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Efficiency Effects of Quality of Service and Environmental Factors: Experience from Norwegian Electricity Distribution

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Abstract

Since the 1990s, efficiency and benchmarking analysis has increasingly been used in network utilities research and regulation. A recurrent concern is the effect of environmental factors that are beyond the influence of firms (observable heterogeneity) and factors that are not identifiable (unobserved heterogeneity) on measured cost and quality performance of firms. This paper analyses the effect of geographic and weather factors and unobserved heterogeneity on a set of 128 Norwegian electricity distribution utilities for the 2001-2004 period. We utilize data on almost 100 geographic and weather variables to identify real economic inefficiency while controlling for observable and unobserved heterogeneity. We use the factor analysis technique to reduce the number of environmental factors into few composite variables and to avoid the problem of multi-collinearity. We then estimate the established stochastic frontier models of Battese and Coelli (1992; 1995) and the recent true fixed effects models of Greene (2004; 2005) without and with environmental variables. In the former models some composite environmental variables have a significant effect on the performance of utilities. These effects vanish in the true fixed effects models. However, the latter models capture the entire unobserved heterogeneity and therefore show significantly higher average efficiency scores.

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Efficiency Effects of Quality of Service and Environmental Factors: Experience from Norwegian Electricity Distribution*

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1. Introduction

Since the 1990s, the use of incentive-based regulation in network industries has been on the rise in tandem with the liberalisation trend in infrastructure sectors. While market mechanisms have been introduced in the potentially competitive activities, incentive-based regulation models have sought to improve the efficiency of the natural monopoly segments of these sectors.

The electricity sector presents a comprehensive example of implementation of liberalisation in network industries. Initially, the focus of the early electricity sector reforms was mainly on implementing competition in the wholesale generation and retail supply activities. Meanwhile incentive regulation of the natural monopoly transmission and distribution networks may be characterised as an afterthought (Jamasb and Pollitt, 2007). Some regulatory authorities, inspired by the notion of yardstick regulation first presented by Shleifer (1985) have adopted benchmarking methods as part of the regulatory proceedings. These methods are based on parametric efficiency and productivity analysis techniques stochastic frontier analysis (SFA), and corrected ordinary least squares (COLS), and the non-parametric technique data envelopment analysis (DEA) (see Jamasb and Pollitt, 2001).

However, it soon became evident that there is a potential conflict in the use of incentive regulation and provision of quality of service. Both theoretical arguments presented (e.g. Spence, 1975) and empirical findings (e.g. Ter-Martirosyan, 2003) have suggested that, in the absence of specific arrangements, incentive regulation will lead to reduced quality of service and the outcome will deviate from the socio-economic optimum. Therefore, some studies have argued that incentive regulation and/or benchmarking models should also incorporate quality of service (Giannakis et al., 2005; Growitsch et al., 2009; Yu et al., 2009a).

Moreover, the use of benchmarking techniques in regulation has given rise to the issue that comparisons of firms and their relative efficiency measures should also take the effect of firm-specific non-discretionary factors – factors that are beyond the control of the management – into account. Such factors include economic, regulatory, geographical, climatic and other conditions that can affect the cost and quality of service performance of utilities. It is, however, problematic to ex-ante establish which non-discretionary factors are relevant or how they should be taken into account. There are sound arguments as to how some of these factors can influence the cost and quality performance of utilities. At the same time, it can be argued that, in the long run, utilities adapt, at least to some extent, to their operating environment and the effect of non-discretionary factors on their performance diminishes.

Weather and geographic conditions are among the most commonly debated factors perceived to be affecting the performance of utilities. There are alternative methods on how to include non-discretionary factors such as geography into benchmarking models (Yang and Pollitt, 2007). While the effect of environmental factors on utility performance is of academic and regulatory interest there is rather limited evidence on the nature and extent of their effect.

This paper analyses the effect of geographic and weather conditions (observable heterogeneity) on the cost and quality performance of the Norwegian electricity distribution network utilities. We use a panel of economic and technical data for 128 distribution networks for the period from 2001 to 2004 together with nearly 100 geographic and weather factors in their service area. In order to reduce the number of environmental variables to a manageable number and to avoid the problem of multicollinearity, we estimate composite 'factors' for the geographic and weather conditions applying factor analysis. We then incorporate the estimated factors into an efficiency analysis of the utilities. In order to analyse the effect of controlling for firm specific observable and unobserved heterogeneity on the efficiency estimates, we estimate the established stochastic frontier models of Battese and Coelli (1992,1995) and the recent true fixed effect model of Greene (2004,2005) with and without the composite factors. The next section briefly discusses the regulation of electricity distribution utilities in Norway. Section 3 presents the methodology used in the analysis. Section 4 presents and discusses the results. Section 5 is the conclusions.

