Efficiency in electricity distribution in Sweden and the effects of small-scale generation, electric vehicles and dynamic tariffs

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Abstract

We measure the cost of technical inefficiency for local electricity distribution firms in Sweden using Stochastic Frontier Analysis, and explore how small-scale generation, the number of electric vehicles and the introduction of dynamic pricing schemes affects the transient inefficiency and efficiency scores. Our results show little to no effect of these environmental variables on the cost of technical inefficiency of electricity distribution grids in Sweden.

Keywords SFA · Distributed generation · Efficiency

JEL classification D22 · D42 · Q42 · L51 · L94

1 Introduction

The transition of society towards a low-carbon economy introduces new challenges for electricity markets. Most notably, the share of intermittent (renewable) generation is increasing, more and more households are installing solar panels on their roofs, and the number of electric vehicles is growing rapidly (Hainsch et al. 2022). Sweden is no exception, where, for example, the share of distributed generation (e.g., wind and solar power) has increased from less than one percent to more than 20 percent during the last ten years (SvK 2022), and the number of electric vehicles has increased from zero to 10 percent of all cars during the last 15 years (see https://powercircle.org/english/). This may have profound implications on the operation of electricity distribution grids,[1] that were designed and built for a very different situation, with centralized production and no charging of batteries (see, e.g., Basit et al. 2020; Cossent et al. 2009; Leslie et al. 2020; Pearre and Swan 2020; Vesterberg et al. 2021).

In this paper, we use Swedish firm-level data spanning the years 2014 to 2021 and apply Stochastic Frontier Analysis (SFA) to estimate how the increasing share of small-scale generation (e.g., solar panels and wind mills) influences the cost and technical inefficiency of electricity distribution firms in Sweden. A related question is whether differences in small-scale generation across firms can explain the large heterogeneity in inefficiency among distribution firms that is typically found in the literature (e.g., Musau et al. 2021; Vesterberg et al. 2021; Zeebari et al. 2022). Since our data covers the period up to 2021, we are able to capture the most recent developments of small-scale generation in our analysis. Furthermore, we combine the above mentioned data with muncipal-level car registry data, allowing us to analyze how the increasing number of electric vehicles influence the grids' costs and efficiency. Finally, we also explore whether the introduction of time-varying distribution tariffs influence the

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[1] Specifically, the Swedish regulator distinguishes between transmission and distribution, where the former is operated by the Swedish transmission system operator Svenska Kraftnät, and the latter is operated by approximately 190 public and private distribution firms; we focus our analysis on the latter. See Section 2 for more details on the Swedish electricity market.

cost of technical inefficiency (we have collected data on if and when each firm introduced a demand charge).

The effects of small-scale generation on grid operations may be either positive or negative. For example, on one hand, distribution networks are not designed to accommodate generation, only consumption, and are therefore not necessarily built to accommodate an increasing share of small-scale generation. An increasing share of intermittent small-scale generation may also pose management, planning, and coordination challenges in the delivery of electricity (Mateo et al. 2018). On the other hand, the location of generation close to consumption may, for example, reduce networks losses, which would improve network efficiency (see, for example, Adefarati and Bansal 2016; Cossent et al. 2009; Jenkins and Perez-Arriaga 2017). Which of these effects dominate is an open empirical question, as the few previous findings are mixed regarding these effects. Many previous papers also use relatively old data, covering periods when small-scale generation was still limited.[2]

Furthermore, the increasing number of electric cars may also influence the operation of local electricity distribution grids. For example, charging of electric vehicles may contribute to grid congestion, especially if charging coincides with peak demand, and previous literature has also raised concerns about three-phase voltage imbalance and off-nominal frequency problems (see, e.g., Mohammad et al. 2020).[3] However, and as many previous studies have highlighted, electric vehicles can be viewed as mobile storage (through what is often referred to as vehicle-to-grid), and as such, can contribute to local congestion management and voltage regulation, and improve quality of service and reduce losses in the grid (see, e.g., Venegas et al. 2021). However, as far as we are aware, there are no previous studies on how the electrification of transports impacts the cost side of electricity distribution, and in particular the cost of technical inefficiency of distribution firms.

In response to these developments, the Swedish regulator has mandated that by 2027, all distribution firms will charge their customers based on a so-called demand charge type of tariff, where customers are charged based on maximum consumption during a month, and with prices varying both across seasons and across peak and off-peak hours. The

motivation for these tariffs is to smooth consumption, reduce the need for costly investments, lower costs and improve grid efficiency (see, for example, Bartusch and Alvehag 2014; Bartusch et al. 2011; Lanot and Vesterberg 2021). During the last 10 years, a number of firms have introduced such tariffs. However, there is little evidence for the effects of the introduction of such tariffs on the efficiency of grid operations.

In our analysis of the cost of technical inefficiency, we distinguish between transient and persistent efficiency (sometimes referred to as short-run and long-run inefficiency). Transient inefficiency is the part of inefficiency that is allowed to vary freely over time for each firm, whereas persistent inefficiency remains constant over time, although it is allowed to vary across firms. Filippini et al. (2018) argue that failing to account for both these components of inefficiency can result in incorrect efficiency targets set by regulators, and such non-optimal targets are associated with lower quality compliance by firms. Recent econometric advances have made it possible not only to disentangle transient and persistent inefficiency, but also to include determinants of these in the model (e.g., Badunenko and Kumbhakar 2017; Kumbhakar et al. 2014; Lai and Kumbhakar 2018; Musau et al. 2021). We build on this development and include small-scale generation (as a percentage of total generation) as a determinant of transient inefficiency. This captures the fact that since small-scale generation has increased substantially over the last ten years, and because it is intermittent in nature, its effect on firms' operation may vary over time. We do a similar analysis for the number of electric vehicles and the introduction of demand charges.

In brief, our empirical analysis shows that, in line with previous literature, there is substantial heterogeneity in technical efficiency among electricity distribution firms in Sweden, with the overall efficiency scores ranging from 0.4 to 0.9. Further, we show that small-scale generation reduces the mean and variance of the transient inefficiency, but that the marginal effects of a change in these environmental variables on the cost of technical inefficiency of distribution firms are small. Similarly, the effects of electric vehicles is close to zero, and the effect of the introduction of demand charges is statistically insignificant.

These results have important policy implications. For example, if the results would have revealed large reductions in the cost of technical inefficiency from an increasing share of small-scale generation, regulators would have to take this into account in the design of regulation of electricity distribution. However, as we do not find any such effects on efficiency, there appears to be a limited need for additional policy or regulation to support electricity distribution firms during the transition to more distributed generation. The same appears to be true for the ongoing electrification of

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[2] For example, Vesterberg et al. (2021) use data from 2014 to 2017. Since then, the share of small-scale generation has increased substantially; see Section 5.

[3] According to, e.g., Mohammad et al. (2020), electric vehicles are a mobile single-phase load so they can be randomly plugged in at any one of three phases within distribution networks, leading to a scenario that electrical components in one particular phase, such as power supply cables, overhead lines or transformers may be heavily loaded while the remaining two phases are not. This, in turn, may lead to a series of negative impacts on power quality issue, including transformer failures and equipment loss-of-life.

private transports. Furthermore, the finding of no effect on the efficiency of grids from the introduction of time-varying distribution tariffs is interesting, given that the motivation for these tariffs is to smooth consumption, reduce the need for costly investments, lower costs and improve grid efficiency. According to our results, these effects are questionable, and policy makers should take this into account when mandating firms to introduce such tariffs.

The rest of the paper is structured as follows. In Section 2, we describe the Swedish transmission and distribution system, including the recent developments with more small-scale generation and electric vehicles and the introduction of alternative pricing schemes, and review the recent literature concerning technical and cost efficiency in the electricity distribution market in Section 3. We describe the empirical approach in Section 4, and in Section 5, we detail the data used in this paper. The results from our estimation are presented in Section 6, and Section 7 concludes.

