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Incentives for Optimal Scale in the Regulation of Electricity Distribution Companies

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Abstract

Electricity distribution companies are natural monopolies and need to be regulated to protect customers from the abuse of monopoly power. In Norway, the recent regulation model applied by the Norwegian Water Resources and Energy Directorate is a combination of revenue cap and yardstick regulation. Constant returns to scale (CRS) is assumed to give incentives for optimal scale.

In this paper, we investigate the implications of six scale assumptions in the benchmarking models, including Koopmans frontier, which has not been used in regulation contexts before.

An empirical analysis of the Norwegian network companies shows customers are under limited protection when the convexity assumption is relaxed. Efficiency differences under different scale assumptions are considerable, especially for small and large companies. Inefficient small companies do not receive incentives to expand under specific scaling assumptions. Some larger companies have reference sets under CRS dominated by relatively small companies, which is less prevalent under Koopmans. By studying the case of Hafslund we find the Koopmans technology to be more practical than all the other scale assumptions if merging is conducted. The effects on company profitability and customer prices show that compared to CRS, some assumptions are in favor of small companies and they may keep more revenue, leading to the monopoly power abuse on their customers and limited incentives are given in the setting of restructuring company scales.

Keywords: electricity distribution companies; data envelopment analysis; benchmarking; scale assumption; Koopmans frontier; yardstick regulation

1 Introduction

Natural monopolies, e.g., electricity distribution companies, need to be regulated in order to prevent the abuse of market power. Various regulation approaches have been applied, from rate-of-return regulation, with weak efficiency incentives, to incentive-based regulation schemes, like yardstick regulation (Shleifer, 1985). The responsibility for implementing the regulation is typically delegated to an independent entity. This entity has less information compared to the regulated companies about their cost structures, and it typically uses some specific type of benchmarking method, like data envelopment analysis (DEA) or stochastic frontier analysis (SFA), to estimate efficient costs. By this means, even though the regulator does not have the information about the companies' efficient cost level, the regulation scheme still provides the companies with incentives to reduce costs.

Different assumptions of the benchmarking model, among which scale assumptions, lead to the movement of the frontier and will influence the incentives for the companies. In the case of Norwegian electricity distribution companies, the regulator has chosen constant returns to scale (CRS) in their DEA model in order to give the companies incentives to operate at the optimal scale (The Norwegian Water Resources and Energy Directorate, 2006), and Saastamoinen et al., (2017) point out that the estimator choice and returns to scale assumption have considerable effect on merger incentives. In this paper, we investigate the effects of the DEA scale assumption in the regulation of Norwegian electricity distribution companies. We study how the scale assumptions made by the regulator will affect the incentives for optimal scale for the regulated companies, as well as the effect on customer prices. Some scale assumptions will lead to considerable super efficiency, which may give incentive for excessive pricing by the companies.

The remainder of this paper is structured as follows: Section 2 presents previous literature on incentive regulation, assumptions of frontier models, and different types of frontier models. Section 3 describes the methodological framework. Section 4 gives a brief introduction of the regulation regime in Norway and presents the data structure and variables. Section 5 discusses empirical results, and Section 6 concludes.

2 Literature review

As an important regulatory tool, incentive regulation is widely applied in public utilities. The utility generally has better information about its cost structure and operating environment than the regulator does, known as the situation of asymmetric information (Bogetoft & Otto, 2011) , which exposes the regulator to either moral hazard or adverse selection problem or both (Armstrong & Sappington, 2007; Laffont & Tirole, 1993). It is therefore the regulator's task, which is difficult and subtle, to induce the utility to employ its superior information in the broader social interest (Armstrong & Sappington, 2007). The advantage of incentive regulations over non-incentive regulations is that the former reduces the influence of asymmetric cost structure information between

utilities and regulators, and decreases the tendency to over-invest in capital, known as the Averch–Johnson effect (Averch & Johnson, 1962), thereby avoids 'gold plating' for the utility and cross-subsidize from the regulator. Fixed price/revenue regime as one of the mostly applied incentive regulation strategy involves a predicted productivity development per year as the general requirement on the utility, plus individual requirements which reflect the level of historical costs and the need to catch up with the best practice. More precisely, the revenue caps shall cover costs and depreciations and give a reasonable return on invested capital over time, given efficient operation, utilization and development of the utility (Amundsveen & Kvile, 2016). Yardstick "competition" is a powerful tool for reducing informational asymmetries. The regulator compares the company's performance to that of other companies facing a similar technological environment, by which the regulator receives as much information of the company as possible (Laffont & Tirole, 1993). The yardstick competition model can be implemented as price cap or revenue cap, meaning that fixed price/revenue regimes generally involve some systematic benchmarking approach to guide the choice of individual requirements and the general requirement; such systematic benchmarking approach is often based on non-parametric approaches as DEA or parametric approaches as SFA.

When applying the benchmarking model, the real technology T is substituted by estimating the empirical reference technology T^* according to the minimal extrapolation principle. Combinations of different assumptions on technology T construct different DEA models. There are basically four categories of assumptions: scaling, monotonicity, convexity, and replicability (Bogetoft & Otto, 2011).
Among these assumptions, the scale assumption can be described either qualitatively[1] or quantitatively[2]. Introduced by Charnes, Cooper, and Rhodes (1978), the first DEA model was constructed under the CRS scale assumption. Since then various types of DEA models have gradually been constructed, among which the DEA model under variable returns to scale (VRS) assumption by Banker, Charnes and Cooper in 1984. The efficiency scores obtained from the VRS-DEA model are always higher than those from the CRS-DEA model.

The investigation of optimal scale of enterprises is of interest for regulators and policy makers, and we find examples of such research for various industries, both in the public and private sectors, in many countries. Different voices appear when it comes to the impact of scale economics on firms' performance. Hirschhausen et al. (2006) apply SFA and CRS-DEA models to assess the efficiency of electricity distribution companies in Germany and their results suggest that returns to scale play a minor role, and only very small utilities have a significant cost advantage. On the contrary,

[1] Qualitative descriptions are non-decreasing (NDRS) (or increasing (IRS)), non-increasing (NIRS) (or decreasing (DRS)), constant (CRS), and variable (VRS).

[2] Scale assumptions can be interpreted as scale elasticity in Førsund and Hjalmarsson (2004), where scale elasticities are quantitatively ranged. They show that scale elasticity affects the firm's maximal profit directly. In their 2007 paper, they have also presented both an indirect and a direct approach of obtaining partial derivatives for estimating quantitative scale elasticities.

Filippini et al. (2004) apply a SFA model and prove the presence of increasing returns to scale for Slovenian electricity distribution utilities with most utilities not achieving the minimum efficient scale, and thus suggest the Slovenian regulatory authority induce mergers of small electricity distribution utilities into larger units. Kumbhakar et al. (2015) find empirical evidence of economies of scale and technical progress in Norwegian electricity distribution industry, showing that the potential for economies of scale is greater among small firms. Thereby they suggest merging between firms, which may reduce tariffs for consumers. Similar finding is also made by Mydland et al. (2018) and Mydland (2020) where economies of scale is observed for Norwegian electricity distribution companies and they suggest that the smallest companies increase their outputs, and it would be expedient if they could merge.