2. The Norwegian Electricity Reform and Distribution Networks

Norway was one of the pioneering countries in implementing market-oriented electricity sector reforms. The Norwegian reform was enacted in the Energy Act of 1990 and came into effect in 1991 following Chile (in 1982) and the United Kingdom (in 1990). The reform involved a structural change in the sector by unbundling of the transmission and distribution networks from the potentially competitive generation and supply functions. The Norwegian reform, unlike in some other countries such as the UK, did not involve privatization of the sector which is predominantly under local (municipal/county) and state ownership.

At the time of reform there were 70 generation and 230 distribution network utilities in operation (Bye and Hope, 2005). The large number of utilities is mainly the result of dispersed hydroelectric resources and the established role of local politics in the country. As it became evident later, this was an advantage in introducing competition in generation and implementing advanced benchmarking methods in incentive regulation of networks. The dominant public ownership of the sector did not represent a major obstacle in the introducing of the reform though it may have somewhat slowed down the introduction of competition (Magnus, 2000).

Norway was also among the first countries to introduce benchmarking and incentive-based regulation. Initially, the distribution utilities operated under a rate of return (ROR) regulation regime. The first incentive regulation of these utilities was introduced in 1997 which used efficiency benchmarking of the utilities based on the DEA technique.[1]

Despite its theoretical and conceptual appeal, electricity regulators have not explicitly integrated quality of service in their benchmarking exercise. A notable exception is, however, Norway which introduced quality-dependent revenue caps already in 2001 (Heggset et al., 2001; Langset et al., 2001). Norway is also the only country that explicitly incorporates quality of service in the form of the cost of non-delivered energy from estimated customer willingness-to-pay (WTP) as an integrated part of the benchmarking exercise and incentive regulation of distribution networks in 2001.

Since 2007, the Norwegian regulator for water and energy NVE has adopted annual distribution price controls which are partly based on benchmarking analysis. The regulator has also analysed a large number of geographic and weather variables and has applied the SFA technique to construct composite indices from few selected variables. The actual benchmarking used utilizes measures of snow, forest, and coastal climate as output variables in the DEA model (see NVE, 2006a, 2006b). Hence the model assumes that these affect the firms' production function (rather than efficiency). To control for effects which influence the efficiency level rather than the production technology, the regulator uses a second-stage regression to estimate the efficiency effect of the number of connections to regional networks, capacity of distributed generation sources connected to the network, and the number of islands in the service area.

Although, from a technical point of view, distribution networks can be regarded as relatively simple activities, there is no consensus in the academic literature or among the regulatory practitioners as how to model this activity.[2] In particular, it is often argued that some potentially important contextual and environmental factors that are likely to affect the cost and quality of service of the utilities are not included in the benchmarking models. Norway is the only country where the regulator has systematically examined the effects of environmental factors on the performance of the quality of service and reflected these in the benchmarking models.

Given the above context, Norway represents a particularly interesting case to study the effect of environmental factors. Firstly, the Norwegian sector has been under incentive regulation for a number of years. Second, the incentive regulation regime has removed much of the managerial inefficiency of the networks (Førsund and Kittelsen, 1998; Edvardsen et al., 2006). Third, unlike most other countries, the Norwegian electricity sector consists of a large, though declining due to mergers and acquisitions, number of network utilities which enable the use of analytical methods. And forth, the Norwegian regulator

[1] See Edvardsen et al. (2006) for more details of benchmarking and regulation of quality of service in Norway.

[2] See Jamasb and Pollitt (2001) for a review of the benchmarking in electricity distribution networks and Jamasb and Pollitt (2003) for an overview of the variables used in benchmarking and efficiency studies.

publishes the external cost of quality (cost of energy not supplied) which allows a more comprehensive analysis of a utility's efficiency.

3. Methodology

This section describes the methodology we apply and our estimation approach. First, we present the use of factor analysis in this study. Second, we provide a brief overview of (input) distance functions and their use in efficiency analysis. Subsequently, we describe our estimation methodology based on parametric SFA technique.

