Full-length article

Wind of change: Small-scale electricity production and distribution-grid efficiency in Sweden[☆]

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ABSTRACT

In this paper, we measure the technical efficiency for local electricity distribution firms in Sweden, and in particular how small and micro-scale generation affects efficiency scores. Using a two-stage data envelopment analysis to model the technical efficiency and a double bootstrap approach to estimate the determinants of inefficiencies, we show that firms are heterogeneous in terms of inefficiency, but that a large share of small and micro-scale generation is not associated with more inefficient operations.

1. Introduction

The share of small-scale electricity generation is increasing rapidly in Sweden and elsewhere. For example, between 2007 and 2017, the wind generation, as a share of total domestic generation, increased from less than one percent to more than ten percent.¹ Furthermore, both small and micro-scale generation are heavily subsidized in Sweden, through both direct subsidies on, e.g., installations on photovoltaics Lindahl (2016), and through a tradable electricity certificate mechanism with a government-set quota to promote renewable energy. This development is expected to continue for the foreseeable future if Sweden is to meet its ambitious climate and energy policy goals of 100 percent of renewable generation by 2045. For example, the Swedish Energy Agency forecast wind generation to be up to 60 TWh in 2050, compared to approximately 20 TWh as of today [Energimyndigheten \(2018\)](#).

Many argue that increased penetration of distributed electricity generation, such as solar and wind, will have profound impacts on the efficiency of electricity distribution (e.g., [Mateo et al. \(2018\)](#), [Adefarati and Bansal \(2016\)](#), [Asrari et al. \(2016\)](#), [Jenkins et al. \(2017\)](#), [Cossent](#)

[et al. \(2009\)](#)). Contrary to transmission grids,² distribution networks are not designed to accommodate generation, only consumption. An increasing share of intermittent small-scale generation may also pose management, planning, and coordination challenges in the delivery of electricity. On the other hand, the location of generation close to consumption may, for example, reduce networks losses, which would possibly improve network efficiency. In any case, there is little, if any, empirical evidence on the effects of small and micro-scale generation on the efficiency of electricity distribution networks. This issue is becoming increasingly important to study as the penetration of small and micro-scale renewable energy is sure to continue to increase. This paper fills this gap.

In more detail, this paper contributes to the existing literature by being the first to explore how small and micro-scale generation affects the efficiency of electricity distribution operation. We use a two-stage Data Envelopment Analysis (DEA) approach to model the technical efficiency among the approximately 150 local electricity grids in Sweden. The analysis sets out to capture their heterogeneous environment and firm characteristics that might affect their efficiency. Most notably,

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¹ Source: <https://www.energiforetagen.se/statistik/energiaret/>.

² Transmission and distribution refers to the different stages of carrying electricity over poles and wires from generators to end-users. Transmission refers to the part of electricity delivery that moves bulk electricity from the generation sites over long distances to substations closer to areas of electricity demand, and distribution networks deliver electricity from these substations to the end-user. The primary distinction between the two is the voltage level at which electricity moves in each stage.

we include distributed power from small and micro-scale production, which varies substantially across firm networks, as environmental variables. To a large extent, these small and micro-scale units are wind producing units. To draw inference on how the environmental and firm-specific factors affect the firms operating the grids, a double bootstrap approach, similar in spirit to [Simar and Wilson \(2007\)](#), is employed. In brief, we find that firms in northern Sweden (price areas SE1 and SE2), large firms, and firms with a high customer density, are relatively more efficient. Furthermore, and contrary to previous recent studies (e.g., [Lundin \(2020\)](#)), our findings reveal that there are relatively little differences in efficiency across different types of ownership (which is in line with the findings in [Hjalmarsson and Veiderpass \(1992\)](#)). Finally, we find that the effect of small and micro-scale production on grid efficiency is insignificant or slightly positive.

The rest of the paper is structured as follows: in Section 1.1, we describe the Swedish transmission and distribution system and review the recent literature concerning technical and cost efficiency in these markets. In Section 2, we detail the data used in this paper, and we describe the empirical approach in Section 3. The results from our estimation are presented in Section 4, and Section 5 concludes.

1.1. Background and previous literature

The Swedish power transmission and distribution system is characterized by a three-tier structure, with the national transmission grid owned and operated by a state-owned utility, Svenska Kraftnät (www.svk.se), about thirteen regional grids owned and operated by the large power generators, and about 150 local distribution grids primarily managed by municipal (approximately 67 percent of the firms) and privately owned entities (13 percent).³

The local grids, which distribute electricity to the end-users, are each a monopoly in their region of operation, and they are the focus of our analysis. These firms, typically referred to as Distribution System Operators (DSO's) in the literature, are regulated through a firm-specific revenue cap by the Swedish Energy Market Inspectorate (SEMI, www.ei.se). The revenue cap model can be broken down into three parts of revenue drivers: Controllable costs, non-controllable costs and asset base. These are then adjusted according to efficiency requirements [Wallnerström et al. \(2017\)](#). See [Pandur and Jonsson \(2015\)](#) for details.

The literature on the efficiency of electricity distribution has seen a large expansion. The common findings in the literature are that few firms are fully efficient, but that the efficiency scores vary substantially across firms. These results are typically derived from either DEA or variants of stochastic frontier analysis (SFA).⁴

To give a few examples, [Arocena \(2008\)](#) analyzes the degree of vertical integration and diversification in the electricity industry using DEA on Spanish data on electricity distribution. They show that cost and quality gains from integrating power generation and distribution amount to approximately five percent, whereas diversifying the source of power generation saves between 1.3 and 4.3 percent of costs and quality.