2 Electricity distribution in Sweden

During the 1990s, Sweden, along with many European countries, deregulated their electricity markets. The deregulation was mainly aimed at increasing efficiency by creating competition in the production and retail sectors. Consequently, regulations were removed in the wholesale and retail markets, which allowed market participants to trade electricity with each other. At the same time, the production and distribution of electricity were vertically separated, i.e., they were not allowed in the same legal entity, and the distribution sector remained regulated since the networks were considered natural monopolies. Since then, 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 municipalities (approximately 67 percent of the firms) and privately owned entities (13 percent).[4]

Sweden (together with Austria, Germany, and the other Nordic countries) stands out as having many more distribution firms than many other countries (e.g., Australia, Croatia, Great Britain, Greece, Hungary, Ireland, Lithuania, Netherlands, Portugal, and most of the Latin American countries), see Haney and Pollitt (2009). To give a sense of magnitudes, Sweden has more distribution firms than what Germany, France and Italy have combined.[5] Furthermore,

local distribution firms in Sweden differ markedly in size: the aggregate market share for the largest three firms (Vattenfall, E.ON, and Ellevio) is almost 50 percent, and each of the three largest firms are about three times as large as the fourth largest (Göteborg Energi). The corresponding market share for the 90 smallest firms (corresponding to firms with fewer customers than the median firm) is less than 10 percent.

The local grids, which distribute electricity to the end-users (i.e., households and firms), are each a monopoly in their region of operation, and 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: Controllable costs, non-controllable costs and asset base. These are then adjusted according to efficiency requirements (Wallnerström et al. 2017), and the regulator employs a Data Envelope Analysis model to measure efficiency scores. See Pandur and Jonsson (2015) for details.

Next, we detail three developments that all are related to the ongoing transition of electricity markets, and which may influence the operation of grids, namely an increasing share of small-scale generation, an increasing share of electric vehicles, and time-varying distribution tariffs made possible by the roll-out of smart grids.

2.1 Small-scale generation

During the last ten years, small-scale generation has increased substantially, and in some grids account for almost all of the delivered electricity. On aggregate, since 2000, installed wind capacity as a percentage of total installed generation capacity has increased from less than one percent to almost 25 percent (see SvK 2022).

In Sweden, expansion of renewable generation, including small-scale generation, is supported by various feed-in tariffs, green certificates and subsidies to installations. For household photovoltaic generation (i.e., solar panels), households receive a subsidy of up to 20 percent of the installation costs for photovoltaic generation, and a tax reduction of 60 öre/kWh (approximately 0.05 €/kWh) for the electricity sold to the grid (see, e.g., Lindahl 2016). Similar support mechanisms are in place in more than 140 countries.

It is important to highlight that electricity distribution firms are obliged to connect small-scale generation to the grid as long as the installed small-scale generation adhere to the rules regarding such installations; see, for example, https://ei.se/konsument/el/solenergi-och-solceller and chapter 6, 1-2 §in the Swedish Electricity Act. In that sense, the installed capacity of small-scale generation is driven by investors, not distribution firms.

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[4] The remaining firms are managed by, e.g., co-operatives.
[5] Going further back in time, the Swedish electricity retail distribution sector consisted of approximately 900 firms in 1970, most of which were very small and local (Kumbhakar and Hjalmarsson 1998).

2.2 Electric vehicles

Electric vehicles in Sweden was subsidized up until late 2022 through the so-called bonus-malus system, and similar subsidy schemes are in place in, e.g., Norway, Germany, Austria, and France; see, for example, Habibi et al. (2019). Bonus-malus schemes are designed to give a premium (bonus) to car buyers who purchase a car with low CO_2 emissions and to penalize (malus) those who buy a car with high CO_2 emissions. In the Swedish case, the bonus-malus system featured credits (up to SEK 60,000, or € 5300) for cars with CO_2 emission no higher than 60g/km and higher annual road tax (depending on the CO_2 emissions and fuel-type) for the first three years for cars exceeding 95g/km.

This subsidy, in combination with increased range of electric cars and other technological developments (e.g., Habibi et al. 2019) has resulted in a large increase in the number of electric vehicles, with more than half of all new cars sold in Sweden being electric (see https://mobilitysweden.se/and https://powercircle.org/english/).

2.3 Demand charges

Since 2000, ten Swedish distribution firms have introduced so-called demand charges as a way of charging for electricity distribution, and the regulator has mandated that all firms should have introduced such tariffs by 2017.[6] Demand charges can be understood as a non-linear distribution tariff, where households are charged for the distribution of electricity based on the largest hourly consumption in any given month.

Whenever these have been implemented in Sweden, the tariff structure is very similar across firms, and in all cases, the marginal price typically varies by several orders of magnitude as the quantity consumed increases infinitesimally. For example, for one of the firms, the highest per-unit price is more than three Euro, while the lowest price is less than 0.1 Euro (see Lanot and Vesterberg 2021), and prices are similar for other firms. Hence, the individual marginal incentives to reduce peak demand appear very large. This contrasts with the standard residential distribution tariff in Sweden, which charges a constant price for every unit of consumption, typically coupled with a subscription fee; i.e., a two-part tariff. As far as we are aware, demand charges are the only type of time-varying distribution tariff introduced in Sweden.[7]

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[6] Similar tariffs have been implemented in Finland, and Norway and in the US. See, for example, Lanot and Vesterberg (2021)

[7] However, households are free to choose any retail contract, including tariffs with time-varying prices such as real-time pricing. The demand for such contracts have, however, been limited; see, for example, Brännlund and Vesterberg (2021); Karimu et al. (2022); Vesterberg and Krishnamurthy (2016).

The distribution firms' motivations for encouraging customers to reduce peak consumption are multifaceted. Most importantly, reducing peak demand reduces the need for costly peak capacity that remains unused most of the time. Furthermore, in addition to avoiding or postponing costly investments in the grid, a reduction in peak demand can also lead to cutting costs associated with subscriptions to the overlying grid, power losses, wheeling charges and maintenance.

3 Previous literature

Turning to previous studies of electricity distribution firm operations, the literature on measurements of electricity distribution firm efficiency using SFA has increased substantially over the last 20 years, and has seen many methodological developments. The common findings in the literature are that few firms are fully efficient, and that the efficiency scores vary substantially across firms.

Some recent examples of papers estimating efficiency of electricity distribution firms using SFA include Musau et al. (2021) who use data on Norwegian electricity distribution firms to estimate both transient and persistent technical inefficiency, as well all allocative inefficiency (or input miss-allocation). Furthermore, they allow for all three type of inefficiencies to depend on covariates. They show that the average values of transient efficiency and persistent efficiency are high, at 0.98 and 0.86, respectively. These estimates are generally in the upper end of the range of previous estimates of the efficiency scores. The authors also show that costs of the distribution firms increase with more disruptions to the service, and that this has a negative impact on their efficiency scores. In addition, their results reveal that there is a negative association between firm size and persistent inefficiency.

Similarly, Kumbhakar et al. (2020) estimate the persistent and transient components of technical inefficiency and input mis-allocation of Norwegian electricity distribution firms, using panel data from 2000 to 2016. They use the proportion of underground cables as a determinant of persistent inefficiency, and the value of lost load per kilometer of network as a determinant of transient inefficiency, and show that the costs of input mis-allocation of Norwegian electricity distribution firms are non-negligible. The transient technical efficiency ranges from 0.76 to 0.92, depending on specification, whereas persistent inefficiency is estimated to be 0.85.

Kumbhakar and Lien (2017) estimate the transient and persistent efficiency of Norwegian electricity distribution companies for the period 2000-2013. The environmental variables (the proportion of underground cables, the proportion of air cables, the average slope in terrain and the

coastal climate) have all positive and significant parameters. This means that they contribute to higher production costs, on average. Their results reveal more inefficiency in the long run than in the short run, but that efficiency scores vary substantially across specifications, indicating that the regulators and practitioners should take extra caution in using the proper model in practice, especially when the efficiency measures are used to reward/punish companies through incentives for better performance. They also illustrate how the environmental variables proportion of underground cables, average slope in terrain and coastal climate have positive and significant parameters for all models. This means that they contribute to higher production costs, on average.

Zeebari et al. (2022) use data on Swedish electricity distribution firms to measure technical inefficiency, and allow estimates of the inefficiency to vary across ownership structure (public and private). They find technical inefficiency among all type of firms. Orea and Álvarez (2019) study inefficiency among Norwegian distribution utilities over the years 2004 to 2011 and allow inefficiency to depend on a number of firm characteristics, such as share of overhead lines, customer density and the number of transformation stations to examine, for example, whether larger utilities tend to be more efficient than smaller utilities. They show, among many things, that all determinants of inefficiency are significant and contribute negatively to the inefficiency scores.