3.1 Factor analysis

Modeling and analysis of the effect of non-discretionary factors on the utilities' performance is not straightforward. Yang and Pollitt (2007) present an overview of the main approaches to treatment of non-discretionary factors. The number of potentially relevant factors can be large. Also, the selection of appropriate variables needs to be justified. In particular, in the non-parametric technique of DEA an increase in the number of variables leads to the 'dimensionality' issue.[3] Selection of non-discretionary variables has often been based on received experience or ex ante cost driver analysis. With regards to the choice and analysis of the effect of non-discretionary factors the approaches vary from ex ante analysis and in-model inclusion to different types of ex post analysis of efficiency results. In parametric techniques such as SFA the independent variables can be examined for possible multi-collinearity which can result in leaving out some of the highly correlated variables.

An alternative approach to analyze the effects of a large number of non-discretionary variables is to reduce these into a limited number of composite factors. A useful approach to achieve this is to use factor analysis (FA). FA is a set of multivariate statistical techniques that analyses the interdependencies between a set of related variables in order to extract a smaller number of composite factors. Econometrically, FA identifies a number of latent constructs that explain the variance shared by a set of variables. That is, factor extraction is based only on the variance that is shared among a set of observed variables and excludes any unique and error variances form the solution. In contrast, principal component analysis (PCA), another frequently used data reduction technique, extracts components on the basis of all variance. The question of when one of the two techniques is to be preferred is not fully agreed upon among statistical theorists. Some argue in favor of FA, while others argue in favor of PCA, and still others argue that there is almost no difference between the two techniques (Costello and Osborn, 2005). As we consider a set of weather and geographical

[3] That is, as the number of variables increases, the dimensionality of the model increases. This in turn reduces the discriminatory power of the model when measuring the relative efficiency among the observations in the sample.

variables, where measurement errors and outliers in the date might result in a relatively high portion of error and unique variance in total variance, we choose the FA technique.

FA is a particularly useful technique for efficiency analysis involving geographic and weather conditions. These factors constitute and interact within a complex system with causal effects. Therefore, the use of composite factors rather than elimination of some seemingly correlated variables preserve the holistic nature of geographic and weather systems. Despite its apparent benefits only a small number of non-parametric efficiency studies have applied FA to address the dimensionality issue and to introduce statistical inference in the analysis (Wheelock and Wilson, 2001; Wilson and Carey, 2004; Yu, et al., 2009b). To the best of our knowledge, FA has not been used in parametric efficiency analysis, before.

We aim to examine the effect of weather and geographic variables on performance of the utilities. The data available includes 95 such variables. As we have no prior knowledge of which variables or combinations represent the underlying factor structure and we found significant multicollinearity we use exploratory factor analysis (EFA) to narrow down and group the relevant ones.[4]

In order to decide how many factors to retain we apply two tests. First, using the Kaiser criterion we drop all factors associated with eigenvalues lower than unity.[5] As this criterion leads to a rather high number of factors, we additionally apply the Scree test. This graphical method suggest to plot the factors against their eigenvalues in descending order (Scree plot) and to retain only the important factors with large eigenvalues represented by data points above the break in the slope of the plot. All other factors with lower eigenvalues are considered as unimportant and can be dropped.

Ultimately, we retain 7 factors which cumulatively explain more than 71 % of the shared variance of the data (see Appendix). We estimate the factor loadings (the correlation between observed variables and factors) through extraction and use varimax (orthogonal) rotation to maximize the difference between two factors. Finally, we use the Bartlett scoring to obtain factor scores for any single observation.[6]

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[4] Another type of FA is the confirmatory factor analysis (CFA). This approach is used if a predefined assumption on the relationship between the observed variables and the underlying factor structure exists. CFA then tests this assumption on the basis of an a priori specified factor model.

[5] Eigenvalues indicate the proportion of variance explained by each factor.

[6] Due to the high number of variables, we omitted tables of factor loadings and Bartlett scores. Information is available from the authors upon request.

3.2 Distance functions and stochastic frontier analysis

In order to determine whether and how observable and unobservable heterogeneity influence utilities' cost-quality performance, we measure firm-specific technical (cost) efficiency within a parametric input distance function framework. The results can be interpreted as inefficiency due to over-usage of costs. Distance functions were first introduced by Shephard (1953) and can be of input or output orientation. While an input distance function seeks a production technology's minimal proportional contraction of the input vector for a given output vector, an output distance function maximizes the output vector, given an input vector.

The use of input distance functions in modelling electricity distribution is common, since output use (i.e. network services) is a derived demand and is exogenously determined by final customers' electricity demand. Further, we apply an input distance function approach in this study, as it allows the estimation of firm-specific inefficiency even when availability of input price data is limited. In such cases, a distance function approach is superior to the estimation of a cost function (Coelli et al., 2005).

