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Economies of scale in Norwegian electricity distribution:

A quantile regression approach

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ABSTRACT

In this paper we investigate scale economies in Norwegian electricity distribution companies using a quantile regression approach. To the best of our knowledge, this is the first attempt to apply this estimation technique when analyzing scale economies. We estimate the cost elasticities of the two output components; *network length* and *number of customers,* to calculate returns to scale. Our results show large potential of scale economies, particularly for the smallest companies. We also find that returns to scale is increasing over time. These findings have important implications for policy makers when they are deciding the structure of the industry in the future.

KEYWORDS: *Norwegian electricity distribution companies, policy makers, Economies of scale, returns to scale, quantile regression.*

HIGHLIGTHS

- Large potential for economies of scale in Norwegian electricity distribution companies.
- Economies of scale is especially large for small companies.
- Quantile regression shows that returns to scale varies with company size and increases over time.

1. Introduction

In this paper, we investigate whether there are any unexploited economies of scale among Norwegian electricity distribution companies across company size. To address this issue, we apply a quantile regression model to a unique data set with detailed information on the characteristics of the distribution companies over the period from 2000 to 2013. To the best of our knowledge, this is the first attempt in the literature to apply this method when analyzing economies of scale. The quantile regression approach is particularly useful in our context as it allows us to examine the economies of scale across the whole distribution of companies. That is, while ordinary least square estimates only provide the mean effect of the output components, and a corresponding mean estimate of any returns to scale, a quantile regression model provides the corresponding effects across all quantiles of interest. (see, e.g., Davino et al., 2014). It is thus a more flexible modelling approach, which also will provide more relevant results for policy makers as the effects can be examined directly by company size.

Our results show that there is a large potential for economies of scale in the Norwegian electricity distribution sector, and particularly so for small companies. That is, the returns to scale estimates based on our quantile regression are in general higher for the lower quantiles (the smallest companies measured in total costs), compared to the higher quantiles (the biggest companies). This means that the efficiency gains from increasing the output components for small companies are higher than for big companies. An implication of this finding is that it is beneficial from a productivity point of view that small companies should increase in size before big companies do so. Put differently; small companies should either expand or merge.

Our results also show that the returns to scale has increased over time. This means that the companies, in general, have become less productive and/or efficient under the given regulations.

This finding holds across all quantiles, but particularly so for big companies. For policy makers this means that there may be a need to revise the current regulations to change this negative trend.

A range of studies already exist concerning economies of scale in the electricity distribution industry, (e.g., Giles and Wyatt, 1993; Filippini, 1996; Burns and Weyman-Jones, 1996; Kumbhakar and Hjalmarsson, 1998; Yatchew, 2000; Kwoka, 2005; Farsi et al., 2010; Tovar et al., 2011; Alaeifar et al., 2014). From Norway (e.g., Salvanes and Tjøtta, 1994; Førsund and Kittelsen, 1998; Førsund and Hjalmarsson, 2004; Growitsch et al., 2009; Miguéis et al., 2011; Kumbhakar et al., 2015). The findings of these studies are somewhat mixed, both around the world and in Norway, but most provide at least some evidence of unexploited scale economies, including the recent Norwegian study of the period 1998 to 2010 by Kumbhakar et al. (2015).

In this study, we model the electricity distribution sector as a single-input multi-output production process, characterizing the production process with a cost function. To control for firm heterogeneity, we introduce several environmental variables in our models. Moreover, as the effects from the multi-output production process may vary in size and nature across the distribution of the total costs (TOTEX), we use a quantile regression approach. This method allows us to estimate a range of conditional quantile functions and, hence, provides a more complete picture of the conditional density of the covariate effects.[1, 2]

The remainder of the paper is organized as follows. Section 2 gives an overview of the Norwegian electricity distribution industry. Section 3 presents model specification. Section 4

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[1] E.g., the effects from the various outputs (such as length of network or number of customers) could be different in the lower and upper tail of the TOTEX distribution.

[2] The Skewness and kurtosis indicates that our dependent variable, total costs (TOTEX) and ln(TOTEX) are not normally distributed. This is supported by the Shapiro-Wilk test which rejects the null-hypothesis of normal distribution in both TOTEX and ln(TOTEX). See Table A1 in the appendix for test statistics.

describes the Norwegian electricity distribution data followed by discussion of the econometric models and cost elasticities in section 5. Empirical results are presented in section 6 and section 7 provides our concluding comments.

2. The Norwegian electricity distribution industry.

The Norwegian electricity sector has undergone significant reorganization and restructuring. Until 1991, Norwegian national, county, and municipal governments largely owned the sector, with electricity generation, wholesale and retail supply, and transmission and distribution activities more or less woven together. The basic premise of the 1991 restructuring under the *Energy Act* was to unbundle services in the value chain of delivering electricity to consumers and to expose some parts of the industry, including electricity generation, wholesale and retail supply, to greater competition. As the distribution of electricity displays the characteristics of a natural monopoly, this part of the industry continued to consist of monopoly producers, with each distribution company operating its own concession area (see Salvanes and Tjøtta, 1998). As part of the 1991 *Energy Act*, Norway's regulatory agency, the Norwegian Water Resources and Energy Directorate (in Norwegian: *Norges vassdrags- og energidirektorat* or NVE), regulates the distribution companies. The purpose of the regulation is to introduce competition through the regulation model given that the companies do not actually compete with each other directly. The regulation of the distribution companies works through a revenue cap system. NVE use Data Envelopment Analysis (DEA) to calculate each company's efficiency level. The most efficient companies constitute a production possibility frontier and all of the other companies get a measure of efficiency in relation to this frontier. The efficiency scores determine 60% of the revenue cap which the regulator calculate for each company. As discussed in Kumbhakar et al. (2015), until 2013 the revenue cap regulation system was specified in such a way that it discouraged mergers among the distribution companies. The current structure of the electricity distribution network is partly the result of the preexisting structure of the locally owned, vertically integrated and regulated power sector prior to the 1991 reforms. Consequently, the discussion above and the ongoing policy debate about the structure of the electricity distribution network in Norway (e.g., Reiten et al., 2014) makes it interesting to question whether there are too many distribution companies in Norway and how we can best describe the economies of scale across distribution company size.