A few papers have studied how firm efficiency depends on an increasing share of intermittent generation. Arocena (2008) analyzes the degree of vertical integration and diversification in the electricity industry using Data Envelope Analysis on Spanish data on electricity distribution. He shows 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 improves quality. Zhang et al. (2022) allow efficiency scores to depend on renewable energy access, and shows that renewable energy has a significant positive impact on the mean of inefficiency. Vesterberg et al. (2021), using a sub-set of our data, find that the effect of small-scale production on technical grid efficiency is insignificant or slightly positive.

Turning to the literature on the impacts of EVs on electricity grids, Burlig et al. (2021); Qiu et al. (2022) illustrate how EV charging may contribute to peak demand, which generally impose costs on the distribution network (see, for example, Lanot and Vesterberg 2021). Furthermore, several studies have focused on the scope for so-called vehicle-to-grid (or V2G) systems, where plug-in vehicles contribute with demand response to the grid, either through discharging or through reductions in charging (e.g.,

Venegas et al. 2021). While this literature appears to agree that storage provided from EVs may act as a flexibility option in power systems with high shares of variable renewable energy sources (e.g., Despres et al. 2017; Yu 2021), the actual impacts on grid operation are unknown and the literature on the magnitude of the economic benefits of vehicle-to-grid applications shows inconsistent and contradictory results (see the discussion in Heilmann and Friedl 2021).

The empirical literature on the impact of demand charges is sparse, but Lanot and Vesterberg (2021) show that households' response to the marginal incentives presented by demand charges is small. Bartusch and Alvehag (2014); Bartusch et al. (2011) find similar results. However, as far as we are aware, there are no previous studies on the impacts on the grid. While the limited demand response suggests that the effects are expected to be small, it may be the case that even small demand responses imply relatively large effects on firms' cost, and this motivates our empirical investigation of this issue.

4 Empirical approach

The methodology of applying SFA to panel data has evolved from the early work proposed by, for example, Pitt and Lee (1981), to the more recent four-component SFA model (e.g., Kumbhakar et al. 2014). In this model, the error term captures (i) unobservable unit-specific heterogeneity, (ii) transient inefficiency, (iii) persistent inefficiency, and (iv) random noise, each of which is separately identified given distributional assumptions.

The four-component SFA model improves upon the earlier models because it can separate unobserved heterogeneity from persistent inefficiency, and transient inefficiency from random noise. The model is more flexible in the sense that it allows for the inefficiency of a unit (e.g., firm) to be correlated with itself over time, and a unit may reduce part of its inefficiency over time by reducing short-term rigidities. In contrast, earlier SFA models generally assumed that inefficiency is independently distributed over time, which is a rather restrictive assumption (Lien et al. 2018). Other developments of the four-component error term SFA model allow identification of determinants of inefficiency (e.g., Battese and Coelli 1995; Lai and Kumbhakar 2018). For example, this allows the estimation of how firm characteristics, such as the amount of distributed generation, affects inefficiency.

We estimate the cost function of firms:

$$\ln C_{it} = \beta_0 + f(\boldsymbol{p}_{it}, \boldsymbol{y}_{it}; \boldsymbol{\beta}) + b_i + \eta_i + v_{it} + u_{it}(\boldsymbol{z}_{it}), \qquad (1)$$

where C_{it} is the total cost, $\boldsymbol{p}_{it}$ is a vector of input prices and $\boldsymbol{y}_{it}$ is a vector of outputs. b_i is the firm-specific effect that is

time-invariant, η_i is persistent inefficiency, v_{it} is random shocks and u_{it} is transient inefficiency with z_{it} the vector of the determinants for the transient inefficiency. We assume that $u_{it}(z_{it}) \geq 0$ and $\mathbb{E}[u_{it}(z_{it})] = g(z_{it}) \geq 0$. The random shocks v_{it} are assumed to have mean zero and a constant variance. By estimating a cost function, including prices and given level of output, we are avoiding the endogeneity problems often encountered when using a primal production function approach where the regressors are inputs.

We assume that there is no allocative inefficiency, and thus interpret the inefficiency here as cost of technical inefficiency. An alternative approach would be to allow also for allocative inefficiency. This approach—i.e., lumping technical and allocative inefficiency together—has been challenged in, e.g., Kumbhakar and Wang (2006b) as it may bias the estimation of model parameters if allocative inefficiency is not addressed explicitly/separately. Kumbhakar and Wang (2006a) suggest a solution to this, similar to Schmidt and Lovell (1979), where first-order conditions are estimated together with the cost function to explicitly separate out allocative inefficiency. It is outside the scope for the present study to econometrically explore the separation of the two types of inefficiency, and we focus on the cost of technical inefficiency. We refer to Kumbhakar and Wang (2006a, b) and the argumentation therein for further details regarding the biases that may arise if technical and allocative inefficiency are lumped together as 'cost inefficiency'.

We assume that the cost for firm $i = 1, \ldots, N$ in time $t = 1, \ldots, T$ can be described by a translog cost function for k outputs and m inputs, so that

$$
\begin{aligned}
f(\boldsymbol{p}_{it}, \boldsymbol{y}_{it}; \boldsymbol{\beta}) = \ & \sum_k \beta_{1,k} \ln y_{k,it} + \sum_m \beta_{2,m} \ln p_{m,it} \\
& + \tfrac{1}{2} \sum_k \sum_m \beta_{3,km} \ln y_{k,it} \ln p_{m,it} \\
& + \tfrac{1}{2} \sum_k \beta_{4,kj} \ln y_{k,it} \ln y_{j,it} \\
& + \tfrac{1}{2} \sum_m \beta_{5,mn} \ln p_{m,it} \ln p_{n,it}
\end{aligned}
\tag{2}
$$

In addition to this translog specification, we have also estimated a specification where we assume costs to be Cobb-Douglas, and the results are similar (see Section C in the Appendix). However, a likelihood ratio test reveals a significant improvement in model fit for the translog specification over the Cobb-Douglas specification.

Similar to the previous literature, we assume that the outputs are number of customers and network length, and the input prices are wages, cost of capital and price of electricity (firms purchase electricity from producers to replace network losses),

Previous literature on the efficiency of electricity distribution firms have made different assumptions regarding the parametrization of the inefficiency term. For example, Orea and Álvarez (2019) assume these to include the share of overhead lines, the number of transformer stations, and

customer density (customers per km of network length). Musau et al. (2021) assume that the determinant for persistent inefficiency is firm size (measured by logarithm of number of network stations), and that the determinant for transient inefficiency is value of lost load per kilometer network.

Furthermore, while some papers only parameterize the variance of the inefficiency term, and others only parameterize the mean, Wang (2002) argues for a parameterize of both the variance and the mean. According to Kumbhakar et al. (2015), this double parameterization is not only less ad-hoc, but it is also more flexible as it accommodates non-monotonic relationships between the inefficiency and its determinants. We follow this line of reasoning and allow both the mean and variance of the inefficiency term to depend on the same vector z_{it}. Specifically, we assume four different specifications for the determinants of transient inefficiency. In specification 1, we do not include any determinants of the inefficiency term; in specification 2, z_{it} includes small-scale generation (as percentage of total electricity delivered); in specification 3, we add the number of electric vehicles sold since 2012; in specification 4, we add an indicator variable taking the value one if firm i has introduced a demand charge tariff in year t. The persistent inefficiency is assumed to be iid with $\mathbb{E}[\eta_i] = a$ which is a constant.

To estimate Equation (1), we follow the three-step procedure in Musau et al. (2021). In the first step, we assume the firm-specific effects to be random. We then rewrite Equation (1) as

$$
\begin{aligned}
\ln C_{it} &= [\beta_0 + a + g(z_{it})] + f(\boldsymbol{p}_{it}, \boldsymbol{y}_{it}; \boldsymbol{\beta}) + [b_i + \eta_i - a] \\
&\quad + [v_{it} + u_{it}(z_{it}) - g(z_{it})] \\
&= h(z_{it}) + f(\boldsymbol{p}_{it}, \boldsymbol{y}_{it}; \boldsymbol{\beta}) + \alpha_i + \epsilon_{it}
\end{aligned}
\tag{3}
$$

where $h(z_{it}) = \beta_0 + a + g(z_{it})$, $\alpha_i = b_i + \eta_i - a$ and $\epsilon_{it} = v_{it} + u_{it}(z_{it}) - g(z_{it})$. The model in Equation (3) is a partial linear model for random effects panel data.