An input distance function can be defined as

$$D^I(x, y) = \max\{\rho : (x / \rho) \in L(y)\}, \tag{1}$$

where the input set L(y) represents all input vectors x that can produce the output vector y, and ρ measures the proportional reduction of the input vector x. Färe and Primont (1995) show that the following properties hold for an input distance function: $D^I(x,y)$:

- linearly homogeneous in x,
- non-decreasing in x and non-increasing in y,
- concave in x and quasi-concave in y, and
- if $x \in L(y)$, then $D^I(x,y) \geq 1$, with $D^I(x,y) = 1$, if x is on the frontier of the input set.

Based on the above, we are able to measure input-oriented technical efficiency (TE). Following Farrell (1957), firm specific technical efficiency can be defined as:

$$TE = 1/ D^I(x,y), \text{ where } 0 \leq TE \leq 1. \tag{2}$$

Technical efficiency is measured as the reciprocal of the value of the distance function. A firm operating on the frontier shows a value of the input distance function of 1 (e.g. Balk, 1998) and an efficiency score of 1, likewise (fully efficient). As noted above, the efficiency scores obtained in this study are denoted technical cost efficiency, as all inputs used represent the firms' costs.

We estimate a parametric input distance function in a translog functional form. Introduced by Christensen et al. (1973), it represents a generalization of the Cobb-Douglas functional form. Our translog input distance function with K inputs and M outputs is parameterized as:

$$\begin{aligned}\ln D_{it}^{I} = \quad & \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\ \sum_{n=1}^{M} \alpha_{mn} \ln y_{mit} \ln y_{nit} + \sum_{k=1}^{K} \beta_k \ln x_{kit} \\ & + \frac{1}{2}\sum_{k=1}^{K}\ \sum_{l=1}^{K} \beta_{kl} \ln x_{kit} \ln x_{lit} + \sum_{k=1}^{K}\ \sum_{m=1}^{M} \delta_{km} \ln x_{kit} \ln y_{mit} + \phi_1 t + \frac{1}{2}\phi_{11} t^2 + v_{it}.\end{aligned} \tag{3}$$

Inputs and output are as presented above; t represents a time trend to cover technical change and v_{it} is a random error term. Subscripts i (i = 1,2,…,N) and t (t = 1,2,…,T) denote firm and time period respectively. The parameters to be estimated are α, β, δ, and ϕ.

To facilitate the interpretation of the first-order translog parameters we normalize all the variables by their sample median. Homogeneity of degree one in inputs is imposed by the constraints

$$\sum_{\mathrm{k}=1}^{\mathrm{K}} \beta_{\mathrm{k}} = 1, \quad \sum_{\mathrm{l}=1}^{K} \beta_{kl} = 0, \quad \sum_{\mathrm{k}=1}^{\mathrm{K}} \delta_{\mathrm{km}} = 0, \quad (k = 1,2,\ldots,K), \quad (m = 1,2,\ldots,M). \tag{4}$$

Symmetry is given if the second order coefficients satisfy

$$\alpha_{mn} = \alpha_{nm}, \quad \beta_{kl} = \beta_{lk}, \quad (k,l = 1,2,\ldots,K), \quad (m,n = 1,2,\ldots,M). \tag{5}$$

In this study, we apply the SFA techniques to estimate the presented translog input distance function, and to obtain measures for firm-individual inefficiency. The input distance function in Equation 3 is transformed into an econometric model which can be estimated directly. Imposing homogeneity by deflating K-1 inputs by the K-th input leads to:

$$\ln D_{it}^{I} - \ln x_{Kit} = \quad g\left[\left(\ln x_{kit} - \ln x_{Kit}\right), y_{mit}, t \right] + v_{it}. \tag{6}$$

Here, g(.) represents the translog functional form. To estimate the distance function, this expression is rearranged as

$$-\ln x_{Kit} = \quad g\left[\left(\ln x_{kit} - \ln x_{Kit}\right), y_{mit}, t \right] + v_{it} - u_{it}, \tag{7}$$

where $u_{it} = \ln D_{it}^{I}$ represents the non-negative technical inefficiency.

3.3 Estimation strategy

In order to estimate the translog input distance function and to measure firm-specific efficiency, we apply models which allow for time-varying inefficiency following Battese and Coelli (1992, 1995) and Greene (2004, 2005). The models differ in their ability to account for unobserved and observable heterogeneity, and, hence, model comparisons allow analysing the effect of controlling for different kinds of heterogeneity on the efficiency estimates.

