Norwegian University of Life Sciences
School of Economics and Business

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Working Papers No. 1/2020

ISSN: 2464-1561

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Abstract

We observe a rapid rise in the number of electric vehicles (EVs) in Norway, and there exists a literature that warns that EV charging will cause substantial future costs to the local grid, unless measures are put in place. If indeed the aggregate uncoordinated charging by EV owners does induce higher costs to local grid companies (hereafter DSOs – Distribution System Operators), then Norwegian data would be the first place to investigate. Detailed data of all Norwegian DSOs and all registered EVs during the last ten years gives a unique opportunity to investigate this relationship. To our knowledge, such an empirical analysis has not been done before on real data in a country-wide analysis. Findings may have implications for how to regulate DSOs, how to price household power usage and how to assess the net social cost of achieving emission reduction targets through promoting EVs. We use a fixed effects regression model and find that increases in EV stock are associated with positive and statistically significant increases in DSO costs when controlling for other DSO outputs and applying year dummies. The point estimates also imply that the effect is economically significant. However, there is a lot of heterogeneity in these results, where the marginal cost estimates are a lot higher for small DSOs in rural areas, and a lot lower for larger DSOs in urban areas.

1 Introduction

Do electric vehicle (EV) owners impose a negative externality on other electricity consumers when they plug in their cars at home during peak hours for electricity? In the absence of any peak pricing scheme, if the high power consumption of EVs leads to higher local grid costs, the resulting increase in uniform grid tariffs will be shared among all customers. Simulation exercises suggest that uncoordinated EV charging might have an impact on the local grid (see e.g., De Hoog, Alpcan, Brazil, Thomas, & Mareels, 2015; Masoum, Deilami, Moses, Masoum, & Abu-Siada, 2011), but the

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empirical evidence is scarce. What can we learn from actual data in the country with the highest EV share, namely Norway?

The high EV share must be viewed as a result of national climate policy, policy which since 2015 aims to fulfill Norway's part of the Paris agreement. The Paris agreement aims to limit the global temperature increase in this century to well below 2°C above pre-industrial levels. The transport sector accounts for approximately one quarter of global energy-related greenhouse gas (GHG) emissions (International Energy Agency, 2017) and about one third of Norway's GHG emissions[2]. This sector would therefore need to reduce emissions substantially in order for the Paris agreement to hold.

Norway's goal is to ensure that all new passenger cars are zero emission vehicles by 2025. Low vehicle taxes, toll road exemptions, and access to bus lanes have been put in place for EVs, which has resulted in the highest penetration of EVs worldwide. By January 2019, there were about 190 000 battery electric vehicles (BEVs) and 90 000 plug-in hybrids (PHEVs) in Norway, a country with only 5.3 million inhabitants. In 2018, BEVs accounted for 31 percent and PHEVs for 17 percent of all new vehicles (Norwegian Electric Vehicle Association, 2019).

The Norwegian Water Resources and Energy Directorate (NVE) presents a scenario where the growth in BEVs in Norway continues and reaches 100% of the new car sales after 2025. This implies 1.5 million BEVs in Norway in 2030, resulting in a 3% increase in domestic electricity consumption (Skotland, Eggum, & Spilde, 2016). So even with rapid electrification of passenger transport, we can expect aggregate electricity generation to cope without major challenges.

However, while a BEV's energy consumption may be modest, its power usage could be quite high. Currently, power demand per electricity consuming unit in a household usually vary from 2.3 to 7.3 kW. Contrast this to fast chargers that currently demand more than 50 kW, and likely demand up to 350 kW in the near future. Skotland et al. (2016) find through a survey that most BEV owners do their daily charging at home (almost 90%). Charging at work or at public charging stations seems at this point to be mainly supplemental. NVE's review indicates that charging of BEVs primarily takes place at night, while some also charge their vehicle immediately after work, which is a peak period for electricity consumption.