3. Model specification

Based on NVE's current regulatory model, firm outputs in the Norwegian electricity industry consist of the numbers of costumers, the length of wires to transport electricity and the amount of electricity delivered. We assume that the outputs of distribution companies are exogenous, whereas cost is endogenous. The cost function is then given by:

$$\mathrm{C} = f(Y_i) \tag{1}$$

where C is the total costs and Y_i is the output variables. By taking the natural logarithm of equation (1), we obtain:

$$\ln \mathrm{C} = ln\ \mathrm{f}(Y_i) + v \tag{2}$$

The above cost function is made stochastic by including the standard error term v. We define return to scale (RTS) as follows

$$\mathrm{RTS} = \frac{1}{\sum_i \partial ln\mathrm{C}/\partial lnY_i} \tag{3}$$

where $\sum_i \partial ln\mathrm{C}/\partial lnY_i$ is the sum of the cost elasticity's for input 1 and 2.

By adding a time component (t) to the model, we can find technical change (TC), defined as:

$$\mathrm{TC} = -\frac{\partial lnC}{\partial t}. \quad (4)$$

If TC is larger, equal or smaller than zero, it means there exists positive, zero or negative technical change respectively.

4. Data

The data comprise economic and technical information on Norwegian electricity distributors from 2000 to 2013, as collected by the NVE and historically used to implement income regulation in the industry. In total, there are 1,750 firm-year observations, constituting an unbalanced panel of 133 Norwegian distribution companies.

We specify a model with a cost function with two outputs based on NVE's current regulatory model. The outputs are the *length of network* (N), and the *number of customers* (Q), representing the main cost drivers in the industry.[3] The output variable *length of network* is the length of the (high-voltage) distribution network in kilometers. The *number of* customers is the total number of entities (both households and firms) that pay the net rent tariff. The endogen variable in our model is *total costs* (TOTEX), and include capital expenditure (CAPEX), controllable operational expenditure (OPEX) and external costs of interruptions for customer.[4] For the entire industry in 2013, total costs were about 12.2 billion Norwegian kroner (NOK) [5], while average

[3] In the regulatory model of NVE, the number of network stations (NT) are also included. However, as one referee pointed out, there are strong multicollinearity between the output variables. The variance inflation factors (VIF) between the output variables reduces from (NT=42.76), (Q=18.04), (N=16,92) to (Q=6.60), (N=6.61) when we drop *number of network stations* from the model to avoid strong multicollinearity.

[4] CAPEX includes annual depreciations and return on book values including 1% working capital. OPEX includes operational- and maintenance costs. External costs of interruptions for customers consists of a cost of interrupted effect in the powerlines and losses per MWh (300 NOK). All distribution companies in Norway are by law obligated to report numbers on production and costs, see the website of the Norwegian Ministry of Petroleum and Energy: https://www.regjeringen.no/no/dokumenter/forskrift-om-okonomisk-og-teknisk-rappor/id507169/.

[5] 1 USD = 7.72 NOK, 1 EUR = 9.56 NOK per 1. February 2018.

total cost per company was approximately 100 million NOK.[6] Furthermore, in 2013, total cost for the largest company (Hafslund) was 1.4 billion NOK and only about 3.1 million NOK for the smallest company (Modalen Kraftlag).

Table 1 presents descriptive statistics for the total cost and output variables, all of which exhibit significant dispersion (large standard deviations). We include various environmental variables (represented by the Z variables in Table 1), which are likely to have an impact on each firm's total costs. However, the output variables N and Q will also to some extent capture the heterogeneity of firms. For instance, it is obvious that the *length of network* relative to the *number of customers* will be higher in rural areas than in urban ones, because rural areas generally have a lower population and a more dispersed pattern of settlement. By including the environmental variables *proportion of underground cables* (Z1), *proportion of sea cables* (Z2), *proportion of air cables* (Z3), *average slope in terrain* (Z4), *average distance to road* (Z5), *number of islands* (Z6), *proportion of deciduous forest* (Z7), and *coastal climate* (Z8), we control better for firm-specific costs and thus firm heterogeneity.

[6] All costs are in 2010 NOK. The evolution of total costs from 2000 to 2013 are presented in Table A2 in the appendix.

Table 1. Descriptive statistics.

Variables	Label	Mean	St. Dev.	Min	Median	Max
Length of network, in km	N	714	1,188	10	306	8,744
Number of customers	Q	19,601	50,837	348	6,037	570,179
Total costs, 1,000 NOK (2010)	TOTEX	88,439	177,682	2,400	32,841	1,748,090
Year	t			2000		2013
Environmental variables						
Proportion of underground cables	Z1	0.30	0.19	0.00	0.25	1.00
Proportion of sea cables	Z2	0.02	0.04	0.00	0.00	0.37
Proportion of air cables	Z3	0.12	0.10	0.00	0.12	0.40
Average slope of terrain	Z4	10.21	3.65	2.97	9.95	22.22
Average distance to road	Z5	64.18	36.20	1.00	65.00	126.00
Number of islands	Z6	2.62	5.49	0.00	0.00	30.00
Proportion of deciduous forest	Z7	0.08	0.09	0.00	0.03	0.31
Coastal climate	Z8	0.23	0.64	0.00	0.02	4.74

5. Econometric models and cost elasticities

We use panel data, but to simplify the notation, we omit the subscript i $(i = 1,2, \dots, N)$ (indicating the distribution company) and the subscript t $(t = 1,2, \dots T)$ (indicating time). However, we include the time variable (t) in the model specification.