We follow Musau et al. (2021) and estimate the parametric component $f(\boldsymbol{p}_{it}, \boldsymbol{y}_{it}; \boldsymbol{\beta})$ in Equation (3) in the following way: first, we take the conditional expectation of each side of Equation (3) with respect to the determinants of the transient inefficiency, z_{it};

$$
\mathbb{E}[\ln C_{it} | z_{it}] = h(z_{it}) + f(\mathbb{E}[\boldsymbol{p}_{it}, \boldsymbol{y}_{it} | z_{it}]; \boldsymbol{\beta})
\tag{4}
$$

since $\mathbb{E}[\alpha_i | z_{it}] = 0$ and $\mathbb{E}[\epsilon_{it} | z_{it}] = 0$.

We then subtract Equation (4) from Equation (3) to obtain:

$$
\ln C_{it}^* = f(\boldsymbol{p}_{it}^*, \boldsymbol{y}_{it}^*; \boldsymbol{\beta}) + \alpha_i + \epsilon_{it}
\tag{5}
$$

where $\ln C_{it}^* = \ln C_{it} - \mathbb{E}[\ln C_{it} | z_{it}]$ and where we have removed the conditional mean from each of the squares

Table 1 Summary statistics

	Mean	Std. Dev.	Min	Max
Cost (MSek)	128,050	186,189.2	1,380	1,401,259
Wage (1000 Sek)	741.515	294.852	101	3705
Rental price of capital (Sek)	0.092	0.005	0.086	0.104
Electricity price (Sek)	0.383	0.116	0.069	1
Network length (km)	1,765.682	3,084.903	44	27,818
No. of customers	20,192.6	31,214	276	270,030
Share of small-scale generation	4.876	9.049	0	88.612
Number of network stations	555.858	1,026.733	15	8,826
Share of overhead lines	0.180	0.174	0	0.751
Customer density	106.849	59.0128	27.090	306.858
Observations	872			

and interactions in $f(\boldsymbol{p}_{it}, \boldsymbol{y}_{it}; \boldsymbol{\beta})$ to get $f(\boldsymbol{p}_{it}^*, \boldsymbol{y}_{it}^*; \boldsymbol{\beta})$. We estimate the conditional means nonparametrically using the local-linear kernel estimator (the local-constant estimator gives similar results).

Estimation of Equation (5), which is a linear random-effects panel data model, gives consistent estimates of $\boldsymbol{\beta}$ irrespective of the distributions of the error components (Kumbhakar and Lien 2017; Lien et al. 2018). It also gives predicted values of α_i and ϵ_{it}, which we use in steps 2 and 3.

In the second step, we use the predicted value of α_i from the first step: $\alpha_i = b_i + \eta_i - a$. Assuming $b_i \sim N(0, \sigma_b^2)$ and $\eta_i \sim N^+(0, \sigma_\eta^2)$,[8] we can estimate this equation using the standard cross-sectional SF technique, where a is a constant (see, e.g., Kumbhakar et al. 2015; Lien et al. 2018), and obtain predicted values of the persistent efficiency as $S_i^p = \exp(-\eta_i)$.

Finally, in the third step, we use the predicted values of ϵ_{it} from the first step to estimate $\epsilon_{it} = v_{it} + u_{it}(z_{it}) - g(z_{it})$. We assume $v_{it} \sim N(0, \sigma_v^2)$ and $u_{it}(z_{it}) \sim N^+(0, \sigma_u^2(z_{it}))$ so that $\mathbb{E}[u_{it}(z_{it})] = \sqrt{2/\pi}\sigma_u(z_{it}) = g(z_{it})$. Furthermore, we assume $g(z_{it}) = exp(\delta_0 + \delta_1 z_{it})$. We then estimate $\epsilon_{it} = v_{it} + u_{it}(z_{it}) - g(z_{it})$, again using the traditional SFA technique, to obtain predicted transient inefficiency values as $S_i^u = exp(-u_{it}(z_{it}))$ and marginal effects of z_{it} on the transient inefficiency.

Although it is possible to estimate the model in a single step (as in, for example, Badunenko and Kumbhakar 2017; Lai and Kumbhakar 2018, 2019, there are at least two advantages of the three-step approach over the single-step

method. First, the regression coefficients $\boldsymbol{\beta}$ estimated using the three-step approach are not affected by distributional assumptions on u_{it} and η_i since they are estimated prior to distributional assumptions (Kumbhakar and Lien 2017; Lien et al. 2018). Second, the three-step approach is relatively easy to implement.

Finally, we also note that previous literature has proposed other alternatives to estimating determinants of inefficiency in a parametric way. For example, Tran and Tsionas (2009) propose a stochastic frontier model with a non-parametric specification for covariates affecting the mean of technical inefficiency. Zhou et al. (2020) extend this work to also include firm heterogeneity in the non-parametric framework. However, none of these approaches allow for distinguishing between transient and persistent inefficiency.

5 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 information on all ($N = 179$) the Swedish DSOs' financial and technological data for the years 2014 to 2021. These data are used by the regulator for measuring firm efficiency.

The data includes firm-specific capital gross investments, which enabled us to create a firm-specific capital stock by applying the perpetual inventory method (Berndt 1991).[9] Specifically, we compute the capital stock at time t as $K_{it} = I_{it} + (1 - \theta)K_{it-1}$ where K_{it} denotes capital at time t, I_{it} denotes gross investments in inventories and machinery, and θ is the depreciation rate which we, following Dahlqvist et al. (2021), assume to be 0.087. Statistics Sweden also provided data on an investment good price index and a long-term interest rate, both at the national level, together with a sector-specific Producer Price Index (the output price), which are used to calculate the user cost of capital as follows: $p_K = p_I/p_Y(r + \delta)$ where p_I and p_Y denote the investment good price index and the output price (sector-specific Producer Price Index), respectively, r denotes the long-term market capital interest rate and $\theta = 0.087$ the depreciation rate as before.

Wage is calculated for each firm by dividing yearly total salary costs over the firm's number of employees (full-time and part-time), thus reflecting the average salary paid to a employee that year. The electricity price is calculated as the annual spending on electricity to cover network losses,

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[8] Greene (1990) compared average inefficiency levels across four main distributional specifications for the one-sided inefficiency term (half-normal, truncated normal, exponential, and gamma) and found that there is almost no difference in average inefficiency for 123 U.S. electric utility providers.

[9] This requires at least two observations on capital gross investments over two consecutive years for each firm. When this is not available, observations have been excluded.

Fig. 1 Box plot of costs, prices and customer density
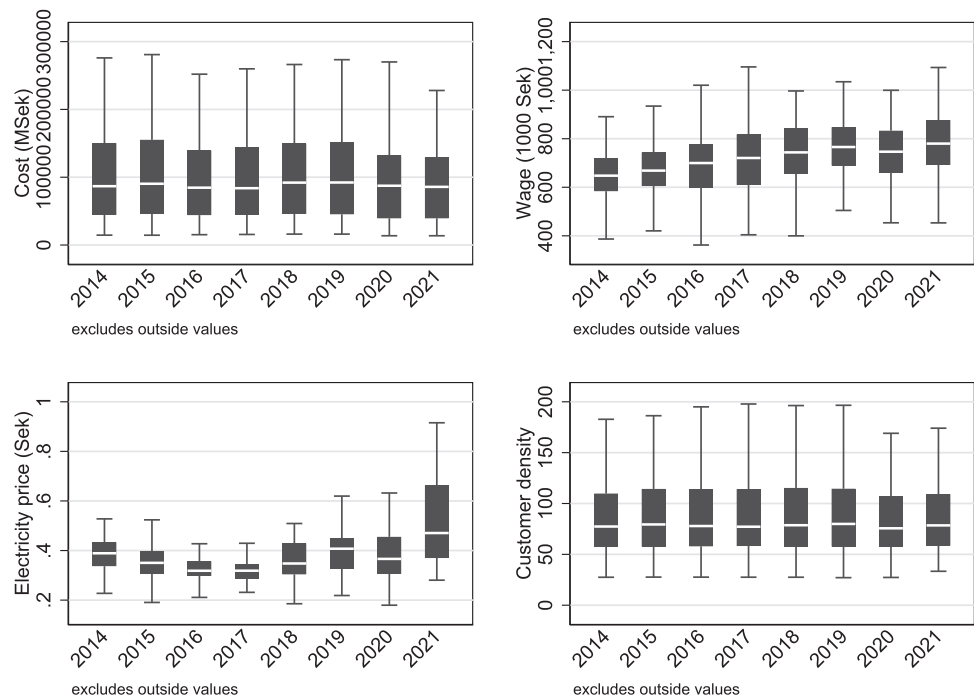
divided by the quantity (in kWh) purchased. All monetary values in this paper are in 2014 SEK.