Uncoordinated charging (or "dumb charging") will increase electricity consumption during the morning and evening peaks (Graabak, Wu, Warland, & Liu, 2016). De Hoog et al. (2015) point out that if EV charging is not controlled, adverse impacts on the distribution network are expected: power demand may exceed distribution transformer ratings; line current may exceed line ratings; phase unbalance may lead to excessive current in the neutral line; and voltages at customers' points of connection may fall outside required levels. A similar point is made by Neaimeh et al. (2015). Skotland et al. (2016) develop a stress-test for neighborhoods with high BEV density. Assuming periods where 70% of the residents charge their BEVs simultaneously during peak hours, it finds that power demand can increase by up to 5 kW per household. This

[2] Statistics Norway: "Emissions of greenhouse gas emissions, by source" (in Norwegian)

results in overload for more than 30% of the transformer stations currently servicing the distribution network.

Our motivation for this paper is as follows: We observe a rapid rise in the number of BEVs, and there exists a literature that warns that BEV charging will cause substantial future costs to the local grid unless measures are put in place. If indeed the aggregate uncoordinated charging from BEV owners does induce higher costs to local grid companies (Distribution System Operators - DSOs), then Norwegian data would be the first place to investigate. Detailed data of all Norwegian DSOs and all registered BEVs during the last ten years gives a unique opportunity to analyze this relationship. To our knowledge, such an empirical analysis has not been done before on real data in a country-wide analysis. It will therefore push the knowledge frontier on a debated, but relatively unexplored topic empirically. Findings may have implications for how to regulate DSOs, how to price household power usage and how to assess the net social cost of achieving emission reduction targets through promoting EVs.

This paper complements previous studies that look at the effects low-carbon technologies such as BEVS and PHEVs can have on the electricity market. Our analysis covers a relatively long time-period of real experiences with increasing BEV density (it has reached over 10% of the car fleet in some areas), while most of the relevant literature up until now have been simulation exercises in numerical models of local grids. Hattam and Greetham (2017) analyze how EVs affect load profiles on neighborhood level in low voltage networks. Azadfar, Sreeram, and Harries (2015) look at charging behavior in terms of time of day, duration, frequency and electricity consumption in light of its implication for electricity network management. Barton et al. (2013) look at the challenges for grid balancing when EV charging becomes more prominent, and stress the importance of demand side management with time-shifting of electricity loads from periods of peak demand to off-peak, and from periods of low renewable energy supply to periods of high supply. Other studies also argue for demand side management (see e.g., Haidar, Muttaqi, & Sutanto, 2014; Masoum et al., 2011) as an alternative to costly upgrades of distribution transformer stations. Some of these studies also argue for pricing schemes that disincentivize charging during peak hours (see e.g., Barton et al., 2013; Clement-Nyns, Haesen, & Driesen, 2011; Masoum et al., 2011; O'Connell et al., 2012). In the future, smart-charging technology and vehicle-to-grid[3] (V2G) and vehicle-to-building (V2B) solutions may also provide a means to mitigate capacity problems in both electricity generation and distribution (Barton et al., 2013; Clement-Nyns et al., 2011; Mwasilu, Justo, Kim, Do, & Jung, 2014; Sioshansi & Denholm, 2010), but bidirectional EV charging is in its infancy (Haidar et al., 2014), and seems to come at a relatively high cost due to increased battery degradation, energy losses, changes in infrastructure, and extra communication between EVs and the grid (Habib, Kamran, & Rashid, 2015).

Exploiting local differences in the growth of the BEV fleet over time, we investigate how an increase in the number of BEVs affects the costs of the local DSO. We look at both total costs and individual cost components. We analyze data on 107 DSOs over the period 2008-2017 using fixed-effects estimation that account for time-

[3] V2G involves using EVs as storage for electricity.

invariant characteristics of the DSO. We also control for growth in output indicators that could be correlated with growth in the BEV fleet.

The main finding is that increases in BEV fleet are associated with positive and statistically significant increases in costs when controlling for other DSO outputs and applying year dummies. The point estimates also imply that the effect is economically significant. However, there is a lot of heterogeneity in these results, where the marginal cost estimates are a lot higher for small DSOs in rural areas, and a lot lower for larger DSOs in urban areas.