In our models to be estimated we use $C =$ TOTEX. Output Y_1 *and* Y_2 are now represented by N and Q, respectively.

We express the econometric specification of the translog function (TL) as:

$$\begin{aligned} \ln C = \alpha + \beta_1 \ln N + \beta_2 \ln Q + 0.5\beta_3 (\ln N)^2 + 0.5\beta_4 (lnQ)^2 \\ + \beta_5 (\ln N \ln Q) + \beta_6 t + 0.5\beta_7 (t)^2 + \beta_8 (\ln Nt) \\ + \beta_9 (\ln Qt) + \beta_{10} Z1 + \beta_{11} Z2 + \beta_{12} Z3 + \beta_{13} Z4 \\ + \beta_{14} Z5 + \beta_{15} Z6 + \beta_{16} Z7 + \beta_{17} Z8 + v, \end{aligned} \tag{5}$$

where $\ln N$, and $\ln Q$ are vectors of *length of network* and *number of customers*, for all distribution companies over the sample period, respectively. α and β_1–β_{17} are parameters to be estimated. Z1–Z8 are control variables (the environmental variables).

Using this specification, we calculate the elasticities for each cost driver as follows:

$$\frac{\partial \ln C}{\partial lnN} = \varepsilon_N = \beta_1 + \beta_3 \ln N + \beta_5 \ln Q + \beta_8 t, \tag{6}$$

$$\frac{\partial \ln C}{\partial lnQ} = \varepsilon_Q = \beta_2 + \beta_4 \ln Q + \beta_5 \ln N + \beta_9 t, \tag{7}$$

and the corresponding RTS is given by:

$$RTS_{TL} = \frac{1}{\left(\varepsilon_N + \varepsilon_Q\right)}. \tag{8}$$

5.1 Firm heterogeneity, unobserved factors and fixed effects

The data used in this study includes several firm specific environmental variables. By introducing all the eight environmental variables, we control for firm heterogeneity. One could argue that to fully control for possible unobserved factors such as economic, organizational, regulatory and additional environmental factors, one should estimate a fixed effect model. However, our main focus in this paper is to show that the quantile regression approach is a better method to analyze economies of scale for various outputs components by company size. To introduce fixed effects to the quantile estimation is problematic due to the number of observations. Hence, we estimate our models by including the environmental variables that control for firm heterogeneity. To check the robustness of our results, we estimate three different models, Fixed effect, True fixed effect SFA and Finite mixture model (latent class model). The estimated cost elasticities and RTS from each of the models are presented in Table A7 in the Appendix.

5.2. Quantile regression and returns to scale

The estimate of RTS in (8) draws on the conditional mean (OLS) estimates in (5). However, in our case, it is particularly interesting to consider the effects in the tails of the distribution of the dependent variable, which will reveal the range of differences in the individual covariates and the range of the values of RTS more generally.

In the general case, the simple linear quantile regression model is:

$$Y_{i,q} = \alpha_q + \beta_q X_i + \varepsilon_{i,q}, \tag{9}$$

where the distribution $\varepsilon_{i,q}$ is left unspecified.[7] The expression for the conditional q (quantile), $0 < q < 1$, is defined as any solution to the minimization problem (see Koenker and Bassett, 1978):

$$\min_{\alpha,\beta} \sum_{i=1}^{n} \left(q - \mathbf{1}_{Y_i \leq \alpha_q + \beta_q X_i}\right)\left(Y_i - \left(\alpha_q + \beta_q X_i\right)\right), \tag{10}$$

where:

$$\mathbf{1}_{Y_i \leq \alpha_q + \beta_q X_i} = \begin{cases} 1 \text{ if } Y_i \leq \alpha_q + \beta_q X_i \\ 0 \text{ otherwise} \end{cases}. \tag{11}$$

[7] Not to be confused with the standard error term from OLS, as the distributional properties are not intended to meet the same criteria as standard regression models.

The least absolute error (the conditional median) is a special case, but the quantile regression method explicitly allows us to model all relevant quantiles of the distribution of the dependent variable.

In our case, we define the quantile regression version of the TL cost function using the following notation:

$$\begin{aligned}\ln C_q \; = \alpha_q &+ \beta_{1,q}\ln N + \beta_{2,q}\ln Q + 0.5\beta_{3,q}(\ln N)^2 + 0.5\beta_{4,q}(lnQ)^2 \\ &+ \beta_{5,q}(\ln N \ln Q) + \beta_{6,q}t + 0.5\beta_{7,q}(t)^2 + \beta_{8,q}(\ln Nt) \\ &+ \beta_{9,q}(\ln Qt) + \beta_{10,q}Z1 + \beta_{11,q}Z2 + \beta_{12,q}Z3 \\ &+ \beta_{13,q}Z4 + \beta_{14,q}Z5 + \beta_{15,q}Z6 + \beta_{16,q}Z7 + \beta_{17,q}Z8\end{aligned} \tag{12}$$

and the corresponding RTS for each quantile as:

$$RTS_{TL,q} = \frac{1}{\left(\varepsilon_{N,q} + \varepsilon_{Q,q}\right)} \tag{13}$$

where q is a given quantile between 0 and 1. The two elasticities ($\varepsilon_{N,q}$, $\varepsilon_{Q,q}$) are calculated in the same way as equations (6) and (7), but for each quantile.