For a translog input distance function the Battese and Coelli 1992 model (BC 1992) takes the shape of Equation (7), where v_{it} is a normally distributed random error term ($v_{it} \sim iid\, N(0, \sigma_v^2)$), and the inefficiency term u_{it} is assumed to be an exponential function of time. That is,

$$u_{it} = \{\exp[-\eta(t-T)]\}u_i, \quad i = 1,2,\ldots,N, \quad t = 1,2,\ldots,T, \tag{8}$$

where η is an unknown parameter to be estimated, and u_i is assumed to follow a non-negative truncated normal distribution ($u_i \sim iid\, N^+(\mu, \sigma_u^2)$). This model incorporates neither observable heterogeneity nor unobserved heterogeneity. It serves as our basic model.

Compared to the BC 1992 model, the Battese and Coelli 1995 model (BC 1995) accounts for observable heterogeneity by modeling the mean of the inefficiency term μ_{it} as a function of the estimated composite factors z_{it}. That is,

$$\mu_{it} = \lambda' z_{it}, \tag{9}$$

where λ' is a vector of unknown parameters to be estimated. The time variant inefficiency term u_{it} is assumed to follow a non-negative truncated normal distribution ($u_{it} \sim iid\, N^+(\mu_{it}, \sigma_u^2)$).

The third model, the true fixed effects (TFE) model of Greene, accounts for unobserved heterogeneity additionally. Compared to both Battese and Coelli models, the TFE model avoids the interpretation of unobserved heterogeneity as inefficiency and therefore upward biased inefficiency estimates. Rather, it may underestimate inefficiency if (a part of) inefficiency is persistent over time. For a translog input distance frontier, the TFE model can be defined as

$$-\ln x_{Kit} = \alpha_i + g\left[\left(\ln x_{kit} - \ln x_{Kit}\right), y_{mit}, t\right] + v_{it} - u_{it}, \tag{10}$$

where α_i represents a firm-specific fixed-effect that accounts for company characteristics that are not captured by the included variables. The assumed distributions of the error term v_{it} and the inefficiency term u_{it} are as before and the firm-specific fixed effect α_i is assumed to enter the mean of the inefficiency term μ_{it}. We estimate two variants of this model (i.e. TFE 1 and TFE 2). While the TFE 1 model accounts for unobserved heterogeneity only, TFE 2 incorporates both observable and unobserved heterogeneity. That is, in TFE 2 the estimated composite factors z_{it} also appear in the mean of the inefficiency term:

$$\mu_{it} = \alpha_i + \lambda' z_{it}. \tag{11}$$

All model estimates are obtained by maximum likelihood estimation techniques. As only the composed error term $\varepsilon_{it} = v_{it} - u_{it}$ is observed, the firm's inefficiency is estimated by the conditional mean of the inefficiency term $\hat{u}_{it} = E[u_{it} \mid \varepsilon_{it}]$ (Jondrow et al. 1982). Finally, the annual firm-specific technical cost efficiency is calculated by $TCE_{it} = \exp(-\hat{u}_{it})$.

3.4 Data

The data set used in this study is a balanced panel for 128 Norwegian distribution utilities for the years 2001 to 2004. We specify a simple model with one input and two outputs. Following the Norwegian benchmarking approach, we incorporate quality of service into our model by using social costs as a single input in monetary terms. Social costs are the sum of total production costs (operating expenditures and capital expenditures) and external quality costs. External quality costs are calculated by multiplying the amount of energy (KWh) not supplied with the estimated customer willingness-to-pay per unit of energy. The two outputs are the number of final customers and energy supplied measure in megawatt-hours (MWh). As noted by Neuberg (1977), these two variables reflect the different marketable goods of the joint service of electricity distribution.

Tables 1 and 2 show the descriptive statistics and the average development over time for the relevant variables. As shown in Table 1, quality costs are comparably low. On average, they account for about 3 percent of the social cost. This result suggests a level of quality comparably close to the customers' preferences.

Table 1: Summary statistics

Variable	Obs.	Mean	Std. Dev.	Minimum	Maximum
Social cost (€'000)	512	77 830	168 191	5 045	1 598 890
Total cost (€'000)	512	75 443	163 018	4 949	1 561 140
Quality cost (€'000)	512	2 388	6 058	9	88 463
Final customers (N°)	512	20 169	53 409	925	516 339
Energy supplied (MWh)	512	533 895	1 497 244	16 504	15 482 400

However, as shown in Table 2, quality cost slightly increased over time, while total cost (private production cost) and social cost decreased. If the firms increase their quality of service we would observe exactly the opposite development: an increase in total cost as a results of more infrastructure investments or higher operating and maintenance efforts, and a decrease in quality cost as a result of a lower amount of energy not supplied. Hence, these results indicate that the social cost, the sum of total cost and quality cost, for supplying lower quality of service are lower than the social cost for an increase in quality of service.