Section 2 presents the regulatory setting for local grid operators in Norway, and why the growth in BEVs may exacerbate existing market failures. Section 3 presents the methods and data. In section 4 we present the results from our empirical analysis. Section 5 discusses the results, and section 6 concludes.

2 EVs and Norwegian DSO regulation

As mentioned in the introduction, there is reason for concern over the costly impact that an increasing number of BEVs and uncoordinated charging behavior may have on the local grid. These costs may or may not accrue to the household that demands higher capacity. Norwegian DSOs are regulated under a revenue cap model with benchmark (or yardstick) competition against other DSOs (see e.g., Decker, 2014, pp. 103-140), where they set their tariffs based on this revenue cap. The revenue cap is composed of 40% cost recovery and 60% cost norm based on benchmark modeling using data envelopment analysis (DEA) (NVE, 2015). This means that an increase in costs increases the revenue cap, which allows the DSO to raise its tariffs. However, the revenue cap, and therefore the tariffs, are constrained by the cost development of the other DSOs that comprise the benchmark competition. Eventually, at least some of the increase in capital cost will lead to higher tariffs, and these will have to be paid by all consumers connected to the local grid, and not just the households demanding more capacity. It can be viewed as a pecuniary external cost in an incomplete market (Greenwald & Stiglitz, 1986). That is, the households demanding more capacity do not face the full cost of the capacity expansion, and indirectly impose costs on other consumers.

We describe the mechanisms for how an increased number of BEVs may lead to higher costs to DSOs and subsequently to higher grid tariffs through the following steps:

1. The BEV share increases in a neighborhood.
2. Households will charge their BEVs at 3.6-7.2 kW, and the demand for power capacity will increase.
3. With a certain size of the BEV share and a certain share of the owners charging simultaneously, the existing distribution transformer and/or the cables between the transformer and the household will not be able to handle the power capacity demand at certain times of day, certain times of year. This may lead to more inspection and maintenance before new investments need to be made.
4. The DSO invests in capacity expansion in the local grid. The cost of such capacity expansion will depend on whether enhancements need to be done for the

transformer and/or the cables, the amount of transformer capacity that needs to be installed, whether the new transformer fits in the old box that contained the old transformer, and the costs of digging (i.e. how many meters of cables need to be laid, and the costs per meter, which is generally higher in denser, urban areas).This induces new investment costs that otherwise would not have occurred, or at least an advancement of investments.

5. The new investment increases the capital stock for the DSO.
   - Regulation then says that the DSO can charge higher grid tariffs to cover costs (subtracted any co-funding of upgraded infrastructure).
   - All of the DSO's customers have to pay the higher tariffs.

The case becomes a little different if a household demands higher power capacity than currently installed in the household, and *this* increased capacity demand leads to exceedings of the capacity of the local distribution transformer. This household may be required to pay for some or all of the capacity expansion of the transformer through connection charges, in addition to paying for the capacity expansion in his own house. Practices between DSOs seem to vary, but the DSO in the Oslo metropolitan area, Hafslund, will in such a case charge the household that induced the new investment in proportion to the added installed capacity for that household[4]. For example, if a household wants to install 20 kW extra of capacity, and the DSO replaces a 315 kW transformer with a 500 kW transformer, the household has to pay 20/(500-315) = 11% of the cost of the capacity increase. Households that expand in-house capacity in the future will also have to chip in on this transformer upgrade in proportion to their in-house expansion. This would mean that less or none of the investment cost will be passed on to the other consumers through increased tariffs. Instead the scheme provides a price signal to the very households that demand more capacity, thus informing their decision to whether the benefits of expanding their in-house capacity outweigh the cost.

The scenario where increased BEV ownership leads to higher capacity demand that eventually exceeds the local transformer's capacity, without any household expanding its in-house capacity, is expected to be most prevalent. The reason is that most households will have the possibility of charging an EV at 3.6 kW power without the need for any in-house capacity expansion (conversation with the DSO Ringeriks-Kraft AS). Most would still have to make some adjustments to their in-house electric system as charging a BEV is required to be on a separate fuse.