6. Results and discussion

6.1. Results for OLS TL function

We initially tested the translog cost function model against the restricted and more parsimonious Cobb–Douglas cost function model. Statistical testing using Wald likelihood-ratio tests (Wald, 1943), rejected the Cobb–Douglas model at the 1 percent level of significance. To account for heterogeneity across distribution companies, we included firm-specific environmental (Z) variables. This is because it is important to account for firm-specific cost factors, including the impact on costs of demographic, geographic and climatic factors (Growitsch et al., 2012).

As shown in Table 2, the output elasticity of *length for network* is 0.374, meaning that if you increase the output value *length for network* by one percent, the total costs will increase by 0.374 percent. For *the number of customers*, the cost elasticity is 0.544.[8]

Table 2. Cost elasticities, returns to scale.

Components	Mean	Std. error
Cost elasticity with respect to output:		
Length of network	0.374	0.009
Number of customers	0.544	0.013
Returns to scale (RTS)	1.089	0.001
Technical change (TC)	0.001	0.001
Notes: Heteroscedasticity consistent standard errors (Davidson and Mackinnon, 1993)		

Evaluated at the means of the variables, RTS exceed unity, (1.089).[9] This suggests the presence of scale economies. In this context, our results support existing findings for the electricity distribution sector in Norway (Førsund and Hjalmarsson, 2004; Growitsch et al., 2012; Kumbhakar et al., 2015) and in Sweden (Kumbhakar and Hjalmarsson, 1998). However, as depicted by the histogram in Figure 1, there is a large variation in the RTS estimates across the companies. We investigate this further by applying quantile regression on our model.

[8] Data and model specifications are available from the authors upon request. Test statistics are available in Table A3 in the Appendix.
[9] RTS > 1 is to be interpreted as follows: if you double your inputs, you will more than double your output. At optimal scale RTS = 1, meaning that if you double your inputs, your outputs will also double.

In Table 2 we also present the value of technical change. The value is small, but positive, meaning that the production possibility frontier "shifts up" indicating that at least some of the distribution companies gets more productive over time.

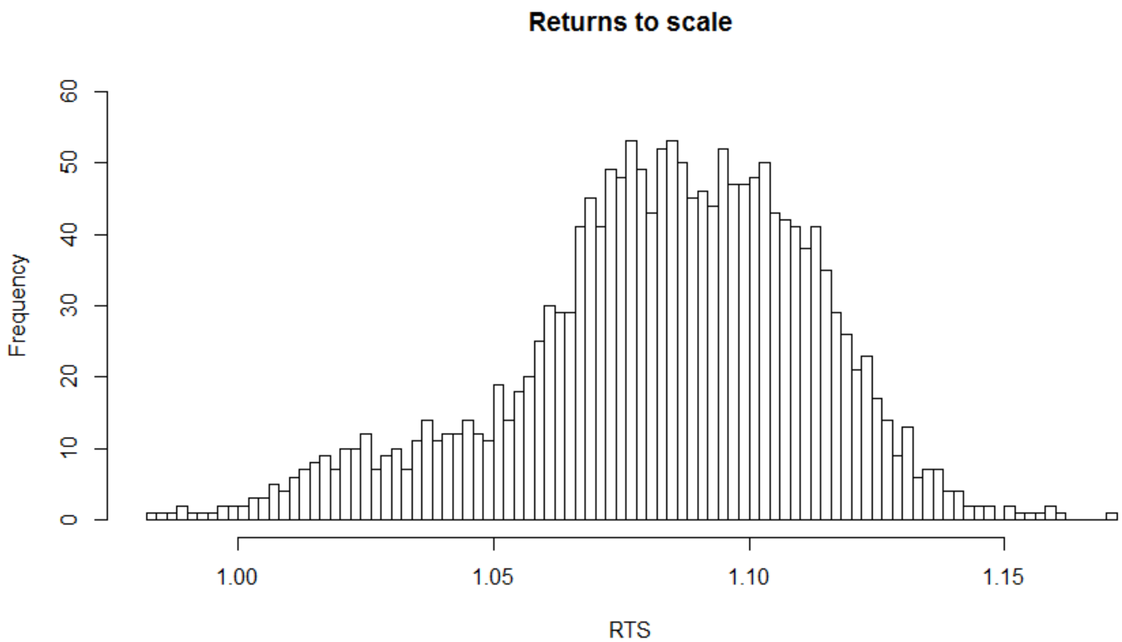

Fig. 1. Histogram of returns to scale for all companies, estimated using the OLS translog function.

6.2 Results for quantile TL function

We estimate the model in (12) for 19 quantiles ranging from 0.05 to 0.95. From all of the observations in each quantile (1,750 × 19), we calculate the elasticities and take the median elasticity for each quantile. [10,11]

[10] For the interested reader tables with mean, median, standard errors, p-values and confidence intervals for each quantile for each cost elasticity and RTS is to be found in the Appendix, see Table A4-A6.
[11] Note that since we apply panel data from 133 firms, ranging from year 2000 to year 2013, some of the firms that have changes in input- and output values, can appear in different quantiles. However, since our goal is to estimate cost elasticities and RTS on the industry, this will not violate the results obtained in our estimation. If someone would like to use this method to derive firm-specific measures, this issue should be handled with caution. By reducing the number of quantiles, the number of "shifts" will be reduced.

The upper panels in Figure 2 depict the parameter estimates for each of the two cost drivers. That is, for each of the two coefficients, we plot 19 distinct quantile estimates. For each quantile, we interpret these point estimates as the impact of a one-unit change in the covariate on *total costs*, ceteris paribus. We also plot 95% confidence intervals for the quantile regression estimates.[12] In the traditional OLS approach, we would obtain the average percentage cost increase for a one percent increase in the cost driver. For example, an OLS parameter of 0.2 (in absolute terms) for the variable measuring *length of network* (log(N)), could be interpreted as meaning that for a one percent increase in the *length of network*, total costs increase on average by 0.2 percent, *ceteris paribus*. However, with our quantile regression approach, we can now see how much total costs will increase for a one percent increase in any of the covariates within each quantile.