[Fallahi et al. \(2019\)](#) evaluate the efficiency and productivity change of 39 electricity distribution companies in Iran over the 2005–2014 period, and focus on regional heterogeneity in efficiency. [Agrell et al. \(2005\)](#) explore different regulatory schemes for Scandinavian electricity distributors using cost information from a productivity analysis model and an agency theoretical decision model. The authors illustrate how the proposed schemes have considerable advantages compared to the popular CPI-X revenue cap regulation. [Giannakis et al. \(2005\)](#)

present a quality-incorporated benchmarking study of the electricity distribution firms in the UK, and compute the utilities' technical efficiency of the utilities using DEA technique and productivity change over time through quality-incorporated Malmquist indices. They find that cost-efficient firms do not necessarily exhibit high service quality and that efficiency scores of cost-only models do not show high correlation with those of quality-based models. The results also show that service quality improvements have significantly contributed to the sector's total productivity change.

Other examples of efficiency analysis of electricity distribution include [Filippini et al. \(2018\)](#), [Bobde and Tanaka \(2018\)](#) and [Mydland et al. \(2019\)](#). For applications to the Nordic context, see [Kuosmanen \(2012\)](#), [Korhonen and Syrjänen \(2003\)](#), [Edvardsen and Førsund \(2003\)](#), [Førsund and Kittelsen \(1998\)](#), and more recently, [Kumbhakar and Lien \(2017\)](#), [Kumbhakar et al. \(2020\)](#). These latter papers have in particular focused on distinguishing between short- and long-run inefficiencies (usually labeled transient or persistent inefficiency) for both technical inefficiency and allocative inefficiency, respectively.

For studies of the efficiency of electricity distribution in Sweden, [Hjalmarsson and Veiderpass \(1992\)](#) illustrate that there are little variation in efficiency across time, ownership and location, and [Lundin \(2020\)](#) examines the effects of privatization, in the form of acquisitions, in the Swedish electricity distribution sector. Somewhat surprising, and as already alluded to, although the literature on the drivers of inefficiency is substantial, we have not found any previous literature on how this heterogeneity is associated with the share of micro- and small-scale generation.

A common way to analyze the drivers of the observed heterogeneity in efficiency scores obtained from DEA is to employ a two-stage strategy where efficiency scores are calculated, and regression techniques are then used to explain the difference in efficiency across DSOs ([Simar and Wilson, 2007](#)). [Llorca et al. \(2014\)](#) use a latent class approach to cluster DSOs in the US market according to technical differences and estimate efficiency within the classes using DEA. They find that minimum temperature and growth in power demands promote efficiency. [Çelen \(2013\)](#) employs a two-stage DEA analysis and a Tobit regression to explain efficiency scores for Turkish distribution firms and shows that customer density and diversified ownership affected firm performance. [Dai and Kuosmanen \(2014\)](#) use a clustering method to group distribution companies according to differences in environmental variables and find a small positive correlation between customer density and productive efficiency of distribution companies in Finland. In a recent paper, [Xie et al. \(2018\)](#), study Chinese DSOs by a meta-frontier approach, where environmental factors are used to explain bootstrapped efficiency scores through a Tobit regression. Of interest to the current paper is that they find that increasing proportion of renewable generation decrease efficiency.

2. Data

The data used for this analysis is publicly available from the regulator's website (Swedish Energy Market Inspectorate, see www.ei.se), and includes data on all ($N = 155$)⁵ the Swedish DSOs' financial and technological data. This data are used by the regulator for regulation. The data on costs come from each firm's final revenue-cap report for the supervisory period 2012–2018, published by the regulator. However, the data only includes information about small-scale production for 2014–2017, so we focus our analysis on these years. Summary statistics of the key variables included in the empirical modeling are presented in [Tables 1 and 2](#). All monetary values in this paper are in 2014 SEK.

The first thing to notice is the substantial heterogeneity across firms in terms of both costs and technical characteristics. Capital cost,

³ The remaining firms are managed by, e.g., co-operatives

⁴ DEA and SFA are typically also used by the regulators; for example, in Sweden, the regulator (the Swedish Energy Market Inspectorate) use DEA to estimate efficiency scores in determining revenue cap for the individual DSO (see [Energimarknadsinspektionen \(2015\)](#)).

⁵ Worth noting is that this is a substantially larger sample size than, for example, [Filippini et al. \(2018\)](#) where $N = 28$.

Table 1

Descriptive statistics, Swedish local distribution service operators, 2014–2017.

Variables	Unit	Min	Mean	Max	SD
Capital costs	MSEK	824	116859	3889155	368506
Controllable operational costs	MSEK	1097	52049	1533303	157920
Non-controllable operational costs	MSEK	278	56998	1821909	185744
Number of customers		310	33748	812178	102327
Number of netstations		27	1072	36257	4048
Maximum power output	MW	1	172	17700	832
Distributed low voltage electricity	MWh	3469	418027	10294043	1236880
Distributed high voltage electricity	MWh	0	155734	3283274	411903

Table 2

Descriptive statistics, Swedish local distribution service operators, 2014–2017.