This will lead to situations where over time some neighborhoods could drive up DSO costs as BEV ownership increases, leading to higher tariffs for all customers. Whether higher BEV ownership will drive up total neighborhood capacity demand will depend on the number of BEVs and their battery sizes, how many that charge at the same time during power peak hours, and the existing capacity on the local transformer and cables.

Currently, no individual household has any incentive to avoid charging at peak hours[5]. Both electricity prices and grid tariffs are the same throughout the day. And there are

[4] https://www.hafslundnett.no/artikler/bygge-og-grave/anleggsbidrag/6l51MrL1vyaCi0WsisqAQQ

[5] Some DSOs are experimenting with hour-by-hour pricing experiments, where participating households will be informed about and charged according to hour-by-hour prices (https://www.frisch.uio.no/prosjekter/?pid=3501&view=project)

many arguments for why BEV owners would want to charge the car right away after coming home. First, it is convenient. You plug in, and there is no need to spend mental capacity on timing. Second, you maximize the probability of always having the battery charged for any activity later; planned, spontaneous or emergency.

DSOs' profitability is determined by their costs and their regulated revenue cap. If policies drive up BEV ownership and subsequently capacity demand, their costs will increase, most likely without a corresponding increase in the revenue cap. Since "local BEV stock" is currently not a variable in the benchmark competition analysis, the cost norm calculation will disfavor DSOs that face increased capacity demand from BEV users. A DSO facing such increases in power demand, will see BEV-favoring policies as a threat to their profitability. An exception would be a DSO that already is among the most productive and remains among them in spite of the increase in capacity demand from BEV owners. Such a company would set the cost norm, and will be able to pass the entire cost increase on to consumers. If then the cost norm is expanded, DSOs who are *not* exposed to higher capacity demand from BEV owners will get a larger revenue cap, but no extra costs.

If capacity demand from BEV owners becomes a major cost driver for DSOs, there are at least two measures the regulator can take. The first is to incorporate a measure of "local EV stock" in their benchmarking model for calculating the cost norm for the sector, so that the relatively low costs for DSOs with low BEV density are not mistaken for efficiency. The second is to allow for peak power tariffs. NVE argues that the introduction of power-based tariffs will provide incentives to shift charging outside peak-hours. An official proposal has been drafted and is currently out on a public hearing[6]. Power-based tariffs have become technologically feasible after January 1st 2019, when smart meters became compulsory for all Norwegian households. This will enable households to closely monitor their temporal consumption profile of electricity, and both distribution grid companies and electricity retailers to bill accordingly.

3 Methods and data

3.1 Model concept

The main objective of our empirical analysis is to isolate the effect that changes in the BEV stock has on DSO costs. Parts of the data that we use to analyze this is the very same data that NVE uses for regulation by calculating the annual revenue cap for DSOs. The main outcome variable for our analysis is the DSOs annual total costs (*tot_cost*) as this is the main basis for calculating the revenue cap. The total costs are the sum of operational costs (*opex*), capital costs (*cap_cost*), depreciation costs (*dep_cost*), CENS - cost of energy not supplied (*cens*) and cost of energy network losses (*eloss_cost*).

In the benchmarking competition DSOs performance is measured by the output variables number of subscribers (*subscribers*), number of transformer substations

[6] NVE is currently working on a new proposal and there is expected to be a hearing in the first quarter of 2019 https://www.nve.no/reguleringsmyndigheten/nytt-fra-rme/nyheter-reguleringsmyndigheten-for-energi/nve-legger-opp-til-ny-horing-om-nettleiestruktur/ [in Norwegian, last accessed 03.12.2019].

(*substations*) and kilometers of high voltage grid, including overhead lines, underground cables and subsea cables (*voltline*).

In the regulatory DEA calculations, NVE controls for a set of contextual factors that can be seen as external cost-driving factors. This is in order not to mistake a difficult operating climate for some DSOs for inefficiency. All of the contextual variables are assumed to be time-invariant in NVE's analysis. The applied variables are displayed in Figure 1. In the model below, all these variables are covered by the vector X_i.

To summarize, in NVE revenue cap calculation the DSO costs are assumed to be driven by three output measures and external cost-driving factors. In our analysis, we want to investigate whether the registered number of BEVs in their operational area is an external cost driving factor that currently is not accounted for. Figure 1 gives an illustration of how we expect the relationship between the variables to be.