Summary statistics of the key variables included in the empirical modeling are presented in Table 1.

As already discussed, firms differ markedly in size, illustrated by the large heterogeneity in costs, network length and number of customers, which mostly reflects variation across firms and not across time. For example, Fig. 1 illustrates that there is little variation in costs over time. Interestingly, there is large variation in customer density, illustrating that firms operate in very different environments. Furthermore, we note that there is large heterogeneity in all of the input prices. However, it is worth noting that while our data have variation across firms in the price of labor and electricity, there is no across-firm variation in the user cost of capital, and this should be kept in mind when interpreting these results. In particular, this means that it might be difficult to distinguish the effects of changes in interest rates to other events that affect firms in similar ways.

The regulator distinguishes between small-scale and micro-scale generation in the collection of data, where the former typically refers to wind power and the latter to solar power installations on roof tops. We briefly discuss the differences between these two measures here, but will in the rest of the paper focus on the aggregate of these two and refer to this quantity as small-scale generation. However, as a robustness analysis, we also estimate specifications where we allow these two measures to have different effects on the transient inefficiency.

While we see a large increase in micro-scale generation over time (and a large variation across firms as well) in the left panel in Fig. 2, it is interesting to note that the small-scale generation is relatively stable over time (right panel in Fig. 2) but varies substantially across firms, with a minimum of zero and a maximum close to 150,000 MWh (note that outside values are excluded in Fig. 2 to make it more easily readable). In shares of total generation within a grid, these numbers corresponds to a range from 0 to 0.9. We also note that the total amount of delivered electricity has been relatively stable over time.

In addition to the above data, we have collected annual data on the total number of new EVs sold since 2012[10] in each municipality from Statistics Sweden (see https://www.scb.se), and matched these municipality-level data to each grid area. However, there are a number of grids that either (i) only serve rural areas, with no metropolitan area, or (ii) serve several grids. Unfortunately, our data does not allow for matching these grids to car sales at the municipality level, and these grids (27 grids) are therefore excluded from the regressions where we explore the effects of EV sales on the cost of technical inefficiency. While the total number of EVs, including cars sold before 2012, and vintage EVS, should be what really matter to the operation of distribution firms (rather than only new cars sold since 2012), we do not have access to such data. However, we expect new EVs per

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[10] In a given year, $EV_{it} = \sum_{t=0}^{t} ev_{it}$ where ev is the number of cars sold in a given year, and EV is the aggregate number of sold cars since $t = 0$ (2012, in our case).
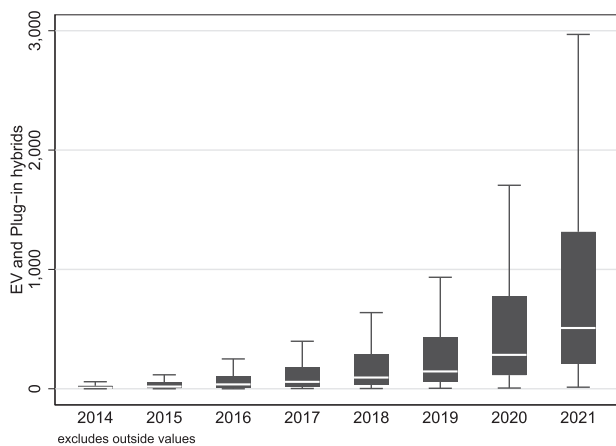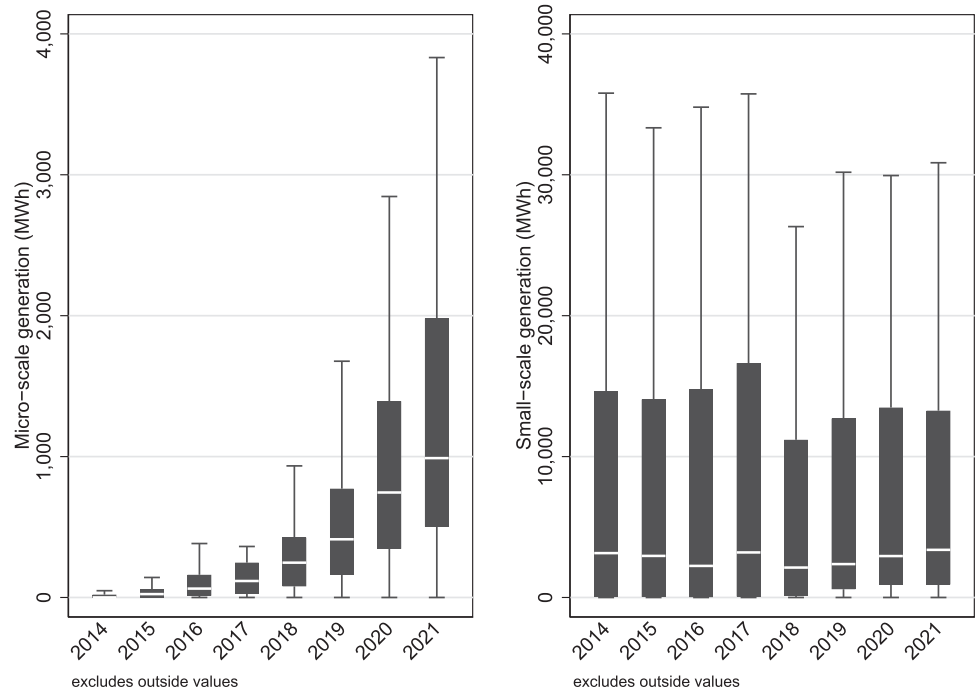
Fig. 2 Small-scale and micro-scale generation

Fig. 3 Number of EVs per grid area over years

Table 2 Elasticities of total cost with respect to prices and outputs

	Elasticity	Std. Err.
Wage	−0.505	0.444
Price of electricity	0.142	0.231
User cost of capital	−39.503	36.238
Cable length	0.605**	0.250
Number of customers	1.901***	0.255

Standard errors are computed using the delta method

Asterisks indicate p-values with $*p < 0.10$, $**p < 0.05$, $***p < 0.01$

municipality to be highly correlated to the total number of EVs.

Figure 3 provides a box plot of the distribution of EVs, by grid area. Evidently, the number of EVs has increased substantially during the latter part of the sample period, but with substantial heterogeneity across grid areas. In particular, some grid areas have seen a much larger increase in the number of EVs than other grids, and this is the case even if we account for the total number of cars sold per price area (e.g., by dividing the number of EVs by the total number of sold cars).

Finally, we have collected information about if and when firms have introduced demand charges. At the end of our sample period, a total of 10 firms had done so, which means that our analysis of pricing schemes on the cost of technical inefficiency relies on a relatively few number of observations of non-zero outcomes. This should be kept in mind when subsequently interpreting the results.