Scale economics is also widely studied in merger analysis. Kwoka (2005) find significant economies in US electricity utilities with low output levels, holding system size and customer density constant, but the benefits of mergers between distribution systems are not yet confirmed. Bogetoft and Wang (2005) introduce production economic models to estimate potential merger gains and they decompose the merger gains into technical efficiency gains, size/scale gains, and harmony/scope gains. The application to the mergers of the Danish agricultural extension service offices shows negative size effects on most of the mergers but one merger of rather small offices; however the total merger gains may still be significant. Kristensen et al. (2010) estimate the potential cost savings from the planned hospital mergers in Denmark by applying Bogetoft and Wang's model. Their results suggest that the expected "best practice" hospitals are efficient, and some large mergers experience dis-economies of scale thus do not lower costs. There are however mergers that lead to considerable cost reductions with potential gains resulting from improving technical efficiency and exploitation of economies of scope. Çelen et al. (2013) employ SFA method and show the mergers between Turkish electricity distribution utilities has increased their efficiencies, and the restructuring activities may lead to the presence of increasing returns to scale in the industry. Agrell et al. (2015) apply Bogetoft and Wang's (2005) model to Norwegian electricity distribution system operators (DSOs) and their results show that mid-size DSOs adjacent to urban or semi-urban DSOs seem actually to be the merger targets in Norway instead of the smallest ones. Low scale and scope effects are observed and the DSOs tend to persue organizational technical efficiency gains rather than radical restructuring of their operations. They in addition support the CRS-DEA model introduce by the Norwegian regulator in 2007 as in their opinion the previous VRS assumption leads to diluted merger incentives. Saastamoinen et al., (2017) explore the effect of varying assumptions (CRS and VRS) under DEA and StoNED/StoNEZD frontier estimators on merger gains of Norwegian distribution industry. They find that the restructuring policies of the industry may be significantly altered depending on how potential gains from the mergers are estimated.

In this paper, we aim at finding out how scale assumptions made by the regulator can affect the performance of natural monopolies such as electricity distribution companies and how natural monopolies can be incentivized to operate at optimal scales.

3 Methodology

In this section we describe the methodology framework. The input-oriented DEA frontier estimator under various scaling assumptions is applied because the outputs of the electricity distribution companies are exogenous and the companies minimize their inputs which are the total costs instead of maximizing their outputs (Saastamoinen et al., 2017).

3.1 Revenue cap regulation

A revenue cap regulation is established to regulate the network companies from gaining excessive monopoly profits and to give them incentives for efficient operating and investment decisions. A cap on annual revenues is set up, covering the total costs, including operation and maintenance costs, depreciation, and an allowed amount of investment return for each individual firm being regulated. In the revenue cap regulation, the aim of the regulator is to limit the total revenue received by each firm by setting prices equal to their average costs. Because of asymmetric information and lack of incentives for regulated firms to reveal their cost structures, the efficient costs are unknown to the regulator, which creates problems for the regulator when deciding the cost norms C^*. Since efficiency analyses are combined with the regulation model to estimate C^*, it indicates that the preciseness of the efficiency scores has a direct influence on the cost norms, and further on, the revenue caps. The revenue cap regulation combining the yardstick analysis can be written as follows:

$$R_{cap} = \rho C^* + (1 - \rho)C \qquad (1)$$

where C^* denotes the cost norm (optimal cost) and C denotes the actual cost of each company. $\rho \in [0,1]$ and it denotes the proportion of the revenue caps that should be strengthened to the cost norm.

3.2 DEA models and scale assumptions

In the DEA approach, the technology is estimated by applying linear optimization on the actual production activities using historical data. Although the true technology T is rarely known, its empirical reference technology can be approximated by using the minimal extrapolation principle, which is the main concept of DEA. By enveloping the data, the minimal extrapolation principle provides the smallest technology set that satisfies a number of postulates. The approximate technology set is the smallest set that contains actual observations, which can be treated as a subset of the true technology[3]. Various DEA models can be created by combining the following assumptions:

[3] However, the approximate production set using the DEA estimation will not necessarily be contained in the true technology set if there exists measurement error in the data.

1. Monotonicity[4]: Free disposability of inputs and outputs, indicating more inputs can be used to produce fewer outputs.
2. Scaling: It is possible to scale production plans with any factor that is in a given set.
3. Convexity: Any combination of the weighted average of feasible production plans is also feasible.
4. Replicability: The sum of two feasible production plans is also feasible.

3.2.1 Constant returns to scale (CRS)

The first DEA model was introduced by Charnes, Cooper, and Rhodes (1978), also called the CCR model, and it is conducted under the CRS assumption. The efficiency of each decision-making unit (DMU) is obtained by aggregating its technical efficiency and scale efficiency. The efficiency scores are estimated with respect to the other DMUs in the whole set, thus relative values are obtained. An input-oriented DEA model under the CRS assumption has the following form:

$$\hat{\theta}_{j_0}^{CRS} = min_{\lambda,\theta}\theta \quad (2)$$

s.t.

$$\theta x_{ij0} \geq \sum_{j=1}^{n} \lambda_j x_{ij} \qquad \forall i = 1, \dots, m \quad (3)$$

$$y_{rj0} \leq \sum_{j=1}^{n} \lambda_j y_{rj} \qquad \forall r = 1, \dots, s \quad (4)$$

$$\lambda_j \geq 0 \qquad \forall j = 1, \dots, n \quad (5)$$

where θ is the estimated efficiency score of the DMU being evaluated, which uses m inputs to produce s outputs. x_{ij0}, y_{rj0} are known inputs and outputs of the DMU being evaluated. x_{ij}, y_{rj} are known inputs and outputs of the j^{th} DMU. As a linear program, the DEA model attempts to estimate efficiency scores by minimizing efficiency (equation $\theta j_0 CRS = min_{\lambda,\theta}\theta$ (2) subject to the constraints (3) and (4). The input constraint (3) indicates that the inputs of the evaluated DMU should be larger than or equal to the sum of the weighted inputs of all the other DMUs. The output constraint (4) indicates that the outputs of the evaluated DMU should be less than or equal to the sum of the weighted outputs of other DMUs. In constraint (5), λ_j is the weight connected to each DMU and is presented in the reference sets for the evaluated DMU.

[4] For the production frontier, monotonicity can be viewed as a first-order curvature condition, convexity as a second-order curvature condition, while the scale assumption can be considered as homogeneity conditions (Kuosmanen, 2011).

3.2.2 Variable returns to scale (VRS) and alternatives

Another type of DEA model, the BCC model, was introduced by Banker, Charnes and Cooper in 1984 and allows for variable returns to scale (VRS). The most important difference between the CRS and VRS assumptions is that there is an additional constraint introduced together with the VRS assumption, namely the sum of lambda (λ_j) equals 1, which ensures that the reference set is convex. The mathematical form of the DEA model under the VRS assumption is written as follows:

$$\hat{\theta}_{j_0}^{VRS} = min_{\lambda,\theta}\theta \qquad (6)$$

Subject to constraints (3), (4), (5) and

$$\sum_j \lambda_j = 1 \qquad \forall j = 1, \dots, n \qquad (7)$$

Since adding a restriction will cause the estimated efficiency score to increase or stay the same, the resulting efficiency of the DEA model under the VRS assumption is always at least equal to that under the CRS assumption. The returns to scale assumption is connected to re-scaling situations, which are presented by the different λ_j values. $\lambda_j \geq 0$ in CRS is the strongest assumption on the scaling possibility, while the weakest assumption on scaling is $\sum_j \lambda_j = 1$ as in VRS. For NIRS the constraint on λ_j becomes the following:

$$\sum_j \lambda_j \leq 1 \qquad \forall j = 1, \dots, n \qquad (8)$$

Constraint (8) means that it is possible for a DMU to be scaled down instead of scaled up. Also the NIRS assumption indicates that a DMU operated at a large scale might have disadvantages compared to a small scale (Bogetoft & Otto, 2011).