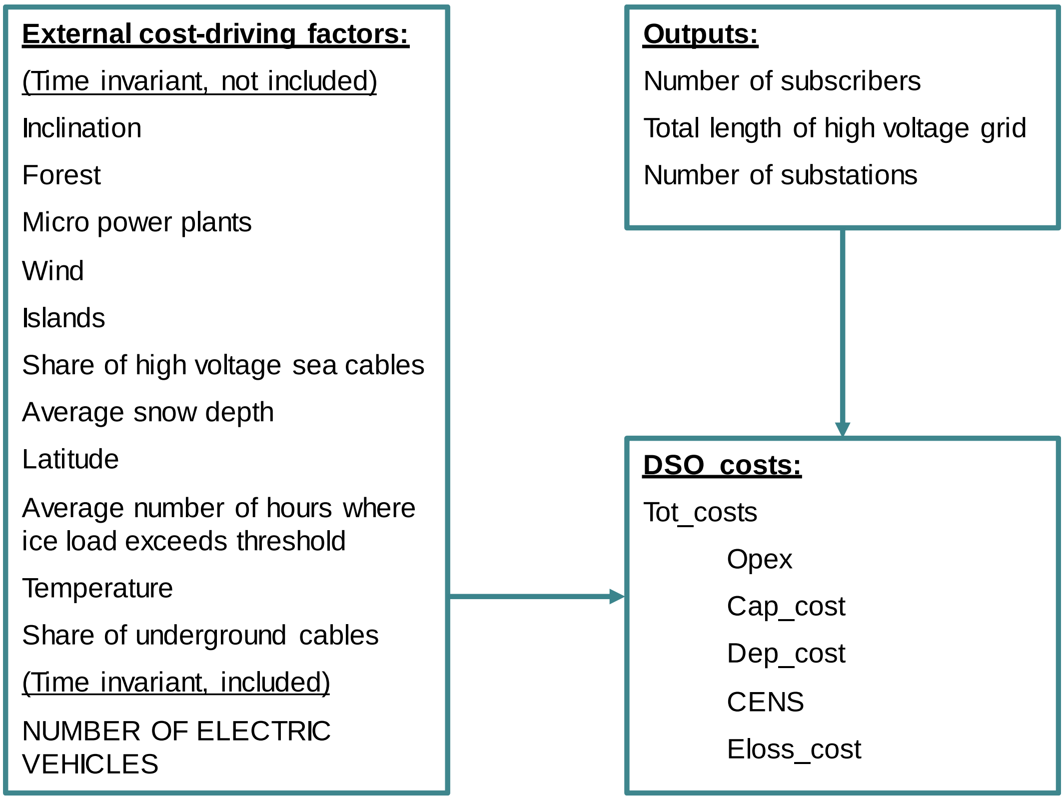

Figure 1: Direction of impacts from outputs and external cost-driving factors to costs

Due to substantial skewness in the distribution of DSO costs (see Table 1), we have decided to transform the model into a log-log format. We will discuss this in section 3.3. Conceptually, our economic model looks like the following:

(1) $$tot\_cost = ASubscribers_{it}^{\beta_1} Voltline_{it}^{\beta_2} Substations_{it}^{\beta_3} BEV_{it}^{\beta_4} X_i^{\gamma}$$

When we do a log-log transformation, we get:

$$log(tot\_cost) = \alpha + \beta_1 log(subscribers_{it}) + \beta_2 log(voltline_{it}) + \beta_3 log(substations_{it}) + \beta_4 log(BEV_{it}) + \gamma log(X_i) \quad (2)$$

Here, $\alpha = \ln(A)$ and the beta coefficients can be interpreted as cost elasticities. We expect them all to be positive. Beta coefficient values of 1 imply constant returns to scale for a given variable, whereas values above 1 imply decreasing returns to scale (disproportionate cost increases) and values between 0 and 1 imply increasing returns to scale. Our default assumption is that these elasticities are constant, but we will in section 4 investigate whether the beta coefficients could depend on the level of the explanatory variable, e.g., $\beta_1 = \beta_{10} + \beta_{11} log(subscribers)$, by adding squared transformations of the variable.