6 Results

We estimate the cost function in Equation (1) for the different specifications of the inefficiency term, using the three-step approach described in Section 4 and the data described in Section 5. Parameter estimate for the first-step estimation (i.e., the random effects model) are presented in Table 4 in the Appendix, associated elasticities at the mean in Table 2 and the distribution of elasticities in Fig. 4, efficiency scores are presented in Table 5, and determinants of the transient inefficiency are presented in Table 3. The number of observations differ across the specifications since there are a number of grids (27 grids) where our data does not allow for matching these grids to car sales at the municipality level, and these grids are therefore excluded from the regressions where we
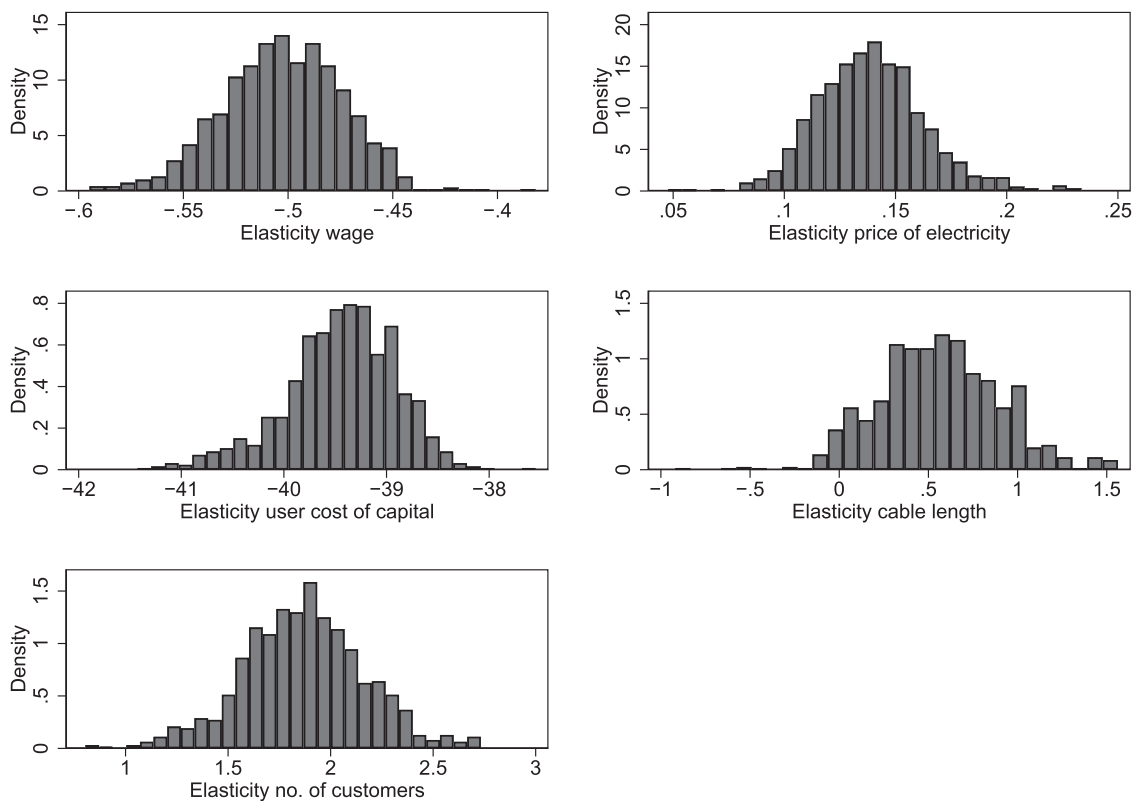
Fig. 4 Distribution of elasticities of total cost with respect to prices and outputs

explore the effects of EV sales on the cost of technical inefficiency. However, using only the smaller sample from specification 3 and 4 to estimate specification 1 and 2 does not change our results to any large extent.

Starting with the parameters in the cost function, a first thing to notice from Table 2 is that the only elasticities that are statistically different from zero are the output elasticities, with estimated elasticities of 0.605 for cable length and 1.901 for number of customers. The former elasticity is in line with previous literature; for example, Orea and Álvarez (2019) finds this to be 0.708 for electricity distribution in Norway. The elasticity with respect to the number of customers is larger than those found in previous literature; for example, Zeebari et al. (2022) find this elasticity to be 0.8087, whereas Orea and Álvarez (2019) find this elasticity to be approximately 0.163 (at the mean values of number of customers and cable length).[11] However, from

Fig. 4, we see that the elasticities vary across firms, with, for example, the elasticity with respect to cable length varying from zero to more than unity.

Furthermore, the mean elasticities with respect to input prices are all positive but statistically insignificant, and with a rather large variation across firms. In Table 10, where we assume the cost function to be Cobb-Douglas instead of translog, we find positive and significant elasticities with respect to the price of capital and the price of electricity, but the elasticity with respect to the cost of labor is insignificant; this is different from, e.g., Zeebari et al. (2022), who find the elasticity with respect to the cost of labor to be positive and statistically significant, with an estimate of 1.1079.

Next, we turn to the estimated efficiency scores, presented in Figs. 5, 6, 7 where we show box plots for the inefficiency scores for all four specifications. We also present mean, min and max efficiency scores in Table 5 in the Appendix. Beginning with the transient efficiency, the mean scores vary between 0.59 and 0.97, depending on specification, and where the efficiency scores from specifications 2, 3 and 4 are lower than for specification 1. For specifications 2 to 4, there is substantial heterogeneity among firms, as indicated by the difference between min and max efficiency. The mean persistent efficiency is relatively large, with a score of 0.915, but again with substantial heterogeneity among firms. The mean overall efficiency varies

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[11] Furthermore, Kumbhakar et al. (2020); Musau et al. (2021) study similar problem as ours for the Norwegian electricity distribution sector, but from an input demand perspective (estimating first order conditions from a cost minimization). Both approaches are input oriented but the elasticity estimates generated are not directly comparable since our more "primal" approach estimates (i.e., $(\partial C/\partial p_i)/(p_i/C)$) and an input demand elasticity - as in the case of Kumbhakar et al. (2020); Musau et al. (2021) - would be $(\partial^2 C/\partial p_i^2)/(p_i/X_i)$, and therefore not directly comparable.

Table 3 Determinants of transient inefficiency, translog specification

	(1)	(2)	(3)	(4)
Mean of u_{it}				
Percent small-scale generation		−0.032*	−0.074**	−0.075**
		(0.018)	(0.035)	(0.038)
EV and Plug-in hybrids			−0.001**	−0.001*
			(0.000)	(0.000)
Demand charge				−0.653
				(0.919)
Constant	−36.095			
	(57.428)			
Variance of u_{it}				
Percent small-scale generation		−0.058***	−0.053**	−0.058**
		(0.020)	(0.025)	(0.027)
EV and Plug-in hybrids			−0.000	−0.000
			(0.000)	(0.000)
Demand charge				−0.543
				(0.726)
Constant	−0.062			
	(1.595)			
Variance of v_{it}				
Constant	−5.422***	−0.425**	−1.163***	−1.277***
	(0.063)	(0.215)	(0.168)	(0.172)
Observations	872	872	639	639

Standard errors in parentheses

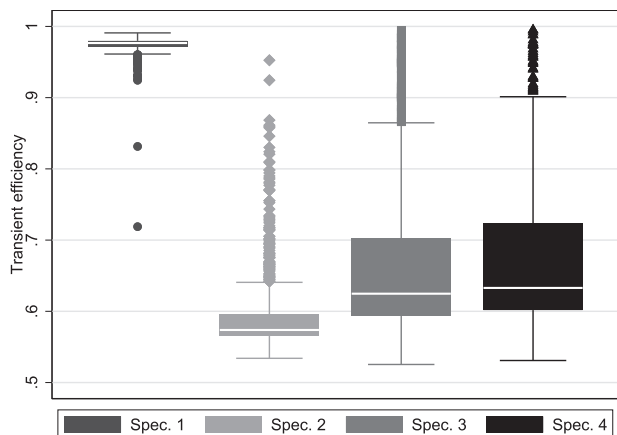*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Fig. 5 Distribution of transient efficiency scores

between 0.54 and 0.89, but where the least efficient firms have an efficiency score of less than 0.4. For comparison, Vesterberg et al. (2021) find technical efficiency for Swedish electricity distribution firms to be in the range of 0.33 to 0.95.