As shown in the upper left panel of Figure 2, the parameter estimates of the *length of network* range from about 0.33 for the lower quantiles to about 0.44 for the upper quantiles. For the highest quantile the estimated cost elasticity for the *length of* network is 0.37. There is a small upward trend, meaning that the increase in costs associated with a one percent increase in the *length of network* is somewhat lower for small distribution companies. The *length of network* describes the size of the network for each firm and an intuitive economic interpretation of this can be that small distribution companies have spare capacity, while larger distribution companies are producing nearer their capacity limit.

In the upper right panel, we present the quantile regression estimates for the *number of customers*. We see from the figure that there are only minor differences in the estimated cost

[12]The 95% confidence intervals are computed by the Delta-method. The Delta-method is a method for deriving the variance of a function of asymptotically normal random variable with known variance using a Taylor series expansion, see https://cran.r-project.org/web/packages/modmarg/vignettes/delta-method.html#fn7 for more details.

elasticities across the quantiles. For the smallest quantile to the highest quantile the range is 0.571 and 0.568 respectively. The minimum cost elasticities, 0.501, we find in the 0.8 quantile, giving the curve a somewhat u-shape. It is likely that the smaller companies generally have their concession area in rural areas, where the population is lower and settlement more scattered. Increasing the number of customers can then be more costly if any new customers are located far from existing customers. In urban areas where the larger distribution companies are typically located, it is more common for households to reside in closely located apartment buildings and houses, so the dispersion of residences is generally over a much smaller area. This can explain the downward trend of the cost elasticities. However, we see that for quantiles above 0.8, the biggest companies, the cost elasticities are increasing with firm size.

The lower right panel reports the RTS across quantiles. As shown, the results indicate that there is a potential for scale economies, particularly for small companies. The RTS exceeds one for all quantiles but is larger in magnitude for the smallest companies. In this situation, firms should increase production. If we consider the Norwegian electricity distribution industry as an autarky with fixed exogenous given demand, the only way for distribution companies to increase their production is to merge with other distribution companies. Based on these plots, we can conclude that there is large potential for scale economies among Norwegian electricity distribution companies, and particularly for small companies.[13]

We have checked the robustness of our results by estimating three different models, *Fixed effect*, *True fixed effect SFA* and *Finite mixture model* (latent class model). We find that the mean values of cost elasticities and RTS are robust across the three model specifications. RTS exceeds unity in all models.[14]

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[13] All Data and R-code used in this analysis are available on request.
[14] The results are presented in Table A7 in the Appendix.

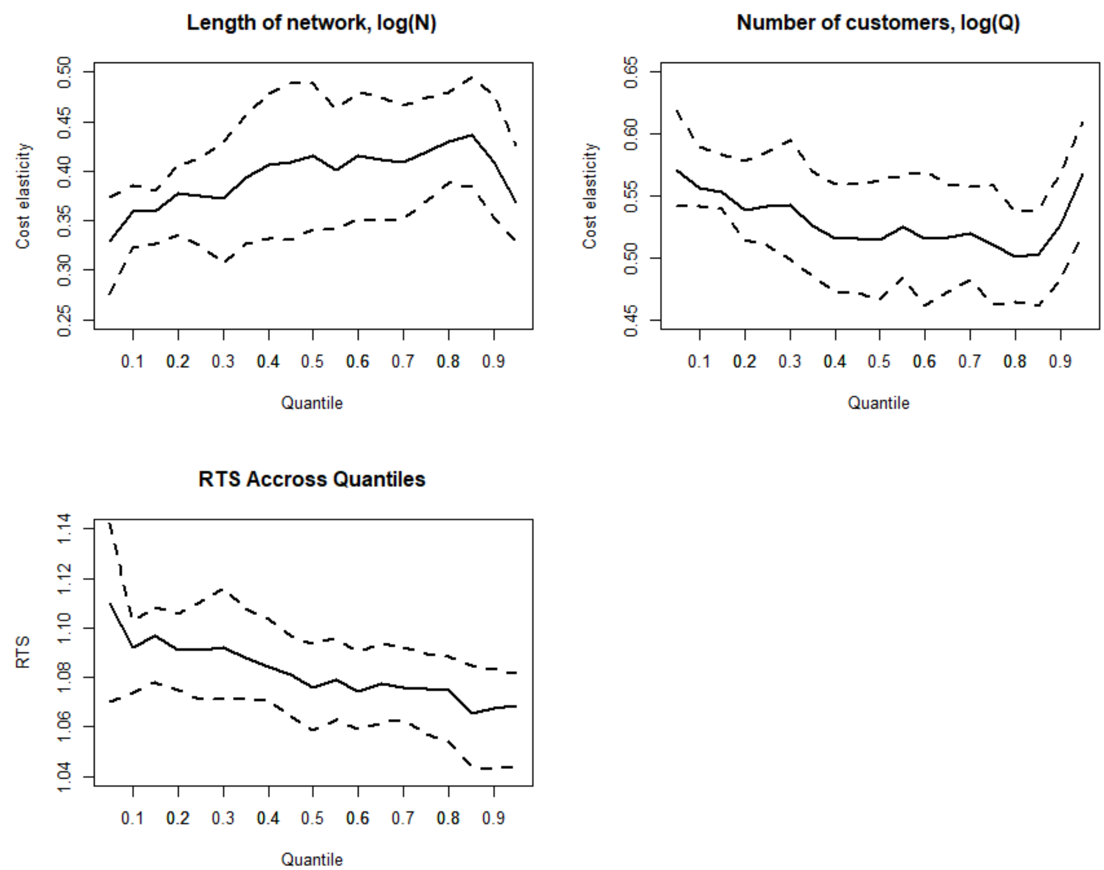

Fig. 2. Median cost elasticity of outputs (multiplied by –1) estimates and RTS across quantiles, based on the TL function. The scattered lines are 95% confidence intervals.