Table 2: Annual averages

Variable	Mean 2001	Mean 2002	Mean 2003	Mean 2004
Social cost (€'000)	78 280	79 677	77 084	76 281
Total cost (€'000)	76 225	77 813	73 814	73 919
Quality cost (€'000)	2 055	1 863	3 270	2 363
Final customers (N°)	20 034	20 083	20 210	20 344
Energy supplied (MWh)	562 875	544 059	504 835	523 809

In addition to the input and output variables we incorporate a variety of weather and geographic variables in our analysis. Altogether, the data available includes 95 such variables which are reduced to 7 composite factors by utilizing FA (cp. Section 3.1). Table 3 provides a summarized overview on the variables used in this analysis.

Table 3: Geographic and weather variables

Weather conditions
• Precipitation (annual rainfall, annual snowfall, highest observed daily rainfall, highest observed daily snowfall, …)
• Temperature (annual average temperature, lowest daily average temperature, highest daily average temperature, …)
• Wind speeds (average wind speeds, lowest wind speeds, highest wind speeds, …)
• Lightning (number of lightnings, average strength of lightnings, …)
• …
Geographic conditions
• Altitude above sea level (average altitude, lowest altitude, highest altitude)
• Distance to coast (average distance, minimum distance, maximum distance)
• Slope (average slope, minimum slope, maximum slope)
• Forest structure (share of coniferous forest with high/low/medium production potential, share of mixed forest with high/low/medium production potential, …)
• Population concentration (share of small towns, share of town centers, share of dense areas, …)
• Share of forest, share of agriculture area, share of wetland, share of shallow soil, share of water/lake
• Mini/micro power plants (number of mini/micro power plants, total effect of mini/micro power plants, …)
• …

4. Results

In order to compare the effect of the choice of model on results we adopt a stepwise approach. We first use the utility data to estimate the established Battese and Coelli (1992, 1995) models. These models can serve as a reference for subsequent models. The first model, the BC 1992 model, does not include the composite geographic and weather factors estimated from the FA. It is a one input and two output model with negative social cost as the dependent variable.

As shown in the second column of Table 4 the first order coefficients of outputs, number of customers and energy supplied, are statistically significant and have the expected signs. Using the expression $\gamma = \lambda^2 / (1+\lambda^2) = \sigma_u^2 / \sigma^2$ the gamma (γ) value is 0.9225 – that is, about 92 percent of total variations in cost are due to technical cost inefficiency. This implies that the share of random error in total variations in cost is small. As shown in Table 5, the estimated average efficiency scores are comparably low.

Table 4: Empirical results[a,b]

Variable	BC 1992	BC 1995	TFE 1	TFE 2
y1	-0.5951*** (0.0440)	-0.6847*** (0.0441)	-0.6965*** (0.1005)	-0.6292*** (0.1191)
y2	-0.2557*** (0.0359)	-0.2148*** (0.0417)	-0.2171*** (0.0693)	-0.2359*** (0.0988)
y1y1	-0.1899 (0.1850)	-0.3044 (0.2237)	0.0170 (0.3156)	0.0859 (0.4144)
y1y2	0.2720* (0.1602)	0.2062 (0.1919)	0.1016 (0.2866)	-0.1493 (0.3772)
y2y2	-0.3885*** (0.1435)	-0.1428 (0.1679)	-0.2201 (0.2692)	0.1770 (0.3530)
t	-0.0144** (0.0060)	-0.0123* (0.0068)	-0.0143*** (0.0042)	-0.0118* (0.0067)
tt	0.0262*** (0.0065)	0.0204 (0.0144)	0.0221*** (0.0076)	0.0234** (0.0115)
Constant	0.3744*** (0.0279)	0.1930*** (0.0282)	0.2047*** (0.0530)	0.1139 (0.1086)
Factor 1		0.0433*** (0.0101)		0.0432 (2.0478)
Factor 2		-0.0086 (0.0092)		-0.0261 (58.411)
Factor 3		-0.0121 (0.0138)		0.0467 (79.455)
Factor 4		0.0672*** (0.0111)		0.0637 (73.918)
Factor 5		-0.2527*** (0.0160)		-0.2457 (29.414)
Factor 6		0.0094 (0.0096)		0.0020 (5.3645)
Factor 7		0.0092 (0.0088)		0.0269 (28.286)
Constant	0.4359*** (0.0373)	0.2327*** (0.0299)	0.1482 (0.6751)	0.1491 (55.450)
Sigma2	0.0515	0.0266	0.0052	0.0086
Gamma	0.9225	0.5459	0.3654	0.3256
Sigma_u2	0.0475	0.0145	0.0019	0.0028
Sigma_v2	0.0040	0.0121	0.0033	0.0058