The determinants of the inefficiency term are presented in Table 3. We also illustrate the distribution of marginal effects in Fig. 8 (see Kumbhakar et al. 2015; Wang and Schmidt 2002 for how these marginal effects are computed) and the the distribution of the percentage of small-scale generation Fig. 9. In the results for specification 2, we see that an increasing share of small-scale generation reduces
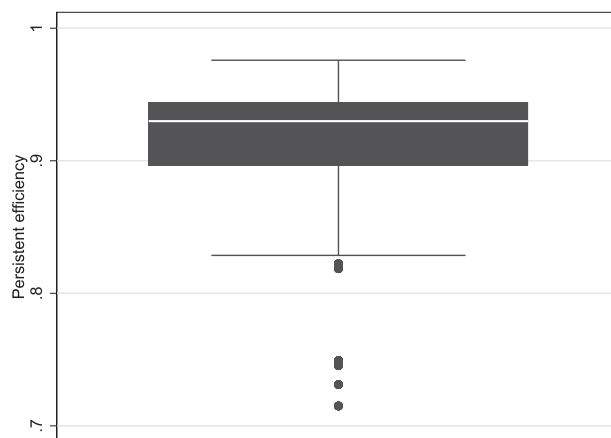

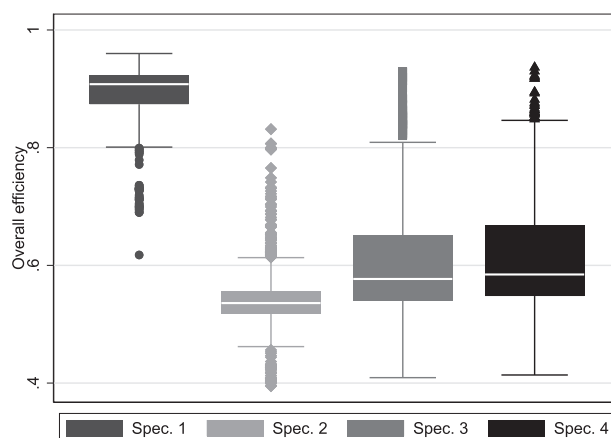**Fig. 6** Distribution of persistent efficiency scores

Fig. 7 Distribution of overall efficiency scores

both the mean and the variance of the transient inefficiency. However, the marginal effects on the mean and variance of the inefficiency term are small and close to zero.[12] Furthermore, the effect of EVs on the mean of the inefficiency is close zero, albeit statistically significant, and the effect of EVs on the variance of the inefficiency is statistically insignificant. We find no significant effect of the introduction of demand charges on the inefficiency, neither on the mean nor on the variance.

6.1 Robustness analysis

To asses the robustness of our empirical analysis, we estimate a number of alternative specifications; the results are briefly summarized below and the estimation output is presented in the Appendix in Section B and Section C.

First, we estimate the third step of the model assuming either that the environmental variables (percentage of

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[12] Furthermore, the association between the marginal effects and the share of small-scale generation is not very clear.

Fig. 8 Marginal effects of the percentage of small-scale generation on the mean and variance of the transient inefficiency term
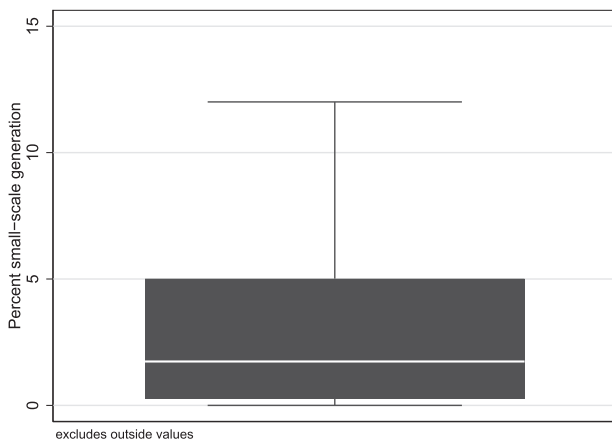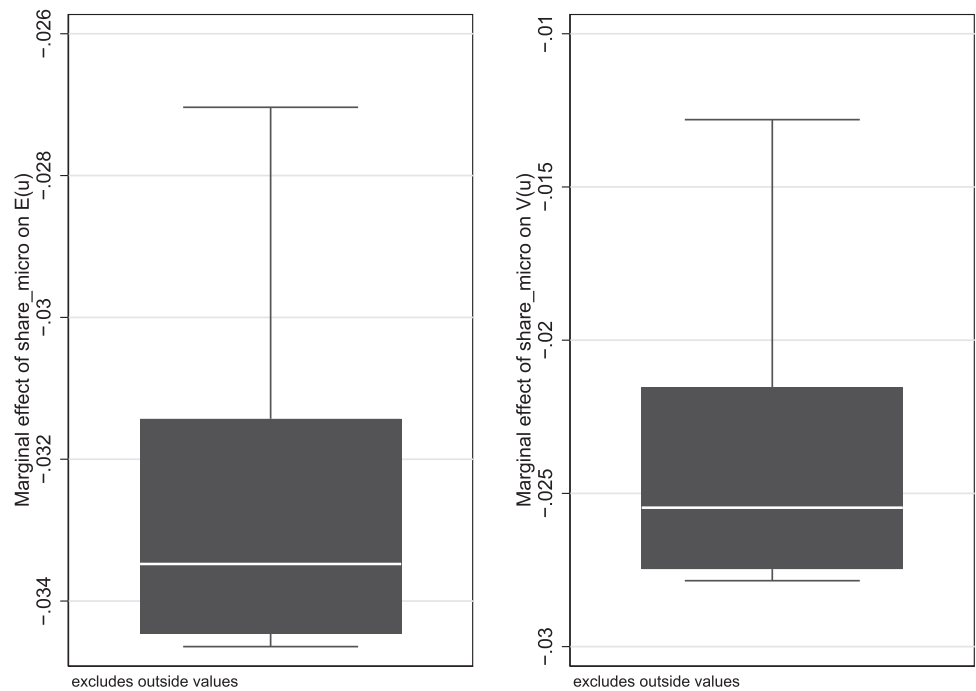

Fig. 9 Distribution of the percentage of small-scale generation

small-scale generation, number of electric vehicles and demand charge) only influence the mean, or only the variance, of the transient inefficiency. These results are presented in Tables 6 and 7. When the environmental variables only affect the mean inefficiency, we find a negative effect of small-scale generation and electric vehicles on the mean transient inefficiency, but the effects are small or insignificant, depending on the specification. Similar to the translog specification, we find no significant effect of introducing a demand charge. Results are similar if we instead the environmental variables only affect the variance of the inefficiency.

Second, we estimate the third step of the model where we only include the environmental variables percentage of small-scale generation, the number of EVs and the introduction of demand charge separately. These results are

presented in Table 8, and show that the percentage of small-scale generation and the number of EVs on the mean has a negative effect on the mean and that the percent of small-scale generation has a negative effect on the variance. However, similiar to our main specification, the effects are very small. Note that the results in the first column are identical to the results in the first column in Table 3; we include these results for comparison.

Third, we estimate a specification where we distinguish between small- and micro-scale generation; see Section 5 for details about these variables. We estimate three specifications; one where both the mean and the variance depend on small- and micro-scale generation, a second specification where the environmental variables only affect the mean, and a third specification where the environmental variables only affect the variance. In all three specifications, the effects of small- and micro-scale generation are very close to zero.

Fourth, we have estimated the model but assuming that the cost function is described by a Cobb-Douglas specification rather than a translog specification. These results are presented in Tables 10, 11 and 12. Worth noting is that a likelihood ratio test reveals a significant improvement in model fit for the translog specification over the Cobb-Douglas specification. A first thing to notice is that the elasticity of total costs with respects to the input prices for capital and electricity are significant and positive (see Table 10), which is a different result than from the translog specification, where all input price elasticities were insignificant. Furthermore, and similar to the translog specification, the elasticities for total cost with respect to outputs are significant and positive. The efficiency scores for the Cobb-Douglas specification (Table 11) are

approximately similar to the efficient scores obtained from the translog specification, and again, we note that there is a large heterogeneity among firms.

For the determinants of the transient inefficiency (Table 12), we first note that in specification 1, small-scale generation has a negative and significant effect on both the mean and the variance of the inefficiency. Second, we note that the effect of EVs on both the mean and the variance are close to zero of insignificant. Finally, we find no significant effect of the introduction of demand charges.

To summarize, we have estimated a range of alternative specifications, and the results appear robust. In particular, the effects of the environmental variables on the mean and variance of the transient inefficiency are small.

7 Conclusions

In this paper, we explore how increasing small-scale generation and an increasing number of electric vehicles affect the cost of technical inefficiency of electricity distribution firms in Sweden. Using a detailed firm-level panel data with information about both the percentage of small-scale generation, and the number of electric vehicles sold, we estimate a SFA model using the three-step approach suggested by Musau et al. (2021).

Our results reveal that there is substantial heterogeneity in efficiency among firms, with mean overall efficiency scores ranging from 0.6 to 0.9, depending on specification. We also show that the mean transient (or short run) inefficiency is larger than the mean persistent (or long term) inefficiency. Furthermore, we find little to no effect of small-scale generation and electric vehicles on the transient inefficiency, with marginal effects being close to zero for most firms.

