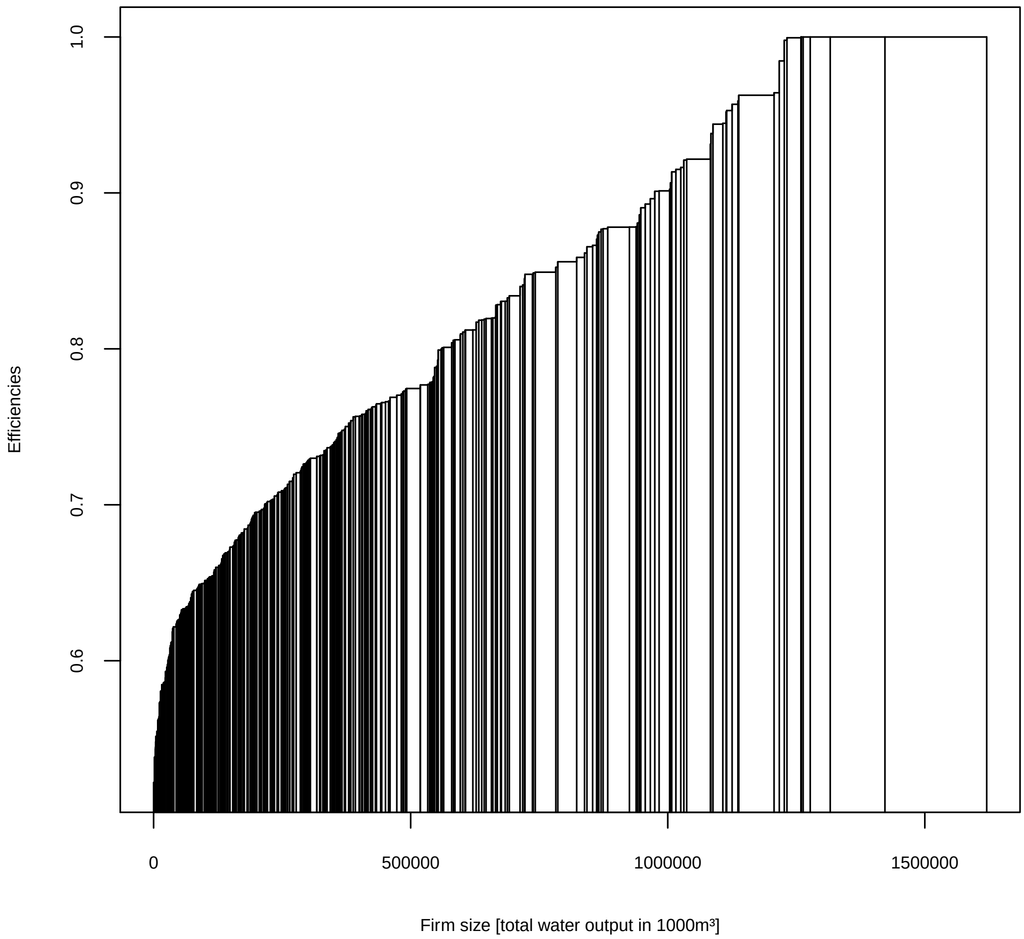
Notes: * significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses.

Fig. 1: Efficiency changes and input quantity changes after input adjustment



Source: Own depiction.

Fig. 2: Salter diagram of DEA technical efficiency scores after inclusion of structural variables



Source: Own depiction.