Variables	Unit	Min	Median	Mean	Max	SD
Customer density	customers/km	3.01	10.33	12.10	43.00	7.03
Micro scale production	%	0.00	0.02	0.16	21.24	1.36
Small scale production	%	0.00	1.42	5.99	96.41	12.13
Power distributed to border point	%	0.00	0.00	2.44	68.44	9.26
Vertical integration	%	0.00	0.14	9.85	100.00	17.82

illustrated in Table 1 is a good example, varying from 824 MSEK to over 400 000 MSEK. Similarly, the number of customers varies from 310 to over a hundred thousand. Turning to the key variable of this paper, presented in Table 2, we note that the average share of small-scale production is small; less than two percent, but that for some firms, this share is very large: more than 95 percent. As is illustrated by Tables A.1–A.4 in Appendix A, there are some interesting differences in firm characteristics across small-scale production levels. For example, firms with small-scale production above the mean on average are somewhat smaller, with lower costs and fewer customers, but the heterogeneity within this group is large.

3. Empirical approach

3.1. Efficiency measurement

Similar to previous literature, efficiency is defined in this paper as the ratio of optimal to actual inputs, holding outputs fixed. Assume that firms use a vector of N inputs $x = (x_1, \dots, x_N)$ to produce a vector of M outputs $y = (y_1, \dots, y_M)$. The technology can be defined as: $T = \{(x, y) : x \text{ can produce } y\}$, which is assumed to be closed and bounded, implying that a finite amount of inputs can only produce a finite amount of outputs. To apply the production technology T to empirical applications, we can represent it by using DEA. Assume that there are $k = 1, \dots, K$ observations of inputs and outputs, each of which is associated with a firm. The technology that allows for constant returns to scale (CRS)⁶ can be represented by:

$$T = \{(x, y) : \sum_{k=1}^K z_k y_{km} \geq y_m, m = 1, \dots, M \quad \sum_{k=1}^K z_k x_{kn} \leq x_n, n = 1, \dots, N \quad z_k \geq 0, k = 1, \dots, K\} \quad (1)$$

The intensity variables, $z_k, k = 1, \dots, K$ serve as coefficients to perform linear combinations of all observed firms' inputs and outputs, and determine the reference point. Then, the DEA model for measuring

the efficiency of firm, $k' = 1, \dots, K$ can be written as:

$$\delta_{k'} = \min_{z_k, \delta} \delta \quad \sum_{k=1}^K z_k y_{km} \geq y_{k'm}, m = 1, \dots, M \quad \sum_{k=1}^K z_k x_{kn} \leq \delta x_{k'n}, n = 1, \dots, N \quad z_k \geq 0, k = 1, \dots, K \quad (2)$$

The value of δ_k is in the range of $(0, 1]$. An efficient firm has $\delta_k = 1$, while an inefficient firm will have $0 < \delta_k < 1$: a higher value indicates higher efficiency.

3.2. The econometric model

We use an econometric model to examine what factors affect efficiency. This is achieved by regressing the efficiency estimates on a set of environmental and control variables. Suppressing subscript i denoting year, the regression equation can be written as:

$$\delta_k = f\beta + \varepsilon_k \quad (3)$$

where δ_k is the efficiency score obtained from estimating Eq. (1), f is the vector of explanatory variables, e.g., small-scale production, β are parameters to be estimated, and ε_k is the disturbance term.

To estimate Eq. (3), we can use the method of ordinary least squares (OLS). An alternative method is to treat δ_k as being censored (for $\delta_k > 1$) and use the Tobit model. However, Simar and Wilson (2007) point out that there exist serious problems associated with estimating Eq. (3) using the usual estimation methods. Specifically, when δ_k is used as the dependent variable in regression analysis, two issues must be considered. One issue is that δ_k is serially correlated. Another issue is that δ_k is biased, though consistent. Simar and Wilson (2007) show that it is not possible to provide consistent and valid inference for the coefficients estimates which are obtained by using either OLS or Tobit. To overcome the difficulty, Simar and Wilson (2007) suggest a double bootstrap procedure, which yields consistent and valid inference for β in Eq. (3) by using the method of maximum likelihood estimation. Briefly, the first bootstrap is used to produce a bias-corrected $\hat{\delta}_k$ for δ_k ; replacing δ_k with $\hat{\delta}_k$, and the second bootstrap is used to provide valid

⁶ We compare with a VRS specification, and find very similar results.

inference about β . The Simar and Wilson (2007) bootstrap algorithm is applied to our regression analysis.⁷

A key criticism of standard DEA is that the method does not lend itself to statistical inference concerning the efficiency scores and that outliers in the data could be very influential for the results. Another common criticism of the two-stage procedure is that determinants used in the second stage could be important in that they influence the first stage scores, and therefore should have been included as variables in that stage already. This problem could be remedied by using stochastic frontier analysis (SFA), where it is possible to do this kind of one-shot estimation of both stages (the inefficiency is modeled explicitly as dependent on determinants when generating the scores). This necessitates parameterizing the frontier function, which can be restrictive and significantly impact the results.

Simar and Wilson (2011) discuss several statistical challenges using two-stage DEA. They claim only two statistical models have been proposed in which two-stage regressions are statistically meaningful and provide consistent estimation: Simar and Wilson (2007) propose a truncated regression that provides consistent estimation in the second stage, and the model proposed in Banker and Natarajan (2008). Simar and Wilson (2011) propose that two-stage OLS estimation is consistent only under peculiar assumptions on the data-generating process that limits applicability. They also comment on ad-hoc specifications of two-stage regressions that ignore the part of the data-generating process that yields data used to obtain the initial DEA estimates. The two-stage DEA is widely used in empirical applications (hundreds of papers, and counting). We do not claim to progress methodology in this paper, but simply follow a large previous literature and use an empirical methodology that is commonly accepted in applied work today. We apply the two-stage estimation procedure proposed by Simar and Wilson (2007) as this still seem to be the state-of-the-art approach, but we are aware of its potential flaws and try to mitigate them as much as possible (more on this below).