Our results have important policy implications. First, there has been a worry that an increasing share of intermittent distributed generation may pose management, planning, and coordination challenges in the delivery of electricity, and that since distribution networks are not designed to accommodate generation, only consumption, this may reduce grid efficiency. Our results suggest that this worry may be exaggerated, and that the effects of distributed small-scale generation has only small effects on grid efficiency.

Second, there has been similar discussions about how the increasing number of electric vehicles may affect the grid: e.g., charging of electric vehicles may contribute to grid congestion, especially if charging coincides with system peak demand, and that electric vehicles may lead to a series of negative impacts on power quality. However, our results suggest that an increasing number of electric vehicles does not have any effect on grid efficiency.

Third, we find no effect on the efficiency of grids from the introduction of time-varying distribution tariffs. The motivation for these tariffs is to smooth consumption, reduce the need for costly investments, lower costs and improve grid efficiency, but these effects are questionable, according to our results. On the other hand, it should be kept in mind that these type of tariffs are still rare among distribution firms, and that in our data, few firms have introduced such tariffs. Thus, our results regarding this development should be interpreted with caution, and we call for more research on the impact of time-varying distribution tariffs and their effects on grid operation.

To summarize, we show little to no effect of small-scale generation and electric vehicles on the efficiency of electricity distribution grids in Sweden. Further research is needed, however, to confirm these results, and especially demand charges should be studied in the future, as more and more firms adopt these pricing strategies.

Author contributions T.L. and M.V. initiated the project together (including ideas and method). M.V. collected the data, and did a majority of the estimation. T.L. and M.V. wrote and revised the manuscript text together.

Compliance with ethical standards

Conflict of interest The authors declare no competing interests.

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8 Appendix A: Additional results

Tables 4, 5

Table 4 Cost function parameter estimates

	Coefficient	Std. Err.
Wage	−0.507	0.445
Price capital	−39.532	36.249
Price electricity	0.143	0.232
Network length	0.617**	0.253
No. of customers	1.914***	0.254
Wage x Price capital	−0.194	0.302
Wage x Price electricity	−0.044	0.060
Wage x Network length	−0.017	0.044
Wage x No. of customers	0.067	0.041
Price capital x Price electricity	−0.089	0.145
Network length x Price capital	0.005	0.024
Price capital x No. of customers	0.906***	0.104
Price electrcity x Network length	0.042	0.043
Price electricity x No. of customers	−0.066*	0.040
Network length x No. of customers	−0.418***	0.124
Wage squared	−0.004	0.053
Price capital squared	−15.711	15.330
Price electricity squared	−0.071*	0.041
Network length squared	0.256***	0.064
No. of customers squared	0.104*	0.061
Constant	−0.068	0.072
Observations	872	

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 5 Efficiency scores, translog specification

	Mean	Std. dev.	Min	Max
Transient efficiency 1	0.974	0.012	0.718	0.990
Transient efficiency 2	0.592	0.052	0.534	0.952
Transient efficiency 3	0.662	0.102	0.525	0.994
Transient efficiency 4	0.673	0.104	0.530	0.995
Persistent efficiency	0.915	0.049	0.714	0.975
Overall efficiency 1	0.891	0.050	0.617	0.960
Overall efficiency 2	0.542	0.055	0.394	0.831
Overall efficiency 3	0.604	0.098	0.409	0.929
Overall efficiency 4	0.614	0.101	0.413	0.936
Observations	872			

Table 6 Determinants of transient inefficiency, z_{it} only affect mean

	(1)	(2)	(3)
Mean of u_{it}			
Percent small-scale generation	−0.251***	−0.503***	−0.482***
	(0.033)	(0.105)	(0.110)
EV and Plug-in hybrids		−0.003***	−0.002***
		(0.001)	(0.001)
Demand charge			−0.023
			(0.546)
Variance of u_{it}			
Constant	−1.048***	−0.315	−0.766**
	(0.243)	(0.332)	(0.369)
Variance of v_{it}			
Constant	−2.307***	−1.825***	−2.203***
	(0.440)	(0.452)	(0.483)
Observations	872	639	639

Standard errors in parentheses

Asterisks indicate p-values with *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 7 Determinants of transient inefficiency, z_{it} only affect variance of u_{it}

	(1)	(2)	(3)
Mean of u_{it}			
Constant	−0.025	−0.005	−0.000
	(0.134)	(0.046)	(0.003)
Variance of u_{it}			
Percent small-scale generation	−0.165***	−0.234*	−0.214***
	(0.027)	(0.123)	(0.062)
EV and Plug-in hybrids		−0.002	−0.003*
		(0.001)	(0.002)
Demand charge			−0.023
			(0.831)
Variance of v_{it}			
Constant	−2.001**	−2.995*	−0.538**
	(0.824)	(1.570)	(0.242)
Observations	872	639	639

Standard errors in parentheses

Asterisks indicate p-values with *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

9 Appendix B: Robustness analysis

Tables 6, 7, 8, 9

Table 8 Determinants of transient inefficiency, separate environmental variables

	(1)	(2)	(3)
Mean of u_{it}			
Percent small-scale generation	−0.032*		
	(0.018)		
EV and Plug-in hybrids		−0.009***	
		(0.001)	
Demand charge			−0.160
			(0.362)
Variance of u_{it}			
Percent small-scale generation	−0.058***		
	(0.020)		
EV and Plug-in hybrids		0.000*	
		(0.000)	
Demand charge			−4.073***
			(1.322)
Variance of v_{it}			
Constant	−0.425**	−3.140***	−8.758***
	(0.215)	(0.176)	(0.969)
Observations	872	639	857

Standard errors in parentheses

Asterisks indicate p-values with *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 9 Determinants of transient inefficiency, separate small-scale and micro-scale

	(1)	(2)	(3)
Mean of u_{it}			
Small-scale generation (MWh)	−0.000	−0.000**	
	(0.000)	(0.000)	
Micro-scale generation (MWh)	−0.000*	−0.002***	
	(0.000)	(0.001)	
Constant			−1.734***
			(0.199)
Variance of u_{it}			
Small-scale generation (MWh)	−0.000		−0.000*
	(0.000)		(0.000)
Micro-scale generation (MWh)	−0.000		−0.000***
	(0.000)		(0.000)
Constant		−0.674***	
		(0.137)	
Variance of v_{it}			
Constant	−0.935***	−1.265	−1.902***
	(0.133)	(.)	(0.183)
Observations	872	872	872

Standard errors in parentheses

Asterisks indicate p-values with *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

10 Appendix C: Cobb-Douglas results

Tables 10, 11, 12

Table 10 Elasticities of total cost with respect to prices and outputs, Cobb-Douglas specification

	Elasticity	Std. Err.
Wage	−0.024	(0.024)
Price capital	0.996***	0.253
Price electricity	0.024*	0.013
Network length	0.374***	0.024
No. of customers	0.600***	0.022
Constant	−0.111***	0.032
Observations	885	

Standard errors are computed using the delta method

Asterisks indicate p-values with *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 11 Efficiency scores, Cobb–Douglas specification

	Mean	Std. dev.	Min	Max
Transient efficiency 1	0.591	0.052	0.532	0.952
Transient efficiency 2	0.655	0.103	0.518	0.995
Transient efficiency 3	0.670	0.104	0.528	0.995
Persistent efficiency	0.997	0.000	0.997	0.997
Overall efficiency 1	0.590	0.052	0.531	0.950
Overall efficiency 2	0.653	0.103	0.517	0.993
Overall efficiency 3	0.668	0.104	0.527	0.993
Observations	885			

Table 12 Determinants of transient inefficiency, Cobb–Douglas specification

	(1)	(2)	(3)
Mean of u_{it}			
Percent small-scale generation	−0.032*	−0.076**	−0.077**
	(0.018)	(0.033)	(0.037)
EV and Plug-in hybrids		−0.001**	−0.001
		(0.000)	(0.000)
Demand charge			−0.619
			(0.904)
Variance of u_{it}			
Percent small-scale generation	−0.058***	−0.049**	−0.056**
	(0.020)	(0.023)	(0.026)
EV and Plug-in hybrids		−0.000	−0.000
		(0.000)	(0.000)
Demand charge			−0.534
			(0.726)
Variance of v_{it}			
Constant	−0.413*	−1.064***	−1.254***
	(0.214)	(0.166)	(0.170)
Observations	885	643	643

Standard errors in parentheses

Asterisks indicate p-values with *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

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