The NDRS assumption has the constraint on λ_j opposite to the NIRS assumption, as follows:

$$\sum_j \lambda_j \geq 1 \qquad \forall j = 1, \dots, n \qquad (9)$$

Under the NDRS (or IRS) assumption a DMU might have disadvantages when operated at a small scale compared to a large scale. Thus, it is possible for it to be scaled up rather than scaled down.

3.2.3 Koopmans frontier

Introduced by Koopmans in 1977, the Koopmans technology can be considered as a type of NIRS technology regarding the scaling assumption; it includes the sum of the observed points and their convex combinations. However, in Koopmans (1977), the strong disposability of inputs is not imposed (Grosskopf, 1986). The Koopmans technology can be obtained from CRS by combining constraint (5) and part of constraint (8), which is written as follows:

$$0 \leq \lambda_j \leq 1 \qquad j = 1, \dots, n \qquad (10)$$

Namely, the mathematical form of Koopmans model consists of an objective function, as follows:

$$\hat{\theta}_{j_0}^{Koopmans} = min_{\lambda,\theta}\theta \quad (11)$$

Subject to constraints (3), (4), and (10).

The advantage of Koopmans frontier over the CRS and VRS assumptions is explained in Figure 1. Compared to CRS and VRS, Koopmans frontier focuses on aggregating production relations, meaning that the aggregation of several parts of production plans is allowed, but without repeated aggregation.

A vital and unique trait that separates the Koopmans frontier assumption from the other scale assumptions is that a DMU can possibly be its own peer company though it is not fully efficient. We come back to this point in section 5.2 and 5.3. When merging is considered, Koopmans frontier indicates that the companies will be merged in a descending order of productivity gained by output(y)/input(x) (Grosskopf, 1986). As shown in Figure 1 Comparing the CRS, Koopmans, and VRS , suppose there are seven companies, labelled A to G, in the industry, the productivity of the companies is ranked as $B > E > D > C > H > A > G > F$, thus the Koopmans frontier is constructed by merging the companies in their descending order of productivity. In this concept, the Koopmans frontier assumption is less sensitive to the error reporting of the companies, especially small ones. This characteristic also implies that Koopmans frontier might provide companies with better incentives to operate at an optimal scale than the VRS assumption would. In addition, for the large companies, the Koopmans frontier might be a more practical or gentler benchmarking assumption compared to the CRS assumption considering merging, given that Koopmans frontier only estimates the mergers that are the combinations of the existed companies, while under the CRS assumption the companies may be scaled up or down, and thus the estimation might not be based on the actual data set.

The estimated results by Koopmans model are normally larger than $\hat{\theta}_{j_0}^{CRS}$ and smaller than $\hat{\theta}_{j_0}^{VRS}$, i.e. $\hat{\theta}_{j_0}^{CRS} \leq \hat{\theta}_{j_0}^{Koopmans} \leq \hat{\theta}_{j_0}^{VRS}$.

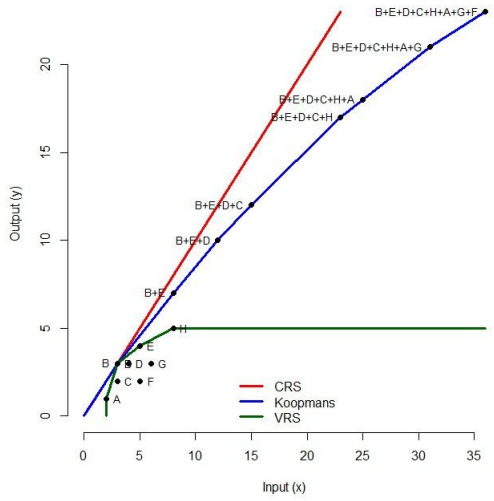


Figure 1 Comparing the CRS, Koopmans, and VRS frontiers

3.2.4 Free disposal hull (FDH)

Introduced by Deprins et al. (1984) and Tulkens (1993), the FDH model relaxes the convexity assumption adopted by DEA models under CRS or VRS assumptions. By relaxing convexity, when an input and output pair is in a production possibility set, then any pair of more input and less output for the specific pair is also in the production possibility set, indicating free disposability. The FDH model measures the efficiency of a DMU against an actually observed performance rather than against a 'synthetic' DMU obtained as a linear/convex combination of a number of efficient DMUs (Green & Cook, 2004). The FDH model is, however, an underused estimation model, as Green and Cook (2004) note. The FDH model has the following form:

$$\hat{\theta}_{j_0}^{FDH} = min_{\lambda,\theta}\theta \qquad (12)$$

Subject to constraints (3), (4), (5), (7), and (8)
And

$$\lambda_j \in Z \quad \forall j = 1, \dots, n \qquad (13)$$

The integer constraint above together with constraints (5), (7), and (8) indicate that in the FDH model, λ_j should be binary, meaning they can only take values of zero or unity. This binary constraint is further expressed as follows:

$$\lambda_j \in \{0,1\} \quad \forall j = 1, \dots, n \qquad (14)$$

The FDH model is then equation (12) constrained by (3), (4), and (13). The relationship between the efficiency scores estimated by the FDH model and the previous three

models is as follows: $\hat{\theta}_{j_0}^{CRS} \leq \hat{\theta}_{j_0}^{Koopmans} \leq \hat{\theta}_{j_0}^{VRS} \leq \hat{\theta}_{j_0}^{FDH}$. A comparison of the six model constraints is listed in Table 1.

Table 1 Common and specific constraints of the six model assumptions

Model assumption	Specific constraints	General constraints
CRS	$\sum_j \lambda_j$ free	$\theta x_{ij0} \geq \sum_{j=1}^{n} \lambda_j x_{ij} \quad \forall i = 1, \dots, m$
VRS	$\sum_j \lambda_j = 1$	
NIRS	$\sum_j \lambda_j \leq 1$	$y_{rj0} \leq \sum_{j=1}^{n} \lambda_j y_{rj} \quad \forall r = 1, \dots, s$
NDRS	$\sum_j \lambda_j \geq 1$	
Koopmans	$\lambda_j \leq 1$	$\lambda_j \geq 0 \quad \forall j = 1, \dots, n$
FDH	$\lambda_j \in \{0,1\}$; $\sum_j \lambda_j = 1$	

4 Data

Norway has a relatively well-developed regulation model and rich experience in incentive regulation of electricity distribution companies ever since the Energy Act took effect in January 1, 1991. We apply data set of 115 Norwegian network companies that have constantly been under the regulation of NVE during the period from 2011 to 2015 to test six types of frontier models under different scale assumptions: CRS-DEA, Koopmans frontier, NDRS-DEA, NIRS-DEA, VRS-DEA, and FDH.

The data analyzed in this paper are the average data as estimation errors and exogenous cost shocks can be reduced. Additionally, NVE has used average data in their estimation aiming to remove noise from the data and allow firms to appear as super-efficient relative to their own historical performance (Amundsveen & Kvile, 2015; Bjørndal, Bjørndal, Cullmann, & Nieswand, 2018). We first give an overview of the latest regulation regime in Norway before we introduce the data set and the variables applied in the different stages.

4.1 The revenue cap regulation in Norway

Electricity distribution companies in Norway are regulated by the Norwegian Water Resources and Energy Directorate (NVE) [5] with an incentive-based revenue cap combined with the yardstick regulation. The revenue cap regulation sets a limit on the amount of total revenue for each company based on cost observations from peer companies by using a frontier estimation, which is DEA under the CRS assumption.