3.2 Data and variables

We have combined 3 datasets. 1) NVE's data for DSO costs and outputs applied for regulation, with 2) NVE's data for the DSOs legal operational area, with 3) municipalities, which finally can be merged with Statistics Norway's (SSB) data over registered cars at municipal level.

NVE's data for DSO costs and outputs applied for regulation

The data is extracted by running an R-script according to instructions from NVE's web pages (NVE, 2017). The data consists of cost measures and other characteristics (in total 164 variables) of 134 grid companies operating in either the local grid or the regional grid. Our analysis will only focus on the local grid, so we end up with 114 DSOs for the time period 2008-2017. We want the dataset to consist of all DSOs that distribute electricity to households, as these are the ones that may be affected by home charging of EVs. This leads to an additional 7 grid companies being dropped from the data set, as these are grid companies supplying industry parks or military bases. That leaves us with 107 DSOs supplying households all across Norway.

Following NVE's instructions, operational costs are adjusted to reflect 2015-prices using the consumer price index for the service sector. CENS is adjusted to reflect 2015 prices using the consumer price index. Annual capital costs (or the regulator-allowed return on invested capital) are calculated by multiplying the value of the regulatory assets (*regulat_assets*), which is the value of the total capital stock excluding co-paid assets (*co-paid_assets* – which customers pay for themselves), with the NVE-calculated regulatory interest rate for each year. The contextual variables mentioned in the previous section also follows with this dataset. Since all the contextual variables in vector X_i are time-invariant, they drop out of the fixed effects regressions in this paper.

NVE's data for the DSOs legal operational area

NVE's hydrology department have given us access to data on DSOs' legal operational area and matched this with municipalities. In total 149 companies have areas for grid operation. Using the organizational number as a unique identifier, we can merge together cost data and operational area data. These two data sets were also combined in Orea, Álvarez, and Jamasb (2018) for the purpose of efficiency analysis using a spatial econometric approach.

Statistics Norway's data over registered cars at municipal level

The StatBank of SSB contains data on registered cars at municipal level categorized by fuel type. We have extracted the number of electric passenger cars for each of the years 2008-2017 for all Norwegian municipalities. This can then be merged with the rest of the dataset, using the municipal number as the unique identifier.

Not all municipalities and DSO operational areas match one-to-one. Where a municipality has its area covered by more than one DSO, it is assumed that the DSO's share of the municipality reflects the share of households in the municipality and subsequently the share of EVs. Arguably, this introduces some measurement error into the data, but we expect this error to be small, as 90% of the municipalities have 95% or more of their area covered by a single DSO. This means that observed EVs at municipal level are aggregated up to DSO level and weighted by area to the variable we call *BEVs*.

The variables

For this analysis we will conduct separate regressions with the different dependent variables; *tot_cost* and its sub-components *opex*, *cap_cost*, *dep_cost*, *cens*, and *eloss_cost*. Descriptive statistics of these variables are given in Table 1. We will also conduct regressions with the variables *regulat_assets* (which should yield similar coefficients as *cap_costs*) and *copaid_assets*. With regards to the latter, it would be interesting to see if growth in BEV ownership is associated with growth in customers co-paying directly for upgraded infrastructure (e.g. when setting up a fast-charging stations).

The independent variables will be the DSO output variables *subscribers*, *substations,* and *voltline* and our main variable of interest *BEVs*. We expect the coefficients for the three DSO output variables to be positive for total costs and all the sub-components, as more output should *ceteris paribus* drive up costs. We expect he coefficient for *BEVs* to be positive for total costs and all the sub-components, but also to have the most significant coefficient in the regression on *cap_costs*. This is because the impact that EVs may have on costs for DSOs, if any, would be that they drive up investments in more capacity (cf. Section 2).