6.3 RTS development across quantiles over time

In Figure 3, we present the development in RTS across the quantiles over time. As shown, the difference in RTS for small distribution companies (lower quantiles) compared with large distribution companies (higher quantiles) appears to decline over time. For example, the range in RTS for lower/higher quantiles is larger in 2000 than in 2013. The RTS for each quantile exceeds one in all time-periods. This supports our earlier results, suggesting that smaller distribution companies should merge.

Figure 3 also show that RTS is increasing over time, which is an interesting result. If we regard firms with RTS greater than one as being too small, then an increasing RTS over time suggests that the firms are getting smaller and smaller relative to the optimal scale over time.[15] One interpretation of this could be that only some of the companies causes the technical change (reported in Table 2). All the other companies will then be less efficient as the frontier shifts up. Due to the regulation, they have incentives to increase their efficiency. To get more efficient the companies have to reduce their inputs and keep the outputs constant. We regard the demand for distribution of electricity services as given, so to increase their outputs is not an option. As the companies move towards the new frontier as they are getting more efficient by reducing their inputs, they end up further away from the point of optimal scale. This will lead to an increase in RTS.[16]

[15] We would like to thank the referee that correctly pointed out that the increase in RTS over time could be affected by firms merging over time. Since we use unbalanced panel data in our analysis, this could be the case. However, to check this we have also run the model with a balanced panel data, and the effect on RTS increasing over time is higher, see Figure A1 in the appendix.

[16] There are several reasons that firms experience different RTS (see, e.g., Coelli et al., 2005).

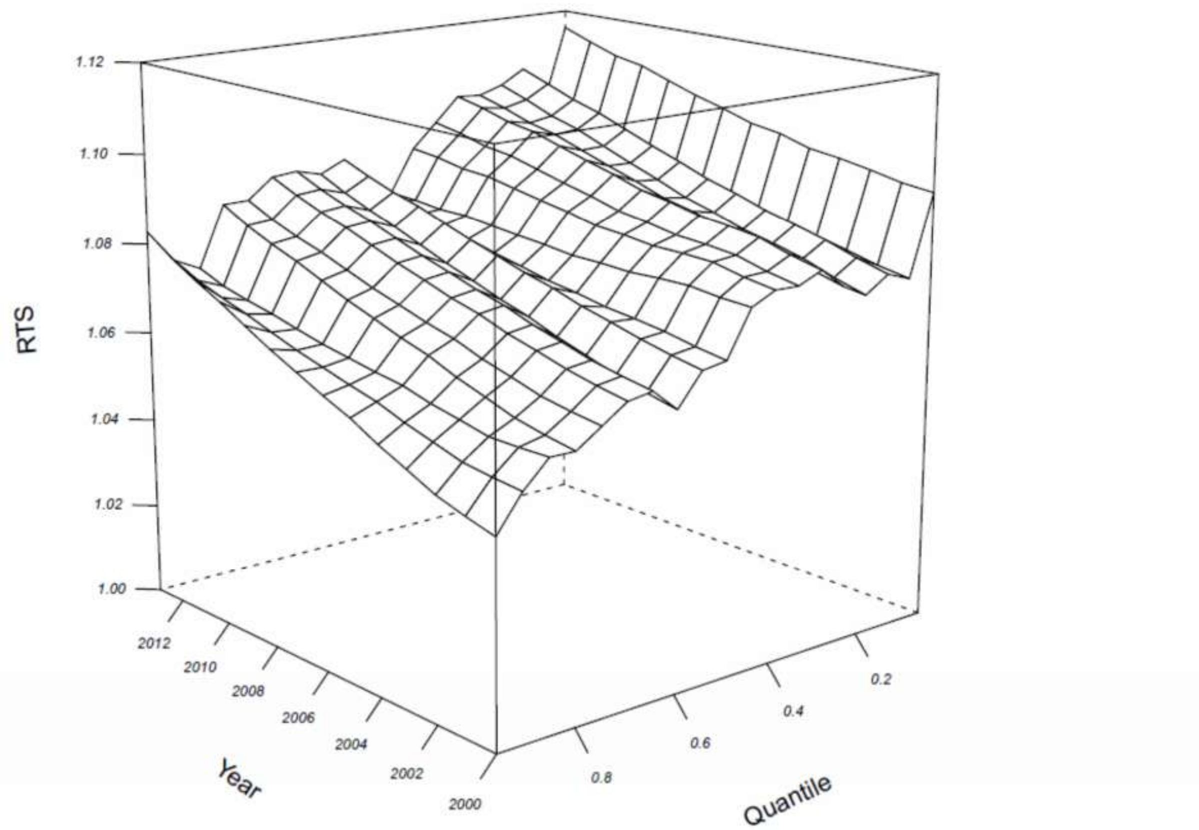

Fig. 3. Returns to scale (RTS) across quantiles and over time.