Bjørndal et al. (2010) provide an overview of the DEA models used by NVE, among which a DEA model under the CRS assumption with one input and three outputs is used to estimate cost efficiency by minimizing the optimal total cost norm of the estimated DMU. This model has been used by NVE since 2007.

[5] The Norwegian Energy Regulatory Authority (NVE-RME) is the national regulatory authority for the electricity and natural gas markets in Norway.

From 1997 to 2006, NVE applied a DEA model under the VRS assumption in the regulation of Norwegian network companies to estimate cost efficiency where five input factors with corresponding factor prices were used (Bjørndal et al., 2010). Since 2007, not only have the inputs of the DEA model been changed from five to one, which is the total cost, but the VRS assumption was also changed to the CRS assumption. The VRS-DEA model applied by NVE from 1997 to 2006 is composed of objective function (6) and constraints (3), (4), (5), and (7). In the report 'Model for Determining the Cost Norm' by NVE in 2006, DEA models under the CRS and VRS assumptions are compared. Several disadvantages of the VRS-DEA model are listed, including that the largest company automatically becomes efficient and the efficiencies of the extremely small companies can be overestimated when the VRS assumption is applied. These disadvantages can, however, be overcome by applying the CRS assumption. Regarding merging, it is the network company owners that make decisions on the scales of their companies and whether the merging process should be implemented. If an owner's decision leads to the use of more company resource, then she cannot expect to receive the same amount of return as those who make opposite decisions. In this context, the CRS assumption provides a better incentive than the VRS does. In addition, the choice of the CRS assumption implies that the additional costs caused by the merging process will mostly be covered by the company owners instead of falling on the customers. Thus, NVE assumes CRS instead of VRS because CRS gives incentives to change the scale of the firm to the optimal size.

In 2007, the yardstick regulation regime was introduced to Norway, when NVE started to establish annual revenue caps for individual network companies aiming at giving incentives for new investments. In this yardstick regulation model, the revenue caps are based on a combination of cost norms and actual cost. Revenue caps are estimated by using the formula introduced in 3.1, as follows:

$$R_{cap} = \rho C^* + (1 - \rho) C \qquad (15)$$

where C^* denotes the cost norm (optimal cost), C denotes the actual cost of each company[6] and ρ indicates the proportion of the revenue caps that should be strengthened to the cost norm. $\rho \in [0,1]$ and it has increased from 0.5 (for 2007 and 2008) to 0.6 (from 2009) (Bjørndal et al., 2010).

To ensure the full-information outcome as the unique symmetric Nash equilibrium among the monopolists, the regulator sets price of each company equal to the average of the marginal cost C^* of the other companies (Armstrong & Sappington, 2007). It is thus crucial for the regulator to approximate C^* as precisely as possible considering the various factors that may affect C^*, among which exogenous factors, such as operating

[6] For a detailed description of the estimation of the actual cost, see NVE's website (in Norwegian): https://www.nve.no/reguleringsmyndigheten-for-energi-rme-marked-ogmonopol/okonomisk-regulering-av-nettselskap/reguleringsmodellen/

environment for distribution companies. Exogenous factors cause heterogeneity in terms of technology, and hence, efficient costs (Bjørndal et al., 2018). [7,8]

The cost norm C^* is estimated by a three-stage method. In stage 1, the efficiency score of each company is estimated by using a DEA model with one input and three outputs. In stage 2, a linear regression is applied, where the efficiency result from stage 1 is implemented as the dependent variable and five geographical variables (Z-variables) are used as the independent variables. The (uncalibrated) revenue caps are acquired in stage 2 using formula (15). NVE calibrates the revenue caps in stage 3 by adding an extra amount of cost to the efficient cost of each company to ensure that total revenue equals the total cost of the whole industry. The higher efficiency score a company obtains over the average, the more revenue the company will earn than the regulated rate of return; similarly, companies that obtain lower efficiency scores than the average earn less revenue than the regulated rate of return (Bjørndal et al., 2018). The revenue cap formula (15) has now become the following:

$$R_{cap} = \rho(C^* + \Delta) + (1 - \rho)C \qquad (16)$$

where C^* is the optimal cost by multiplying the actual cost and the calibrated efficiency score at stage 3. Δ is the amount that is added to the efficient cost of each network company.[9]

4.2 Data and variables

Table 2 shows the major statistical characteristics of the data set analyzed in this paper. The mean of number of customers[10] (25211) is much larger than the median (7020), indicating that the data are right-skewed and the majority of the companies represented in the data are small ones.

[7] DEA and StoNED models with and without environmental variables are applied to 123 Norwegian electricity distribution companies during 2004-2010 respectively in Cheng et al. (2014) with the conclusion that environmental variables have an essential impact on the performance. Bjørndal et al. (2018) demonstrate that regulators fail to implement efficient cost levels and revenue caps by not properly accounting for exogenous firm characteristics.

[8] There are however different voices in the effect of contextual factors. Yu et al. (2009) give the conclusion that weather factors (gale, hail, temperatures, rainfall and thunder) do not have a significant economic and statistical effect on the cost and service performance of electricity distribution networks in the UK, after conducting factor analysis and two-stage DEA analysis.

[9] In the three-stage estimation used by NVE, the estimated efficiency scores from stage 1 are included in a linear regression in stage 2 as the dependent variable and there are five geographical variables as independent variables, which are described in Table 3. An important feature of this stage is that the independent variables are the difference in the environmental variable for the network company itself and its target unit Amundsveen et al. (2014). At stage 3, the efficiency scores are calibrated to ensure that the representative company earns the normal rate of return. The capital-weighted calibration also, to an extent, corrects for the age bias caused by using book values as the basis for the capital costs, which ensures that the averagely efficient company receives a return equal to the reference rate of return (Bjørndal et al., 2010).

[10] We have calculated the arithmetic mean of the number of customers.

Table 2 Descriptive statistics of the data set

Variable	Min.	Mean	Max.	Median	St.dev.
Total cost (1000 NOK)	10665	117536	2074638	45284	243466
Customers	1032	25211	672619	7020	71479
HV lines (KM)	58	870	11478	338	1551
Network Stations	60	1097	17702	384	2237

NVE uses one input and three outputs in the DEA model in stage 1. The total cost, as the only input, is acquired by summing the (adjusted) operation and maintenance cost (*DV*), value of lost load (*VOLL* or *KILE* in Norwegian), depreciation, cost of transfer losses (losses multiplied by power price from NordPool) and return on book capital. The three outputs are the number of customers, length of high voltage lines, and number of network stations.

Considering the geographical environment is essential for a country such as Norway, which has long coastlines and various operation environments. In the regression model in stage 2, there are five geographical variables included, in which three geographical variables are composite variables. A description of the input and output variables is shown in Table 3.

Table 3 Variables included in stage 1 and stage 2

Variable name	Description	Unit	Stage
Total cost	Input variable, consists of 5 variables	1000 NOK	1
Customers	Output variable	Number of customers	1
High voltage lines	Output variable	KM	1
Network stations	Output variable	Number of stations	1
Under	Proportion of high voltage underground cables	Weighted measure	2
Forests	Proportion of overhead high voltage lines through coniferous forest	Weighted measure	2
Geo1	Composite variable: inclination, small hydro power, proportion of overhead high voltage lines through deciduous forest	Index	2
Geo2	Composite variable: wind/distance from coast, number of islands, sea cables/high voltage lines	Index	2
Geo3	Composite variable: snow, dark period, amount of ice, temperature	Index	2

5 Results and discussion

In this section, we report the estimated efficiency scores and the reference sets of both the whole industry and a specific network company, Hafslund Nett AS since it represents the largest[11] company in the industry.