We exclude the variable *substations* as there could be cases where DSOs would build more substations to meet local capacity demand increases stemming from BEV charging, cf. the literature referenced to in Section 2. In such cases, the variable s*ubstations* could be considered what Angrist and Pischke (2008) calls a "bad control". When bad controls are applied the coefficient estimates of the independent variables will be biased and lose their causal interpretation. It is not clear whether we should expect increases in BEVs to drive increases in the number of substations (as it probably would be more common to reinforce existing ones), but in order to stay on the safe side we only include the variable *substations* in robustness checks with alternative specifications.

A linear model in absolute terms would give the easiest interpretation. Then interpretation would be "For every new BEV registered among the customers of the

DSO, we can expect a β_{EV} NOK increase in the DSO's cost, *ceteris paribus*". However, the cost variables have very high numbers for skewness and kurtosis (see Table 1), making it less suited for OLS. This is not surprising given that the Norwegian DSO sector consists of many small operators and a few very large ones. Transforming the main cost variable to a cost-per-customer variable, or taking the logarithm gets it closer to a normal distribution. The log-transformed cost variable is somewhat closer to a normal distribution compared to the per-customer transformation. This can be seen in the two bottom rows of Table 1. We therefore proceed with the log-log[7] model in this paper, and use a per-customer model as a robustness check (see Appendix A).

Table 1: Descriptive statistics

	Mean	*1st percentile*	*Median*	*99th percentile*	*Skewness*	*Kurtosis*
Tot_cost	120 048	7 652	42 935	909 365	5.05	35.39
Opex	62 234	4 445	24 281	415 189	5.78	45.90
Cap_cost	20 433	809	6 361	207 649	4.29	25.46
Dep_cost	21 733	816	7 231	217 133	4.04	22.44
CENS	4 861	61	1 271	58 898	4.02	21.65
Eloss_cost	10 786	342	2 928	89 277	6.74	58.96
Subscribers	26 980	999	6957	208 411	6.57	54.79
Voltline	932	51	339	7138	3.87	21.16
Substations	1177	59	377	10 626	4.47	27.38
BEVs	367	0	6	7900	14.98	276.80
Tot_cost_per subscriber	6.53	3.10	6.29	12.90	0.96	4.41
Log_tot_cost	10.86	8.94	10.66	13.72	0.83	3.66

Note: Cost figures in 1000 NOK. All costs are in 2015-prices. N = 1070 (107 DSOs over 10 years; 2008-2017).

With a log-transformations of the model, along with the included variables gives us the following preferred model specification:

$$\begin{aligned} log(tot\_cost) = {} & \alpha + \beta_1 log(subscribers_{it}) + \beta_2 log(voltline_{it}) \\ & + \beta_4 log(BEV_{it}) + \delta_t + \lambda_i + \varepsilon_{it} \end{aligned} \tag{3}$$

This equation includes DSO fixed effects λ_i, year dummies δ_t and the random error term ε_{it}. As discussed above, time-invariant contextual variables (X_i) drop out of our fixed effects analysis, and *substations* drop out because it is considered a bad control.

[7] For variables for which some values are zero for some DSOs in some years, we add a constant of 1 (e.g. *log_ev* = log(*average_EVs+1*)).

3.3 Fixed effects regression

In this paper we conduct a panel data analysis using a fixed effects regression model on a panel with annual data for 107 DSOs over the time period 2008-2017. This gives us a balanced panel containing in total 1070 observations.

The goal is to investigate how the time varying explanatory variable *BEVs* influence the time-dependent endogenous variable *tot_cost*. A good way to do this is applying fixed effects regression, as the fixed effects will capture all time-constant variation, both time-invariant explanatory variables and unmeasured time-invariant variables (Mehmetoglu & Jakobsen, 2016, pp. 241-242). There has been large variation in when and where the growth in BEVs has taken place, making it a suitable candidate for such analysis. In 2008, more than 25% of the DSOs had zero BEVs registered in their area, and the numbers here have grown to between 1 and 625 in 2017. On the other end of the spectrum, the single DSO with over a 1000 EVs in 2008 has seen the BEV stock grow to over 55 000 in 2017. To illustrate this variation in status and growth, we show the distribution of BEVs in 2008 and 2017 in Figure 2. Because of the large differences in scale, we display these differences in status and growth of EVs across DSOs in the form of BEVs per subscriber.