3.3. The specification of empirical models

3.3.1. The DEA specification

We specify two DEA models with different output variables. In our first specification, $M1$, we follow exactly the DEA model specification used by the Swedish regulator, SEMI, has used to estimate efficiency scores in determining revenue cap for the individual DSOs (see page 71 in Energimarknadsinspektionen (2015)).

The input and output variables for this specification are:

- X1 = controllable operational costs (MSEK);
- X2 = non-controllable operational costs (MSEK);
- X3 = capital costs (MSEK).

The output variables are:

- Y1 = number of customers;
- Y2 = number of net stations;
- Y3 = maximum power outputs (MWh);
- Y4 = distributed low-voltage electricity (MWh);
- Y5 = distributed high-voltage electricity (MWh).

The regulator provides some brief motivations for this specification, including that (i) the output variables are plausible cost drivers; (ii) the model gives rise to higher efficiency scores than models with, e.g., only capital costs as input; (iii) in principal, it is reasonable to include also non-controllable costs; (iv) the model produces similar results to an alternative specification with only capital costs as inputs. See Energimarknadsinspektionen (2015) for additional discussions.

The second DEA model, $M2$, is consistent with the DEA model of Hjalmarsson and Veiderpass (1992) in which the efficiency of the Swedish electricity distribution was studied. From the viewpoint of economic theory, we consider that these variables are closely associated with the firm's revenue. This perspective motivates the second model, and this specification also allows us to compare with previous literature for Sweden. Specifically, $M2$ includes the same input variables as $M1$ but with the output variables:

- Y1 = number of customers;
- Y4 = distributed low-voltage electricity (MWh);
- Y5 = distributed high-voltage electricity (MWh).

To create an incentive for consolidation in the electricity distribution sector and realize economies of scale, SEMI suggests using DEA models with CRS in calculating efficiency scores for Swedish DSOs, even though there is scale effect (Energimarknadsinspektionen, 2015). We follow the SEMI's method and use CRS in both DEA models but compare our results to a VRS model (results are available upon request), which we find to produce very similar results as our main specification.

3.3.2. The econometric model specification

For each of the two DEA models ($M1$ and $M2$), we separately estimate the econometric model corresponding to Eq. (3), including eight independent variables. These variables are:

- f_1 = customer density, which is measured by the number of customers per kilometer power lines;
- f_2 = firm size, a binary variable, which is equal to 1 if a firm is large and 0 otherwise. The size is determined relative to the median value of the number of customers in the population;
- f_3 = electricity price area, a dummy variable, where price area SE1 (out of SE1, SE2, SE3 and SE4) is taken as baseline;
- f_4 = small-scale production, which is measured by the share of delivered electricity that is produced by small-scale generation plants (e.g., wind power plant) in the total delivery;
- f_5 = micro-scale production, which is measured by the share of delivered electricity that is from micro-scale generation plants (e.g., solar panel) in the total delivery;
- f_6 = degree of vertical integration, which is measured by the share of energy produced by the DSO relative to the total delivered electricity;
- f_7 = power distributed to border point, which is measured by the share of electricity that is delivered to the border point;
- f_8 = a year dummy variable that is included to capture the efficiency change over time, where year 2014 is the baseline.

In addition, we also estimate specifications with interaction terms between small-scale generation and customer density, and between small-scale generation and firm size.

To obtain meaningful estimation results in the second stage, environmental factors must satisfy the "separability condition", which means that the environmental factors used in the second stage as independent variables can only affect the distribution of the efficiencies, but not the technology frontier itself, or the attainable input-output combinations Simar and Wilson (2007). We investigate our data using Pearson's correlation test.⁸ The correlation coefficient matrix is presented in Table A.5 in Appendix A. The correlation matrix shows that factors f_4 , f_5 , f_6 , and f_7 are not significantly correlated with any of the input and output variables, while f_1 is not significantly correlated with input variables X2 and X3. Accordingly, it seems reasonable to assume

⁷ The bootstrap algorithm developed by Simar and Wilson (2007) is designed for an output-oriented efficiency measure. For the algorithm adapted for an input-oriented measure, see Zhang et al. (2016).

⁸ A more formal empirical test for the validity of separability condition is suggested by Daraio et al. (2018). However, with the variables correlation results at hand, we do not deem it necessary to do further testing.

Table 3

Average estimates of technical efficiency (bias-corrected) by year, Swedish local distribution service operators, 2014–2017. (*M1*).

Year	Mean	Median	Min	Max	SD
2014	0.7314	0.7318	0.4442	0.9458	0.1166
2015	0.7132	0.7095	0.4318	0.9407	0.1236
2016	0.7281	0.7230	0.5084	0.9316	0.0993
2017	0.7587	0.7562	0.5421	0.9525	0.1001

Table 4

Average estimates of technical efficiency (bias-corrected) by year, Swedish local distribution service operators, 2014–2017. (*M2*).

Year	Mean	Median	Min	Max	SD
2014	0.6711	0.6423	0.3348	0.9554	0.1374
2015	0.6529	0.6264	0.3201	0.9577	0.1393
2016	0.6625	0.6490	0.3424	0.9498	0.1333
2017	0.6925	0.6764	0.3805	0.9705	0.1333

Table 5

Estimated parameters and confidence intervals for the regression model (dependent variable: e_i). (*M1*).