5.1 Efficiency scores

The efficiency scores estimated in this section correspond to the efficiency results reported by NVE at stage 1. We apply the same procedure as NVE does. The statistical characteristics of the estimated efficiency scores are listed in Table 4. Table 5 shows the number of companies that are categorized by efficiency scores.

Table 4 The statistical characteristics of the estimated efficiency scores

Model	Min.	1.Qu.	Median	Mean	3.Qu	Max.
CRS	0.4410	0.6196	0.7086	0.7190	0.8202	1
VRS	0.4955	0.6720	0.7730	0.7728	0.8687	1
NIRS	0.4410	0.6238	0.7168	0.7277	0.8202	1
NDRS	0.4947	0.6669	0.7656	0.7642	0.8544	1
Koopmans	0.4410	0.6238	0.7086	0.7230	0.8202	1
FDH	0.5806	0.9075	1	0.9459	1	1

Table 5 Number of companies categorized by efficiency scores

Efficiency score	CRS	VRS	NIRS	NDRS	Koopmans	FDH
< 0.5	6	1	6	1	6	0
> 0.95	7	16	10	13	7	75
= 1	5	11	8	8	6	67

The six efficiency results (CRS results as the base) are combined in Figure 2.

For the same company, the estimated efficiency scores are highest under the FDH and the VRS assumptions. The restriction (7) on lambda together with the output restriction (4) indicate that when a company is largest with respect to an output, then it is its own reference and automatically becomes 100% efficient (Bjørndal et al., 2010), which is especially obvious in the FDH model when the convexity assumption is relaxed and λ_j becomes binary, i.e., λ_j can only take the value of 0 or 1. Therefore, the VRS-DEA model and the FDH model are considered to be improper benchmarking models for estimating cost norms since the companies can still hold their monopoly power when they are their own references. In this situation, few incentives can be given by applying the VRS-DEA or FDH model because they give customers limited protection against

[11] The input and outputs of Hafslund are the highest among all network companies in Norway.

the abuse of monopoly power. As mentioned in 4.1, the CRS assumption is assumed by NVE instead of VRS because CRS gives better incentives to the companies so that they are able to operate at an optimal size. In this paper, we will also study the scale incentives given by NIRS, NDRS, Koopmans and FDH. We have plotted the efficiency differences between CRS, VRS, and the other assumptions in Figure 3 and Figure 4. The FDH assumption is excluded since over half (75 out of 115 as shown in Table 5) of the network companies have efficiency scores higher than 0.95, and 67 companies are estimated as efficient. The efficiency scores are sorted according to the logarithm of the number of customers from low to high.

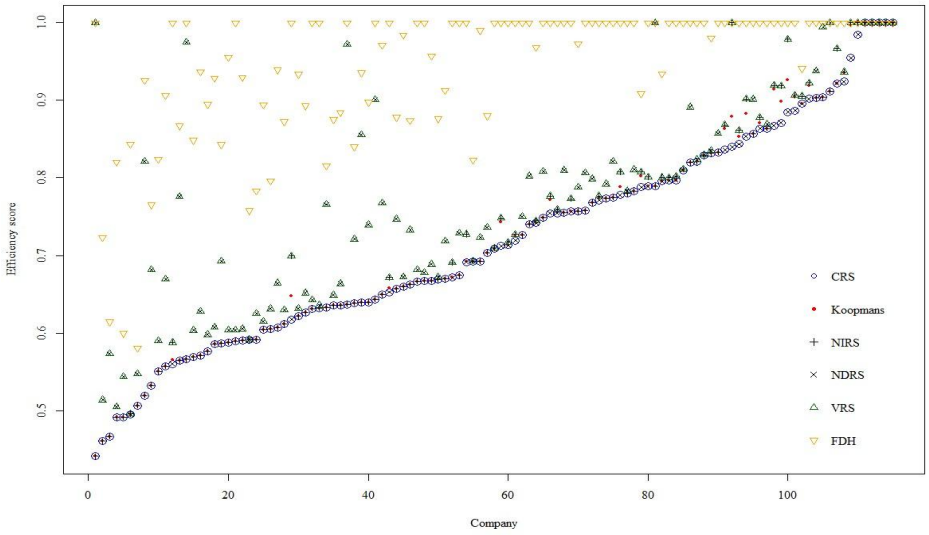


Figure 2 Estimated efficiency scores under six model assumptions

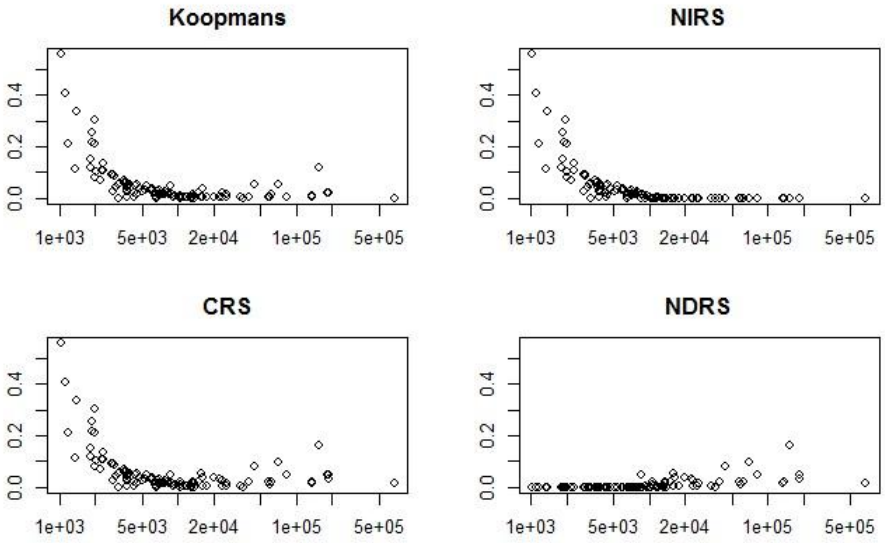


Figure 3 Estimated efficiency differences between VRS and four other assumptions (FDH excluded) $(\hat{\theta}_{j_0}^{VRS} - \hat{\theta}_{j_0}^{RTS})$

The patterns of the efficiency difference between Koopmans and VRS, CRS and VRS are similar. For network companies with fewer than 20,000 customers, there are similar efficiency differences between Koopmans, NIRS, CRS, and VRS and almost no efficiency difference between NDRS and VRS. For companies serving more than 20,000 customers, no efficiency difference is discovered between NIRS and VRS. Also the smaller a network company is, the higher efficiency difference is discovered between VRS and the other assumptions, excluding NDRS, which has an opposite pattern, indicating that under the Koopmans and CRS assumptions, both small and median companies (fewer than 20,000 customers) and large companies (over 30,000 customers except the largest company Hafslund) might receive 'punishments' on their cost norms because of obtaining lower efficiency scores. Under the NIRS assumption, it is the small companies that are least efficient, and under the NDRS, larger companies are less efficient. Such efficiency patterns indicate that compared to VRS, under the NIRS assumption, the network companies might have the incentive to operate at a larger scale because smaller companies obtain lower efficiency scores, while under NDRS, companies are encouraged to operate at a smaller scale.