[a] All maximum likelihood estimates of the models are obtained by using the software packages Frontier 4.1 and Limdep 9.0. [b] Standard errors are reported in parenthesis. ***,**, and *: Significant on the 1%-, 5%-, and 10%-level.

In a second step we estimate the BC 1995 model. This model accounts for the impact of environmental factors on the utilities' performance by allowing the inefficiency term μ_{it} to be a function of the composite geographic and weather factors estimated from the FA. Three out of the seven composite factors are found to be significant. In Factor 1 and 4 the highest loadings are carried by several wind speed and snowfall variables, respectively. Hence, the significant and positive coefficients of these factors suggest that a higher wind and snowfall intensity leads to an increase in maintenance cost and, therefore, to a higher technical cost inefficiency.

In Factor 5, the highest loadings are observed for variables that describe the population concentration. The significant and negative coefficient of Factor 5 therefore indicates a lower technical cost inefficiency for firms operating in an area with a higher population concentration. Compared to the BC 1992 model, the average efficiency score increased by more than 10 percentage points (Table 6). This result indicates that a notable share of the inefficiencies that we initially estimated with our basic model can be interpreted as being beyond managerial control.

In the next step of our analysis we estimate two versions of the TFE model as described in the method section above. In our first specification (TFE 1) we only use social cost as the single input and normal outputs leaving out the environmental factors. In our second specification (TFE 2) we extend the model by allowing the inefficiency term μ_{it} to be a function of the estimated composite factors and the firm-specific fixed effects capturing unobserved heterogeneity.

As can be seen in Table 4, in both TFE models the first order coefficients of the outputs are significant and have the correct signs.[7] However, in the TFE 2 model none of the included composite factors is significant. Referring to the efficiency estimates, the results from the TFE models show rather high efficiency scores (Table 5). Such increase in scores is generally expected from these models (cp. Farsi et al., 2005). Our results show that, in this case, this increase is not due to inclusion of the composite geographic and weather factors in the model.

Table 5: Efficiency scores by model and year

Year	BC 1992	BC 1995	TFE 1	TFE 2
2001	0.6494	0.7630	0.8477	0.8508
2002	0.6473	0.7616	0.8480	0.8505
2003	0.6452	0.7594	0.8485	0.8496
2004	0.6430	0.7587	0.8481	0.8485
2001-2004	0.6462	0.7607	0.8481	0.8498

However, the wide range of scores between the Battese and Coelli (1992, 1995) models and the TFE models justify further studies into the sources of differences. In particular it is important to determine the extent to which TFE models may reflect time-invariant inefficiency elements. Applying a series of mean comparison tests shows that all but the two TFE models produce significantly different efficiency scores. The development of scores over time is, however, not significant for any of the estimators.

[7] Coefficients for firm-specific time-invariant fixed-effect dummy variables are not included due to space limitation.

5. Conclusions

As efficiency and benchmarking analysis are increasingly used in network industries and utilities research and regulatory context a recurrent concern is whether environmental factors affect the firms' performance or the choice of appropriate models. In this paper we present an empirical analysis of the effect of geographic and weather factors on the performance of the Norwegian electricity distribution utilities. Norway is a suitable case for such a study as it has a large number of utilities and detailed data of an extensive range geographic and weather conditions of the utilities service areas are available.

We used FA to reduce the number of environmental factors from nearly one hundred to only seven composite factors. We first estimated conventional SFA models with and without the composite factors as reference point. We found that incorporating environmental factors did increase average efficiency by more than ten percentages points. We then estimated the recently developed TFE models first without and then with the composite factors included. As in other studies using such models we found significantly higher average efficiency scores in both models. However, at the same time, we did neither find one environmental factor to be significant nor a noticeable difference in the average efficiency scores of the two models. This result indicates that the whole impact of the environmental factors is captured by the firm-specific fixed effects or, in other words, is completely covered by unobserved heterogeneity.