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.7277***	(0.6884, 0.7678)
Large firm	0.0530***	(0.0370, 0.0699)
Customer density	0.0049***	(0.0036, 0.0062)
Small scale production	0.0004	(−0.0003, 0.0010)
Micro scale production	−0.0029	(−0.0086, 0.0031)
Power distributed to border point	−0.0006	(−0.0016, 0.0005)
Vertical integration	0.0004	(−0.0002, 0.0010)
Price area SE2	0.0141	(−0.0333, 0.0611)
Price area SE3	−0.0826***	(−0.1224, −0.0446)
Price area SE4	−0.1426***	(−0.1842, −0.1034)
y2015	−0.0183	(−0.0400, 0.0026)
y2016	−0.0022	(−0.0237, 0.0195)
y2017	0.0282**	(0.0058, 0.0513)
Sigma	0.0959***	(0.0903, 0.1020)
Log likelihood: 582.2 on 14 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

that the environmental factors we used may only affect the distribution of efficiencies, but not the attainable set. Thus, the regression analysis performed in the second stage provides meaningful results.

4. Results

Our results from the first DEA model, *M1*, are presented in Table 3 (and in Tables B.1 and B.2 in Appendix B), and for the second DEA model, *M2*, in Table 4 (and in Tables B.3 and B.4 in Appendix B). The regression results, where we explore determinants for efficiency scores, are presented in Tables 5 and 6 (and in Tables C.1–C.8 in Appendix C). These results reveal several interesting results. First, we find substantial heterogeneity in efficiency among Swedish DSOs. This is in line with the findings in previous literature, as discussed in our literature review. The results are also very similar to the regulator's own result, which is expected given that we use a similar approach (see [Energimarknadsinspektionen \(2015\)](#)). Furthermore, we find that there is not much variation in efficiency across the four years (Tables 3 and 4), as expected due to the short time span or our data.

There is a relatively large heterogeneity in efficiency across pricing areas, as illustrated by Tables B.1 and B.3, with a higher efficiency in the most northern pricing areas (SE1 and SE2). This is also evident in Tables 5 and 6, where we see that firms in price area 1 are significantly more efficient than firms in price areas 2, 3 and 4. One possible explanation to this result is that a majority of electricity is

Table 6

Estimated parameters and confidence intervals for the regression model (dependent variable: e_i). (*M2*).

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.5509***	(0.5116, 0.5910)
sizeLarge	0.0480***	(0.0319, 0.0660)
Customer density	0.0131***	(0.0117, 0.0146)
Small scale production	0.0001	(−0.0006, 0.0007)
Micro scale production	−0.0007	(−0.0063, 0.0051)
Power distributed to border point	−0.0017***	(−0.0029, −0.0006)
Vertical integration	0.0001	(−0.0004, 0.0007)
Price area SE2	0.0698***	(0.0243, 0.1159)
Price area SE3	−0.0614***	(−0.1014, −0.0238)
Price area SE4	−0.1105***	(−0.1523, −0.0711)
y2015	−0.0158	(−0.0376, 0.0057)
y2016	−0.0053	(−0.0275, 0.0170)
y2017	0.0231**	(0.0006, 0.0458)
Sigma	0.0958***	(0.0902, 0.1015)
Log likelihood: 583.3 on 14 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

produced in the northern part of Sweden (e.g., hydropower) whereas most consumption is in the southern Sweden. The long distance of transmission from North to South results in a large net loss. As a result, firms in areas SE1 and SE2 are more efficient.

There is relatively little difference in efficiency across ownership types, as illustrated in Tables B.2 and B.4. This finding is somewhat surprising because it seems likely that firms that are owned by, e.g., municipalities have a somewhat different objective, compared to privately owned firms. For example, firms owned by municipalities may be concerned by, e.g., equity, or other objectives that are not necessarily compatible with efficiency. Contrary to previous studies (e.g., [Lundin \(2020\)](#), our findings reveal that this is not the case. Furthermore, large firms, and firms with high customer density, are more efficient; see, for example, Tables 5 and 6. A plausible explanation to this is that distribution of electricity is characterized by economies of scale.

Firm size (above median number of customers) and customer density are positively associated with efficiency in all specification, whereas the effects of power distributed to border point are statistically significant and negative in *M1* and statistically insignificant in *M2*, and the degree of vertical integration is insignificant in both specifications.

We find small-scale production to be positively correlated with efficiency scores in some models (e.g., Tables C.2 and C.4), but the effect is small and in other specifications (e.g., Tables 5 and 6), it is not significantly different from zero. Most importantly, we find no negative effect of small scale production on efficiency in any of our specifications.⁹ This tells us that a large share of small-scale generation does not lead to electricity distribution inefficiencies. This is an important result, given that the share of small-scale generation is increasing steadily in Sweden and elsewhere.

5. Conclusions and policy implications

In this paper, we study how the technical efficiency of Swedish electricity distribution firms vary across firm characteristics. Of particular interest is how the increasing share of small and micro-scale generation affects inefficiency. Even if small and micro-scale generation on average is relatively small in Sweden, heterogeneity across firms in this respect is substantial, which makes Sweden a useful context for such analysis. Using detailed firm-level data and a two-stage Data

⁹ In addition, as illustrated by Table C.9, there is no statistically significant relation between small scale generation and net losses.

Table A.1Descriptive statistics, Swedish local distribution service operators, 2014–2017, small scale production $\geq$ mean.