7. Concluding comments

In this study we investigate scale economies in Norwegian electricity distribution companies using a quantile regression approach. We find potential for scale economies and especially for the smaller companies. By applying quantile regression we find how the costs will be effected by an increase in outputs for each quantile, meaning that we can tell how the results varies with firm size. Our results show highest RTS for the smallest companies, which suggests that the smallest firms in the industry should increase their outputs. Since the demand for distribution services are fixed, the distribution companies cannot readily increase their production of distribution services. This implies that there are too many small distribution companies in the Norwegian electricity industry and it would be expedient if the smallest companies would merge. Our results also suggest that RTS is increasing over time, implying that it is getting more and more expedient, from a cost minimization point of view, to increase outputs for the smallest distribution companies. There might be several reasons for RTS to increase over time. One explanation supported by our results is that some of the companies in the industry experience positive technical change, while others do not. An interesting question to address for future research would be to find out which firms in the industry that experience technical change, and if there are differences between firm size.

The electricity industry plays an important part in the economy, not only in Norway but in most countries. This naturally leads to political debate. We believe that this paper brings useful knowledge when political strategy and visions within the electricity industry are being compiled in the future.

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Appendix

Table A1. Descriptive statistics and Shapiro-Wilk test for normal distribution

	Descriptive statistics		Shapiro-Wilk test, H_0: normal distribution	
Variable	**Skewness**	**Kurtosis**	**z**	**p-value**
TOTEX	5.158	37.278	16.195	0.000
ln(TOTEX)	0.841	3.835	9.958	0.000

Notes: Skewness and kurtosis indicates that our dependent variable (TOTEX) and ln(TOTEX) are not normally distributed. This is supported by the Shapiro-Wilk test which rejects the null-hypothesis of normal distribution in both TOTEX and ln(TOTEX).

Table A2. Evolution of Total costs (all prices are in 2010 Norwegian Kroner)

	Year	**Mean**	**St. Dev**	**Min**	**Median**	**Max**	**CPI**
Total costs, 1,000 NOK (2010)	2000	61,381	94,795	5,682	28,335	665,174	1.617
	2001	75,068	137,870	5,831	27,469	840,839	1.523
	2002	75,494	134,700	3,070	28,483	859,966	1.445
	2003	73,841	129,683	2,559	29,670	857,095	1.373
	2004	88,041	189,225	2,491	30,980	1,656,051	1.314
	2005	85,317	176,397	2,695	30,215	1,436,703	1.261
	2006	90,766	187,983	2,399	31,316	1,523,005	1.204
	2007	90,028	189,119	2,691	32,995	1,620,911	1.148
	2008	96,627	202,989	2,807	33,707	1,716,352	1.088
	2009	95,726	197,202	3,066	37,414	1,748,090	1.042
	2010	97,069	195,365	3,059	35,365	1,637,310	1.000
	2011	108,389	214,386	3,306	40,438	1,660,168	0.964
	2012	98,326	187,757	3,162	37,881	1,614,091	0.934
	2013	107,435	207,284	3,447	41,636	1,634,736	0.903

Notes: The consumer price index (CPI) is retrieved from Statistics Norway, Table 03363-*Other services with wages as dominating price factor*. http://www.ssb.no/en

Table A3. Wald likelihood-ratio test

Wald likelihood-ratio test, Cobb-Douglas v.s. Translog function.		
F	**DF**	**P**
24.75	7	0.000

Table A4. Results quantile estimation, cost elasticities for *network length* (N)

QUANTILES	Median	Mean	Std.error (Delta-method)	p-value (Delta-method)	95% Conf. Interval (Delta-method)	
0.05	0.329	0.324	0.025	0.000	0.275	0.373
0.10	0.359	0.354	0.016	0.000	0.323	0.385
0.15	0.359	0.353	0.014	0.000	0.327	0.380
0.20	0.378	0.371	0.018	0.000	0.336	0.407
0.25	0.375	0.369	0.022	0.000	0.326	0.413
0.30	0.373	0.369	0.031	0.000	0.307	0.430
0.35	0.393	0.391	0.033	0.000	0.326	0.456
0.40	0.406	0.405	0.037	0.000	0.331	0.448
0.45	0.410	0.410	0.040	0.000	0.331	0.489
0.50	0.415	0.415	0.037	0.000	0.342	0.488
0.55	0.402	0.402	0.031	0.000	0.342	0.426
0.60	0.415	0.416	0.033	0.000	0.351	0.480
0.65	0.411	0.412	0.032	0.000	0.350	0.474
0.70	0.409	0.410	0.029	0.000	0.353	0.467
0.75	0.419	0.422	0.027	0.000	0.370	0.474
0.80	0.430	0.434	0.024	0.000	0.388	0.480
0.85	0.436	0.440	0.029	0.000	0.384	0.496
0.90	0.410	0.415	0.032	0.000	0.353	0.477
0.95	0.368	0.378	0.025	0.000	0.329	0.426

Notes: The Delta-method is a method for deriving the variance of a function of asymptotically normal random variable with known variance using a Taylor series expansion, see https://cran.r-project.org/web/packages/modmarg/vignettes/delta-method.html#fn7 for more details.

Table A5. Results quantile estimation, cost elasticities *number of customers* (Q)

QUANTILES	Median	Mean	Std.error (Delta-method)	p-value (Delta-method)	95% Conf. Interval (Delta-method)	
0.05	0.571	0.582	0.061	0.000	0.725	0.965
0.10	0.556	0.566	0.060	0.000	0.738	0.972
0.15	0.553	0.562	0.063	0.000	0.736	0.984
0.20	0.539	0.547	0.074	0.000	0.710	1.000
0.25	0.542	0.548	0.077	0.000	0.654	0.957
0.30	0.543	0.547	0.070	0.000	0.653	0.927
0.35	0.526	0.527	0.080	0.000	0.564	0.880
0.40	0.516	0.516	0.074	0.000	0.547	0.837
0.45	0.516	0.516	0.071	0.000	0.461	0.738
0.50	0.514	0.515	0.081	0.000	0.409	0.726
0.55	0.525	0.525	0.068	0.000	0.392	0.657
0.60	0.515	0.515	0.076	0.000	0.328	0.626
0.65	0.517	0.516	0.078	0.000	0.248	0.555
0.70	0.520	0.519	0.069	0.000	0.230	0.501
0.75	0.511	0.510	0.072	0.000	0.171	0.455
0.80	0.501	0.500	0.079	0.001	0.108	0.417
0.85	0.503	0.500	0.071	0.001	0.097	0.374
0.90	0.527	0.526	0.074	0.003	0.077	0.368
0.95	0.568	0.564	0.098	0.016	0.045	0.428