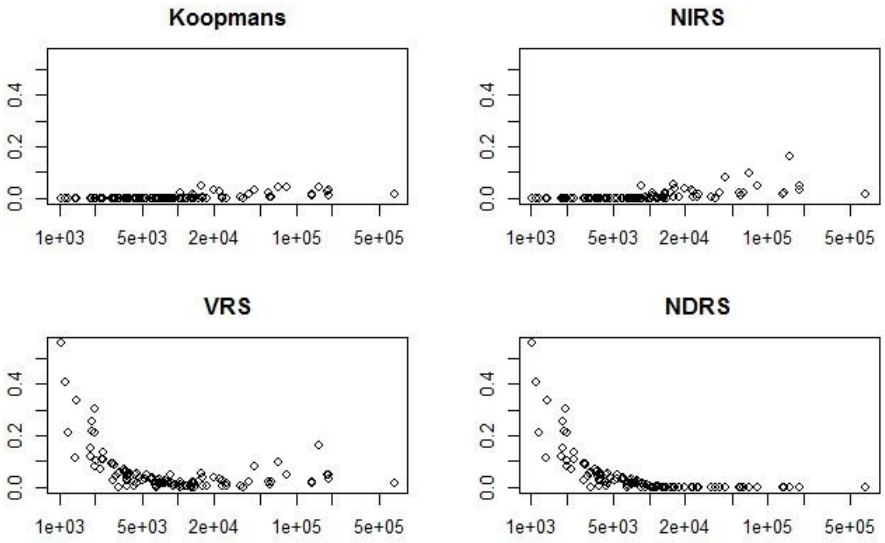


Figure 4 Estimated efficiency differences between CRS and four other assumptions (FDH excluded) ($\hat{\theta}_{j_0}^{RTS} - \hat{\theta}_{j_0}^{CRS}$)

Figure 4 shows that no efficiency difference exists between the CRS and Koopmans assumptions or the CRS and NIRS assumptions for network companies with fewer than 20,000 customers. Under VRS and NDRS compared to CRS, the fewer customers a company serves, the higher efficiency difference is found. Thus, smaller companies receive higher efficiency scores under the VRS and NDRS assumptions, which do not give them incentive to expand their scales. More specifically, under the VRS and NDRS assumptions, extremely small companies (fewer than 5,000 customers) obtain the highest efficiency scores; for companies with fewer than 20,000 customers, the smaller a company is, the higher efficiency score it obtains compared to the CRS assumption. For companies serving 20,000 to 100,000 customers, the efficiency scores under the VRS and NIRS assumptions tend to be higher than those under the CRS assumption. Thus, under VRS and NIRS, the large companies do not have the incentives to operate at a smaller scale.

To conclude, companies that serve 20,000 or fewer customers receive limited incentives from the VRS and NDRS assumptions to expand their scales. Meanwhile, for companies serving more than 20,000 customers, the VRS and NIRS assumptions do not give them incentive to scale down.

5.2 Reference set

A reference sets is the group of the efficient DMUs that the analyzed (efficient or inefficient) DMU_{j0} is compared with. It is given by the optimal weight λ_j of each DMU_j.

The efficient cost of DMU_{j0} is equal to the sum of the contributions from the DMUs in the reference set, i.e.,

$$\theta_{j0} \cdot C_{j0} = \sum_j \lambda_j \cdot C_j \qquad (17)$$

Figures 5 to 8 show the reference sets of each network company in the whole industry under the various scale assumptions. The width of each stacked column is equal to the efficient cost of a company, i.e., the left hand side of (17). The height of each element in the stacked column is equal to the relative contribution from each reference company j' to the efficient cost, i.e., $\frac{\lambda_{j'} \cdot C_{j'}}{\sum_j \lambda_j \cdot C_j}$.

Hence, the area of the figure is equal to the efficient cost for the entire industry. The numbers in parenthesis represent the relative share contributed by each reference company to the efficient cost of the industry. Figure 5 shows that there are 5 reference companies under CRS, with one company contributing 49.6% of the industry cost norm. We see from Figure 6 that Koopmans assumption yields reference sets that include 9 companies, and where the weight of the most influential reference company is reduced to 33.5%. NIRS and NDRS also have more reference companies than CRS, but here the relative contribution of the most influential reference company is larger than under CRS.

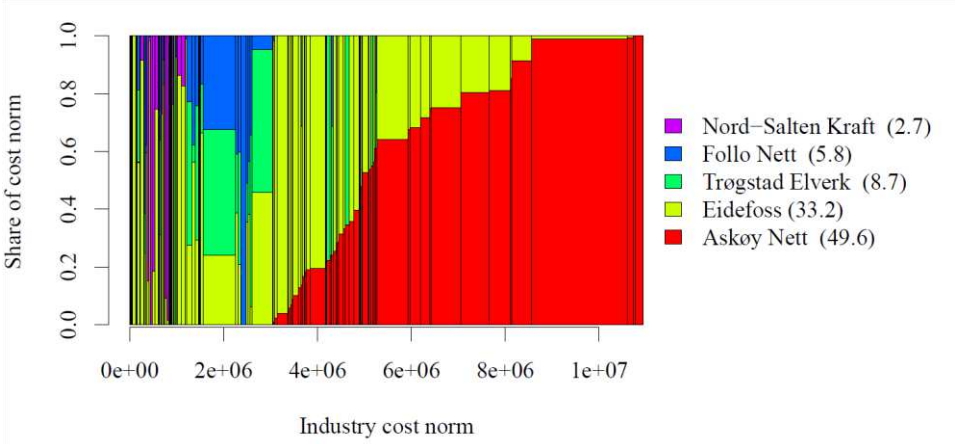


Figure 5 Reference sets under CRS

5.3 Self-referencing and implicit super efficiency

Some companies may appear in their own reference set, either alone or together with other companies. When this happens, it poses a challenge to the regulator,