On the whole, the results suggest that the choice of the type of SFA model is more important than whether to include the environmental factors in them. Moreover, the difference between the levels of average efficiency scores between the conventional and the TFE SFA models imply that we need to be aware of the extent to which time-invariant inefficiencies may be embodied in the efficiency scores of the latter model types. This is in particular important for their use in regulatory benchmarking.

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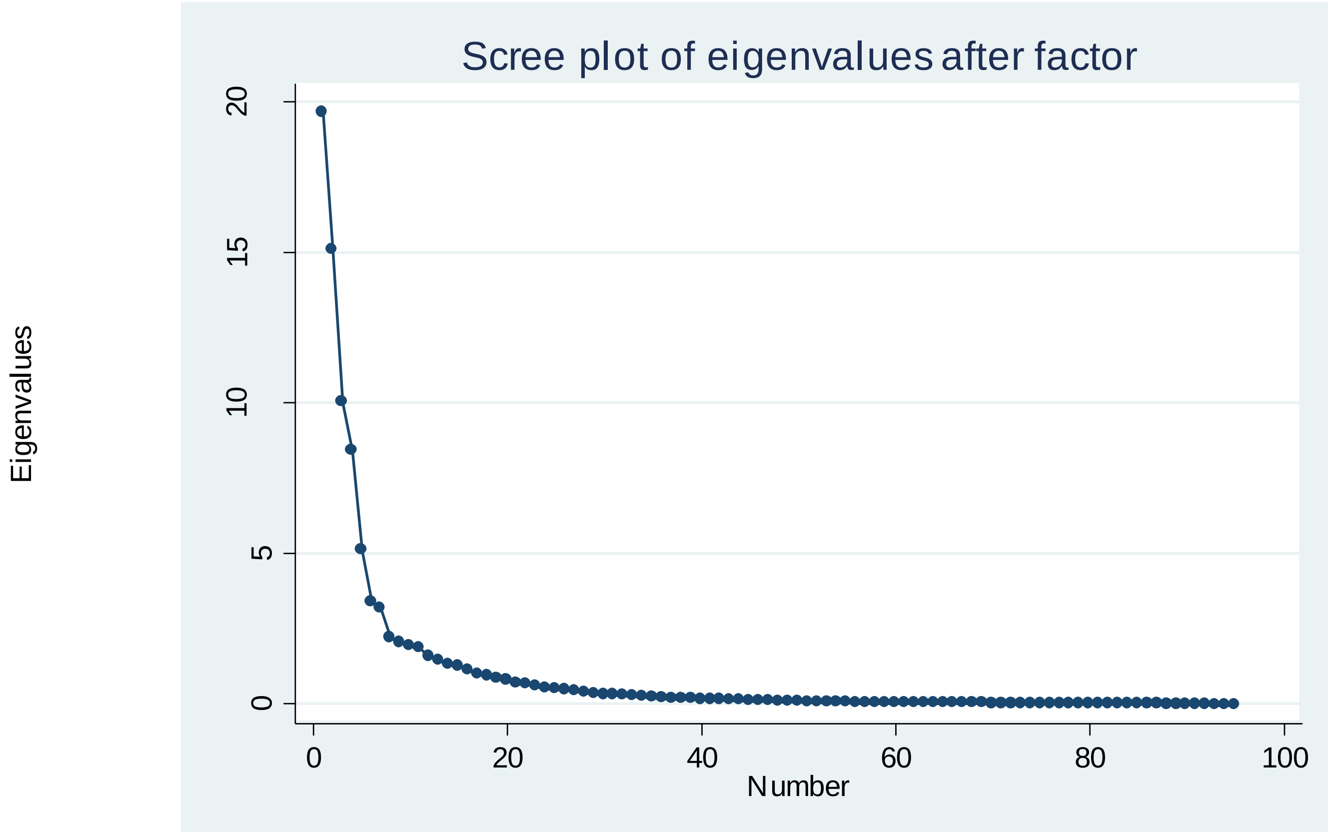
Appendix



Graph A1: Scree plot of eigenvalues

Table A1: Results of Factor Analysis

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	19.62557	4.55790	0.2180	0.2180
Factor 2	15.06768	5.05379	0.1674	0.3854
Factor 3	10.01388	1.62706	0.1112	0.4966
Factor 4	8.38682	3.28869	0.0932	0.5898
Factor 5	5.09813	1.73995	0.0566	0.6464
Factor 6	3.35819	0.21618	0.0373	0.6837
Factor 7	3.14201	0.95295	0.0349	0.7186