Variables	Unit	Min	Mean	Max	SD
Capital costs	MSEK	1352	75648	1304059	167478
Controllable operational costs	MSEK	1162	35314	730574	87033
Non-controllable operational costs	MSEK	476	35675	588586	82249
Number of customers		512	22391	564677	67451
Number of netstations		40	707	9555	1526
Maximum power output	MW	3	93	1826	230
Distributed low voltage electricity	MWh	3469	270116	5718447	713748
Distributed high voltage electricity	MWh	0	111958	2302841	312113

Table A.2Descriptive statistics, Swedish local distribution service operators, 2014–2017, small scale production $<$ mean.

Variables	Unit	Min	Mean	Max	SD
Capital costs	MSEK	824	130415	3889155	413080
Controllable operational costs	MSEK	1097	57554	1533303	174806
Non-controllable operational costs	MSEK	278	64012	1821909	208471
Number of customers		310	37483	812178	111249
Number of netstations		27	1192	36257	4579
Maximum power output	MW	1	199	17700	949
Distributed low voltage electricity	MWh	4272	466682	10294043	1363016
Distributed high voltage electricity	MWh	0	170135	3283274	439155

Table A.3Descriptive statistics, Swedish local distribution service operators, 2014–2017, small scale production $\geq$ mean.

Variables	Unit	Min	Median	Mean	Max	SD
Customer density	customers/km	3.29	8.45	9.99	42.90	6.07
Micro scale production	%	0.00	0.02	0.51	21.24	2.71
Small scale production	%	6.02	15.21	20.62	96.41	17.42
Power distributed to border point	%	0.00	0.00	4.79	68.44	13.47
Vertical integration	%	0.00	0.00	15.19	85.47	23.86

Table A.4Descriptive statistics, Swedish local distribution service operators, 2014–2017, small scale production $<$ mean.

Variables	Unit	Min	Median	Mean	Max	SD
Customer density	customers/km	3.01	10.92	12.79	43.00	7.19
Micro scale production	%	0.00	0.02	0.04	2.11	0.12
Small scale production	%	0.00	0.27	1.18	5.76	1.56
Power distributed to border point	%	0.00	0.00	1.66	63.86	7.23
Vertical integration	%	0.00	0.54	8.10	100.00	14.94

Table A.5

Correlation matrix of Pearson correlation coefficients.

	X1	X2	X3	Y1	Y2	Y3	Y4	Y5	f_1	f_4	f_5	f_6
X1												
X2	0.97**											
X3	0.99**	0.97**										
Y1	0.98**	0.97**	0.96**									
Y2	0.93**	0.96**	0.95**	0.89**								
Y3	0.50**	0.50**	0.49**	0.50**	0.48**							
Y4	0.98**	0.98**	0.97**	1.00**	0.92**	0.50**						
Y5	0.93**	0.92**	0.91**	0.96**	0.82**	0.47**	0.94**					
f_1	0.12**	0.08	0.07	0.20**	-0.08*	0.03	0.15**	0.24**				
f_4	-0.04	-0.03	-0.03	-0.05	-0.01	-0.04	-0.04	-0.04	-0.20**			
f_5	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.01	-0.05	0.14**		
f_6	0.03	0.01	0.04	0.02	0.04	0.00	0.02	0.02	-0.01	0.01	-0.04	
f_7	-0.01	-0.01	-0.01	-0.02	0.01	0.04	-0.02	-0.03	-0.22**	0.02	-0.02	0.56**

Note: * and ** represent significance at the 5% and 1% levels, respectively.

Envelopment Analysis (DEA) approach to model the technical efficiency among the approximately 150 local electricity grids in Sweden, we find that efficiency scores vary substantially across firms, but that small and micro-scale generation does not lead to a decrease in efficiency.

In addition to these results, we also show that there is relatively little difference in efficiency across different types of ownership, which stands in contrast to some of the recent literature Lundin (2020) but are in line Hjalmarsson and Veiderpass (1992), among others. Finally, we

show that both firm size and customer density are positively correlated with efficiency, and these results are in line with, e.g., Hjalmarsson and Veiderpass (1992). Finally, it is important to note that even though, for example, small and micro-scale generation does not seem to be associated with inefficiencies in the distribution of electricity, many firms are still inefficient in their operations, and measures should be taken to reduce such inefficiencies.

Table B.1

Average estimates of technical efficiency (bias-corrected) by electricity price area (Epa), Swedish local distribution service operators, 2014–2017. (M1).

epa	2014	2015	2016	2017	Mean
SE1	0.8052	0.8152	0.7162	0.7738	0.7776
SE2	0.8143	0.7861	0.8033	0.8301	0.8084
SE3	0.7376	0.7195	0.7310	0.7607	0.7372
SE4	0.6703	0.6497	0.6956	0.7242	0.6850
Avg.	0.7569	0.7426	0.7365	0.7722	0.7521

Table B.2

Average estimates of technical efficiency (bias-corrected) by ownership, Swedish local distribution service operators, 2014–2017. (M1).