Table A6. Return to scale (RTS) across quantiles

QUANTILES	Median	Mean	Std.error (Delta-method)	p-value (Delta-method)	95% Conf. Interval (Delta-method)	
0.05	1.110	1.104	0.018	0.000	1.070	1.142
0.10	1.092	1.087	0.007	0.000	1.074	1.102
0.15	1.097	1.092	0.008	0.000	1.078	1.108
0.20	1.091	1.089	0.008	0.000	1.075	1.106
0.25	1.091	1.090	0.010	0.000	1.071	1.111
0.30	1.092	1.093	0.011	0.000	1.071	1.116
0.35	1.088	1.089	0.009	0.000	1.071	1.108
0.40	1.084	1.086	0.008	0.000	1.071	1.104
0.45	1.081	1.080	0.008	0.000	1.065	1.097
0.50	1.076	1.076	0.009	0.000	1.059	1.094
0.55	1.079	1.079	0.008	0.000	1.063	1.096
0.60	1.075	1.074	0.008	0.000	1.059	1.090
0.65	1.077	1.077	0.008	0.000	1.062	1.094
0.70	1.076	1.077	0.007	0.000	1.063	1.092
0.75	1.076	1.072	0.008	0.000	1.057	1.090
0.80	1.075	1.070	0.009	0.000	1.054	1.088
0.85	1.065	1.063	0.010	0.000	1.044	1.085
0.90	1.067	1.062	0.010	0.000	1.043	1.083
0.95	1.068	1.062	0.009	0.000	1.045	1.082

Table A7. Cost elasticities, returns to scale and technical change for alternative models

Model	**Fixed effect[1]**		**True FE SFA[2]**		**Finite mixture model[3]**			
Class					1. class		2. class	
	Mean	Std. error	Mean	Std. error	Mean	Std. error.	Mean	Std. error.
Cost elasticity:								
Length of network	0.33	0.05	0.38	0.16	0.32	0.02	0.31	0.02
Number of customers	0.46	0.05	0.54	0.16	0.45	0.02	0.57	0.02
Returns to scale (RTS)	1.28	0.10	1.09	0.22	1.34	0.03	1.15	0.01
Technical change (TC)	0.003	0.002	-0.001	0.005	0.006	0.003	-0.005	0.003

Notes:

[1] Fixed effect panel data estimator

[2] True fixed effect stochastic frontier panel data estimator by Greene (2005)

[3] Finite mixture model, or latent class model (McLachlan and Peel, 2000). Total costs (TOTEX) is use as independent variable for class probabilities. The average total cost for sample “1. class” is NOK 21,080,000, while it for “2. class” is NOK 165,163,000.

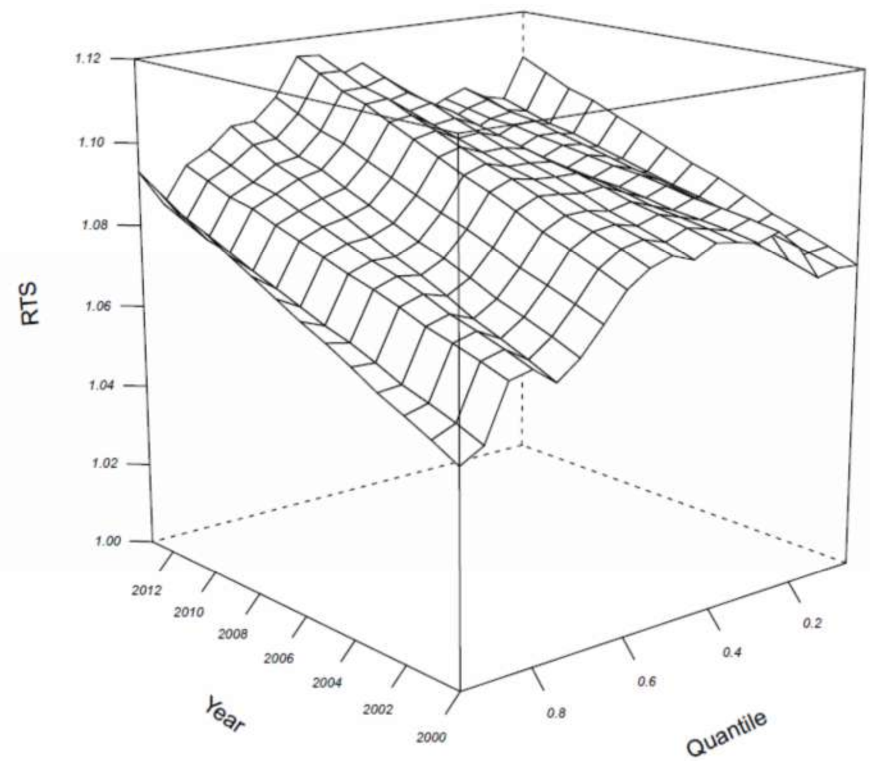

Fig. A1. Returns to scale (RTS) across quantiles and over time. Balanced panel data. Number of observations reduces from 1 750 to 1 414.

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