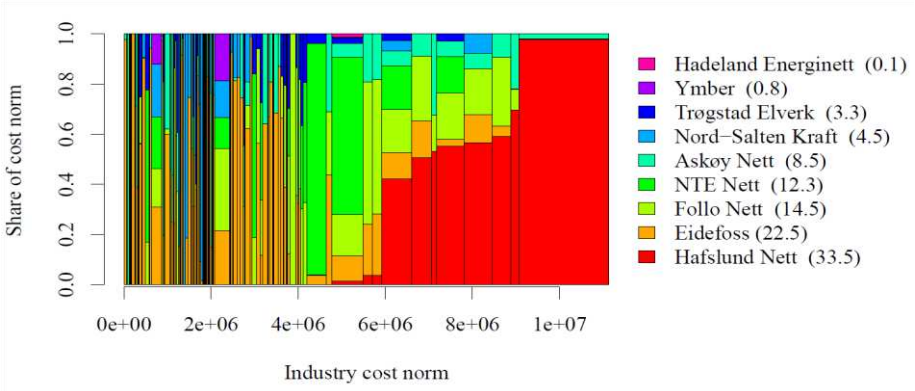


Figure 6 Reference sets under Koopmans

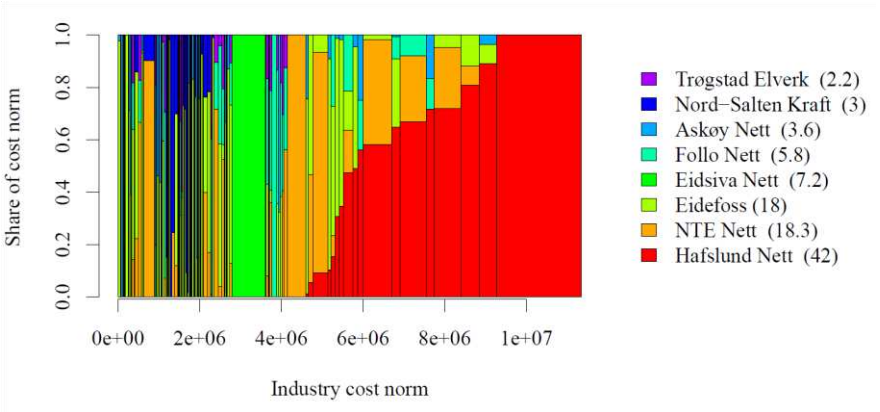


Figure 7 Reference sets under NIRS

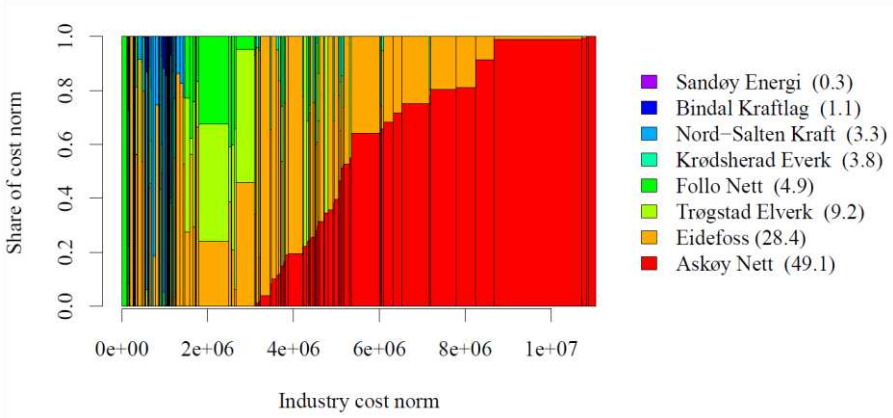


Figure 8 Reference sets under NDRS

since the company in question may, to a certain extent, increase its cost norm by increasing its own cost. Hence, for such companies, the customers' protection against abuse of monopoly power is limited. We illustrate this phenomenon with data of the largest company in our data set, Hafslund Nett. Its reference sets under different scale assumptions are shown in Table 6.

Table 6 Reference sets of Hafslund Nett

Model assumption	Eff. score	Reference company		
CRS	0.9850	Askøy Nett (51.0045)	Eidefoss (0.3059)	
VRS	1	Hafslund Nett (1)		
NIRS	1	Hafslund Nett (1)		
NDRS	0.9850	Askøy Nett (51.0045)	Eidefoss (0.3059)	
Koopmans	0.9997	Askøy Nett (1)	Follo Nett (0.0301)	Hafslund Nett (0.9789)
FDH	1	Hafslund Nett (1)		

The potential consequences for customers of self-referencing may be estimated by using the super efficiency formulation introduced by Andersen and Petersen (1993). To further illustrate the differences between the scale assumptions, we describe the reference set of Hafslund Nett AS, the largest company in the industry, in Table 6. Under CRS and NDRS, Hafslund is not considered as efficient, and its reference is made up of 51.0045 times Askøy and 0.3059 times Eidefoss. Since Hafslund is the largest company with respect to all the three output factors, it will be its own reference under VRS, NIRS and FDH. Under Koopmans assumption, Hafslund is evaluated as inefficient, but here we see that Hafslund also enters the reference set.

Hafslund Nett AS is inefficient under the CRS, NDRS, and Koopmans assumptions. Under CRS and NDRS, its reference set consists of Askøy AS and AS Eidefoss; both are fully efficient companies, indicating that the optimal cost of Hafslund Nett AS should only be 98.5% of its present total cost, which, theoretically, equals the sum of 51 times the present cost of Askøy Nett AS and 30.59% of the present cost of AS Eidefoss. However, in practice, when merging is taken into consideration, it will be impossible to find and merge as many as 51 small network companies as Askøy Nett AS. In this context, the CRS and NDRS assumptions might not be practical benchmarking models for the network companies when merging is considered.

Under the VRS, NIRS, and FDH assumptions, Hafslund Nett AS is estimated as fully efficient and its reference set consists of only itself. Hence the VRS-DEA, NIRS-DEA, and FDH models may also be considered as improper benchmarking models. Under

Koopmans, Hafslund is one of its peer companies even though it is not fully efficient. In addition, Askøy Nett AS and Follo Nett AS are still Hafslund Nett AS's peer companies with more practical lambdas than under the CRS assumption.

The idea of super efficiency was first introduced to rank fully efficient DMUs. In practice, companies that have an efficiency score of 1 will have limited incentives to improve their performance. Thus, the concept of super efficiency is important in DEA under the circumstances when it is possible for a DMU to increase its inputs or/and decrease its outputs without being inefficient. The efficiency scores of 1 for Hafslund Nett AS under VRS, NIRS, and FDH estimated in Table 6 indicate that Hafslund is fully efficient except under the CRS, NDRS, and Koopmans assumptions. It is, therefore, necessary to investigate if super efficiency exists in the industry.

Table 7 lists the main characteristics of the estimated super efficiency scores in the whole industry. As is known that the super efficiency approach can be infeasible under VRS, NIRS and FDH, the maximum values and the mean values in Table 7 are calculated by eliminating the only company (Hafslund) that causes the infeasibility. Agder Energi obtains the highest super efficiency score under the FDH assumption. Under Koopmans, Hafslund obtains a super efficiency score of 18.77%. The companies with the highest super efficiency scores may still be efficient after their total cost is increased by 25.52% under the NDRS assumption, 18.77% under the Koopmans assumption, and 14.14% under the CRS assumption. When super efficiency is considered, the number of fully efficient companies increases under the Koopmans model assumption.

Under the CRS and NDRS assumptions, Hafslund Nett AS is not efficient and there is no difference in the efficiency scores with and without super efficiency. Under the NIRS, VRS and FDH assumptions, the super efficiency scores are equal to infinity, indicating that the estimated company, Hafslund Nett AS, can be considered as fully efficient no matter how much inputs (total cost) are increased, which implies that customers are not protected against the abuse of monopoly power. In Table 8 we list the companies that are super efficient under the Koopmans frontier assumption, including their reference sets and their super efficiency scores. Notice from Table 6 the peer companies of Hafslund (under the Koopmans frontier assumption) are Askøy, Follo, and Hafslund itself[12]. There exists super efficiency for all the peers. Askøy and Follo may increase their total cost by 5.05% and 6.19%, respectively. Under Koopmans, there also exists the possibility for Hafslund Nett AS to increase its input (total cost) by approximately 18.77% while still being estimated as efficiently operated. Interestingly, note that both Hafslund and NTE Nett AS with super efficiency scores of 1.1877 and 1.1300 are inefficient (with efficiency scores of 0.9997 and 0.9963) when super efficiency is not considered. And both companies are their own reference under the Koopmans frontier assumption.

[12] In fact, all super-efficient companies' peer companies include themselves.