Ownership	2014	2015	2016	2017	Mean
Municipal	0.7344	0.7144	0.7357	0.7648	0.7373
Private	0.7567	0.7434	0.7539	0.7860	0.7600
Economic org	0.7041	0.6878	0.6842	0.7178	0.6985
Avg.	0.7318	0.7152	0.7246	0.7562	0.7319

Table B.3

Average estimates of technical efficiency (bias-corrected) by electricity price area, Swedish local distribution service operators, 2014–2017. (M2).

epa	2014	2015	2016	2017	Mean
SE1	0.6579	0.6935	0.6005	0.6173	0.6423
SE2	0.7633	0.7216	0.7235	0.7480	0.7391
SE3	0.6730	0.6546	0.6605	0.6921	0.6700
SE4	0.6340	0.6147	0.6575	0.6881	0.6486
Avg.	0.6820	0.6711	0.6605	0.6864	0.6750

Table B.4

Average estimates of technical efficiency (bias-corrected) by ownership, Swedish local distribution service operators, 2014–2017. (M2).

Ownership	2014	2015	2016	2017	Mean
Municipal	0.7056	0.6841	0.6981	0.7251	0.7032
Private	0.6508	0.6224	0.6229	0.6626	0.6397
Economic org	0.5664	0.5659	0.5617	0.5894	0.5708
Avg.	0.6409	0.6241	0.6276	0.6590	0.6379

From a policy perspective, our findings of no effect of small and micro-scale generation on the efficiency of electricity distribution is good news as Sweden's ambition is to increase renewable generation further, and thus more small/micro-scale units, in the electricity production system. Our results suggest that this will not harm the efficiency of the DSOs, and that the regulator does not need to take this into account when regulation distribution firms, at least not in the short run. However, the share of small and micro-scale generation in Sweden are still relatively small, and our findings of no effect of such distributed generation on the efficiency of electricity distribution may change as these shares continue to increase. Here, a more structural model of electricity distribution in relation to small and micro-scale generation could be used to predict the long-term effects, and is suggested for further research. Another suggestion for further research is to explore the effects of small and micro-scale generation on regional grids and the transmission grid.

Appendix A. Additional descriptive statistics

Tables A.1–A.5

Appendix B. Additional results, DEA model

Tables B.1–B.4

Table C.1

Estimated parameters and confidence intervals for the regression model (dependent variable: e_i). (M1 with interaction term)

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.7277***	(0.6889, 0.7671)
Large firm	0.0520***	(0.0331, 0.0710)
Customer density	0.0049***	(0.0036, 0.0062)
Vertical integration	0.0004	(−0.0001, 0.0010)
Small scale production	0.0003	(−0.0004, 0.0011)
Large firm × small scale production	0.0002	(−0.0015, 0.0019)
Micro scale production	−0.0029	(−0.0086, 0.0029)
Power distributed to border point	−0.0006	(−0.0017, 0.0004)
Price area SE2	0.0144	(−0.0326, 0.0617)
Price area SE3	−0.0825***	(−0.1220, −0.0449)
Price area SE4	−0.1427***	(−0.1839, −0.1028)
y2015	−0.0183	(−0.0390, 0.0036)
y2016	−0.0022	(−0.0238, 0.0192)
y2017	0.0282**	(0.0065, 0.0506)
Sigma	0.0959***	(0.0900, 0.1021)
Log likelihood: 582.1 on 15 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

Table C.2

Estimated parameters and confidence intervals for the regression model (dependent variable: e_i). (M1 with interaction term).

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.7255***	(0.6869, 0.7662)
Large firm	0.0509***	(0.0347, 0.0674)
Customer density	0.0053***	(0.0038, 0.0068)
Vertical integration	0.0005*	(−0.0001, 0.0010)
Small scale production	0.0017**	(0.0002, 0.0032)
Customer density × small scale production	−0.0002*	(−0.0004, 0.0000)
Micro scale production	−0.0026	(−0.0082, 0.0032)
Power distributed to border point	−0.0007	(−0.0018, 0.0004)
Price area SE2	0.0090	(−0.0371, 0.0558)
Price area SE3	−0.0823***	(−0.1228, −0.0444)
Price area SE4	−0.1441***	(−0.1876, −0.1037)
y2015	−0.0186*	(−0.0403, 0.0025)
y2016	−0.0022	(−0.0246, 0.0204)
y2017	0.0283**	(0.0050, 0.0511)
Sigma	0.0958***	(0.0900, 0.1019)
Log likelihood: 582.8 on 15 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

Table C.3

Estimated parameters and confidence intervals for the regression model (dependent variable: e_i). M1 without vertical integration.

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.7264***	(0.6840, 0.7680)
Large firm	0.0536***	(0.0373, 0.0705)
Customer density	0.0051***	(0.0038, 0.0064)
Small scale production	0.0004	(−0.0003, 0.0011)
Micro scale production	−0.0031	(−0.0087, 0.0030)
Power distributed to border point	−0.0001	(−0.0010, 0.0008)
Price area SE2	0.0154	(−0.0324, 0.0624)
Price area SE3	−0.0811***	(−0.1220, −0.0426)
Price area SE4	−0.1411***	(−0.1849, −0.0996)
y2015	−0.0181	(−0.0407, 0.0048)
y2016	−0.0017	(−0.0227, 0.0201)
y2017	0.0292**	(0.0062, 0.0518)
Sigma	0.0960***	(0.0901, 0.1020)
Log likelihood: 581.6 on 13 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

Appendix C. Additional results, regression model

Tables C.1–C.9

Table C.4

Estimated parameters and confidence intervals for the regression model (dependent variable: e_j). *M1* with quadratic small scale production.