Table 7 Descriptive characteristics of the estimated super efficiency scores

Assumption	Maximum	# super efficient	# infeasible	Mean
CRS	1.1414 (Trøgstad)	5	0	0.7225
VRS	1.2552 (Trøgstad)	10	1 (Hafslund)	0.7839
NIRS	1.2334 (NTE)	7	1 (Hafslund)	0.7331
NDRS	1.2552 (Trøgstad)	8	0	0.7728
Koopmans	1.1877 (Hafslund)	7	0	0.7298
FDH	2.6601 (Agder)	66	1 (Hafslund)	1.1377

Table 8 Super-efficient companies under Koopmans with corresponding reference sets

Company	Without s.e.	Reference set	With s.e.	Reference set
Askøy	1.0000	Askøy	1.0505	Follo, Hafslund
Follo	1.0000	Follo	1.0619	Askøy, Trøgstad, Hafslund, NTE
Eidefoss	1.0000	Eidefoss	1.0870	Nord-Salten, Trøgstad, Follo, NTE
Nord-Salten	1.0000	Nord-Salten	1.1176	Ymber
NTE	0.9963	Eidefoss, Trøgstad, Follo, NTE	1.1300	Eidefoss, Hadeland, Krødsherad, Gauldal, Nord-Østerdal, Rakkestad, Trøgstad, Hallingdal
Trøgstad	1.0000	Trøgstad	1.1414	NTE
Hafslund	0.9997	Askøy, Follo, Hafslund	1.1877	Askøy, Norgesnett, Klepp, Trønderenergi, Lyse, Skagerak, Follo, EB

5.4 Impact of scale assumptions on company profitability

In this section, we analyze the impacts of scale assumptions on the network company's profitability. To achieve this, we estimate the difference between revenue caps according to book values under the CRS assumption and the other five assumptions to investigate the effect on returns on capital for network companies (shown in Table 9). All the three stages of the regulation model in Section 4.1 have now been applied to calculate the revenue caps under the six scale assumptions.

To investigate the difference of return on capital, we apply the following formula:

$$\frac{\Delta RC_i}{Capital_i} = \frac{RC_i^{RTS} - RC_i^{CRS}}{Capital_i} \quad (18)$$

where *RTS* denotes the five types of assumptions, RC_i is the revenue cap of network company *i*, and $Capital_i$ denotes the book value of network company *i* and is the average value during the period from 2011 to 2015[13].

The difference describes the estimated amount of return that can be kept by the network companies under a specific model assumption compared to that under the CRS assumption. A positive difference indicates a higher return on capital that can be gained than under CRS.

Table 9: Return on capital under different RTS assumptions (%)

Customer size	CRS	Difference relative to CRS				
		VRS	NIRS	NDRS	Koopmans	FDH
[0, 3000)	3.93	0.67	-0.50	1.61	-0.29	1.19
[3000, 10000)	4.53	-0.94	-0.56	0.07	-0.33	1.31
[10000, 30000)	5.70	-0.77	-0.47	0.04	-0.31	0.34
[30000, 100000)	5.80	0.27	-0.01	0.19	-0.16	0.53
[100000, +∞)	6.98	0.46	0.39	-0.19	0.30	-0.77
Industry average	6.12	6.12	6.12	6.12	6.12	6.12

Under the VRS assumption, small companies with fewer than 3,000 customers and large companies with more than 30,000 customers receive higher return on capital than under the CRS assumption. Under NIRS and Koopmans, only the large companies with more than 100,000 customers receive higher return on capital than under CRS, while the return is lower for other sizes of companies. Under NDRS and FDH, companies with fewer than 100,000 customers would be better off than under CRS. To sum up, compared to CRS, the incentives for rescaling vary under VRS. Under NIRS and Koopmans, companies have stronger incentives to scale up; while under NDRS and FDH, the incentives for operating at a larger scale are weaker.

5.5 Impact of scale assumptions on customer prices

We analyze the impacts of scale assumptions on customer prices in this section. We estimate the difference between the revenue cap per kWh under the different scaling assumptions to investigate how the choice of the scale assumption affects customers (shown in Table 10). The revenue caps have already been calculated in Section 5.4.

The difference in the revenue cap per kWh is estimated as follows:

[13] In this paper, NVE's reference rate of 6.12% in 2017 is applied.

$$\frac{\Delta RC_i}{Energy_i} = \frac{RC_i^{RTS} - RC_i^{CRS}}{Energy_i} \quad (19)$$

where RTS denotes the five types of assumptions and $Energy_i$ is the total amount of electricity delivered from network company i. Since our analysis is based on data during the period from 2011 to 2015, $Energy_i$ is then the yearly average of the total amount of delivered electricity.

Table 10 Average customer prices (NOK/kWh)

Customer size		Difference relative to CRS				
	CRS	VRS	NIRS	NDRS	Koopmans	FDH
[0, 3000)	0.3946	0.0075	-0.0056	0.0180	-0.0032	0.0133
[3000, 10000)	0.2615	-0.0075	-0.0045	0.0005	-0.0026	0.0104
[10000, 30000)	0.2422	-0.0062	-0.0038	0.0003	-0.0025	0.0027
[30000, 100000)	0.1867	0.0016	0.0000	0.0011	-0.0009	0.0031
[100000, +∞)	0.1540	0.0022	0.0019	-0.0009	0.0014	-0.0037
Industry average	0.1861	0.1861	0.1861	0.1861	0.1861	0.1861

A positive difference reflects the amount of the energy price (per kWh delivered energy) that the company can lift, which also means the amount of money customers are forced to pay more than under the CRS assumption when a specific scale assumption is applied. Under NIRS and Koopmans, effect on the revenue cap per kWh increases as the company size increases, indicating that, compared to CRS, the larger a company is, the more revenue it collects from their customers under these two assumptions. Meanwhile there exists a negative effect on the revenue cap per kWh for companies serving fewer than 100,000 customers, which is opposite to the effect under NDRS and FDH, where customers have to pay more for delivered energy. Under these two assumptions, the average difference in the customer price increases when companies decrease their scales, which is aligned with the result in 5.1 and 5.4 that small companies are most inefficient in the industry and they might still retain their monopoly power and will not expand under the NDRS and FDH assumptions.

6 Conclusion

In this paper, we have estimated the cost efficiency of 115 distribution network companies in Norway by applying six non-parametric models, including Koopmans frontier, which has not been used in regulation contexts before. According to our results, we find that the VRS-DEA and the FDH models are improper for incentive regulation since many companies are their own reference, giving customers limited protection against the abuse of monopoly power. We take the largest network company, Hafslund Nett AS, as an example and study both its reference sets and super efficiency scores. Our results show that some of the larger companies have reference sets under CRS that

are dominated by relatively small companies, and this pattern is less prevalent under the Koopmans frontier technology. Additionally, a prominent feature of the koopmans frontier is that inefficient companies can still be their own references. When merging is considered, the Koopmans technology has a unique trait that aggregation is conducted in a descending order of company productivity, and without repeated aggregation, which can be a more realistic technology assumption compared to the CRS scale assumption that is implemented in the present regulation model. Our result of super efficiency scores shows that the NIRS, VRS, and FDH assumptions might not protect customers from the abuse of monopoly power, as super-efficient method is infeasible for the largest company and under these three assumptions companies generally obtain higher super-efficient scores than the rest of the assumptions. We have also estimated the impact of scale assumptions on company profitability and customer prices. Our results show that under NIRS and Koopmans, companies have stronger incentives to scale up; while under NDRS and FDH, the incentives for operating at a larger scale are weaker. When the NDRS, VRS, and FDH assumptions are applied, small distribution companies receive a positive return on capital and the customers of the smallest companies are forced to pay the highest price for delivered energy; thus, the customers' benefits are not protected under the NDRS, VRS, and FDH assumptions. To conclude, the importance of the Koopmans frontier technology might have been underestimated by regulators, especially considering the possibility of merging the small companies.

Our findings are relevant for policy makers when applying non-parametric benchmarking regulation models. As companies are not liable to release their efficient cost structures, regulators need to carefully consider the scale assumptions of the regulation model to increase the chance for companies to operate at an optimal scale and not to abuse the monopoly power at the expense of their customers.

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