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.7305***	(0.6898, 0.7708)
Large firm	0.0525***	(0.0361, 0.0697)
Customer density	0.0047***	(0.0035, 0.0060)
Vertical integration	0.0005*	(−0.0000, 0.0011)
Small scale production	−0.0014*	(−0.0028, 0.0002)
Small scale production squared	0.0000**	(0.0000, 0.0001)
Micro scale production	−0.0018	(−0.0077, 0.0037)
Power distributed to border point	−0.0006	(−0.0017, 0.0005)
Price area SE2	0.0148	(−0.0334, 0.0609)
Price area SE3	−0.0800***	(−0.1206, −0.0411)
Price area SE4	−0.1406***	(−0.1839, −0.0993)
y2015	−0.0182	(−0.0399, 0.0051)
y2016	−0.0013	(−0.0228, 0.0217)
y2017	0.0292**	(0.0066, 0.0528)
Sigma	0.0956***	(0.0897, 0.1016)
Log likelihood: 583.8 on 15 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

Table C.5

Estimated parameters and confidence intervals for the regression model (dependent variable: e_j). (*M2* with interaction term).

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.5511***	(0.5116, 0.5918)
Large firm	0.0449***	(0.0259, 0.0635)
Customer density	0.0132***	(0.0118, 0.0147)
Vertical integration	0.0001	(−0.0004, 0.0007)
Small scale production	−0.0000	(−0.0008, 0.0007)
Large firm × small scale production	0.0006	(−0.0010, 0.0022)
Micro scale production	−0.0007	(−0.0065, 0.0051)
Power distributed to border point	−0.0018***	(−0.0028, −0.0007)
Price area SE2	0.0705***	(0.0248, 0.1175)
Price area SE3	−0.0614***	(−0.1002, −0.0219)
Price area SE4	−0.1108***	(−0.1515, −0.0690)
y2015	−0.0156	(−0.0372, 0.0059)
y2016	−0.0050	(−0.0270, 0.0173)
y2017	0.0234**	(0.0017, 0.0462)
Sigma	0.0958***	(0.0903, 0.1014)
Log likelihood: 583.6 on 15 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

Table C.6

Estimated parameters and confidence intervals for the regression model (dependent variable: e_j). (*M2* with interaction terms).

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.5520***	(0.5124, 0.5909)
Large firm	0.0484***	(0.0322, 0.0649)
Customer density	0.0130***	(0.0115, 0.0145)
Vertical integration	0.0001	(−0.0005, 0.0007)
Small scale production	−0.0004	(−0.0019, 0.0011)
Customer density × small scale production	0.0001	(−0.0001, 0.0002)
Micro scale production	−0.0008	(−0.0067, 0.0047)
Power distributed to border point	−0.0017***	(−0.0028, −0.0006)
Price area SE2	0.0726***	(0.0264, 0.1184)
Price area SE3	−0.0616***	(−0.1008, −0.0229)
Price area SE4	−0.1104***	(−0.1517, −0.0702)
y2015	−0.0160	(−0.0370, 0.0061)
y2016	−0.0054	(−0.0272, 0.0157)
y2017	0.0229**	(0.0009, 0.0456)
Sigma	0.0958***	(0.0904, 0.1013)
Log likelihood: 583.4 on 15 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

Table C.7

Estimated parameters and confidence intervals for the regression model (dependent variable: e_j). *M2* without vertical integration.

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.5509***	(0.5127, 0.5911)
Large firm	0.0486***	(0.0328, 0.0651)
Customer density	0.0131***	(0.0117, 0.0146)
Small scale production	0.0001	(−0.0006, 0.0007)
Micro scale production	−0.0008	(−0.0064, 0.0050)
Power distributed to border point	−0.0016***	(−0.0025, −0.0008)
Price area SE2	0.0702***	(0.0258, 0.1173)
Price area SE3	−0.0610***	(−0.1000, −0.0229)
Price area SE4	−0.1102***	(−0.1519, −0.0672)
y2015	−0.0158	(−0.0374, 0.0054)
y2016	−0.0051	(−0.0275, 0.0172)
y2017	0.0234**	(0.0016, 0.0461)
Sigma	0.0956***	(0.0901, 0.1015)
Log likelihood: 584.4 on 13 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

Table C.8

Estimated parameters and confidence intervals for the regression model (dependent variable: e_j). *M2* with quadratic small scale production.

Independent variables	Coefficients	Confidence interval (95%)
(Intercept)	0.5537***	(0.5176, 0.5929)
Large firm	0.0483***	(0.0311, 0.0650)
Customer density	0.0129***	(0.0114, 0.0144)
Vertical integration	0.0002	(−0.0003, 0.0008)
Small scale production	−0.0014*	(−0.0029, 0.0001)
Small scale production squared	0.0000**	(0.0000, 0.0000)
Micro scale production	0.0003	(−0.0055, 0.0061)
Power distributed to border point	−0.0018***	(−0.0028, −0.0007)
Price area SE2	0.0698***	(0.0231, 0.1172)
Price area SE3	−0.0594***	(−0.0973, −0.0225)
Price area SE4	−0.1089***	(−0.1491, −0.0683)
y2015	−0.0156	(−0.0365, 0.0047)
y2016	−0.0046	(−0.0259, 0.0171)
y2017	0.0240**	(0.0020, 0.0467)
Sigma	0.0953***	(0.0897, 0.1009)
Log likelihood: 586.5 on 15 degree of freedom.		
Number of observations: 606		

Notes: *, **, and *** represent significance at the 10, 5, and 1% levels, respectively.

Table C.9

Estimated relation between costs for netloss and small scale production.

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	15.3948	0.2298	66.99	0.0000
Small scale production	−0.0616	0.0151	−4.07	0.0001

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