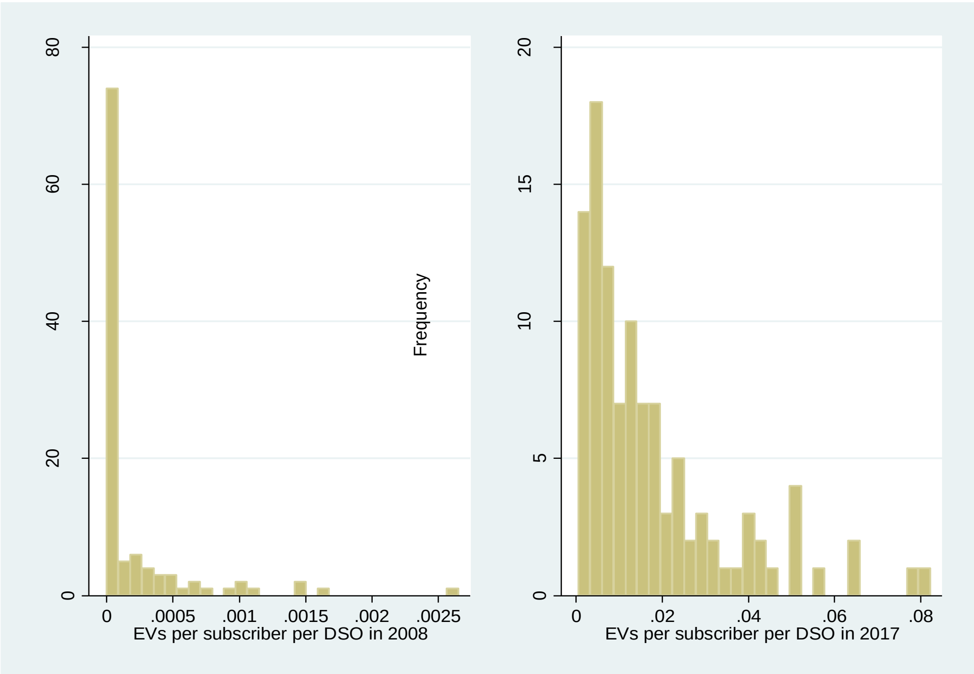

Figure 2: Large variation in BEV numbers across DSOs and over time

The fixed effects model will capture the variation from the time-invariant variables that NVE uses for regulation, some of which may have a relatively strong correlation with the number of BEVs. Most notably are perhaps *Latitude*, which we expect is negatively correlated with the number of BEVs as most of BEVs are registered in the southern half of Norway, and *Temperature*, which we expect is positively correlated with the number of BEVs as colder winters have a negative impact on the range of the

BEVs (Figenbaum & Weber, 2017). In addition, there are *unmeasured* time-invariant variables that we expect to have an effect on both our explanatory variable of interest and the endogenous variable, so controlling for it in the fixed effects model reduces the problem of spurious relationships leading to biased estimates. An example of this could be distances between populated areas within a DSO's operational area, i.e. how sprawled people live. This can be expected to drive up DSO costs (need for more infrastructure per customer) and drive down EV demand as such distances would indicate a need for driving range that would make most EVs less favorable.

As for the question of reverse causality, there are *a priori* reasons to believe that this is unlikely. As we discussed in the previous section we expect higher BEV density to drive up the cost for DSOs, but even if higher costs for DSOs would lead higher tariffs for their customers, dramatic price hikes would be needed to make noticeable changes in EV demand. In the calculations in Wangsness (2018), the cost of electricity comprises about 15% of the distance-based cost for EVs. And grid rent makes up less than half of the total electricity bill before taxes. And it is not certain that the DSO can pass on all of their cost increase to their customers, as they are regulated by a revenue cap based on yardstick competition with other DSOs. In other words, we expect EVs to affect grid costs, and have very little feedback the other way around.

4 Results

Table 2 shows the effect of the size of the local BEV fleet on the total cost of the DSO, based on six different specifications. Table 4 presents estimates for each of the cost components. All of the models use robust standard errors clustered at DSO level, acknowledging that even though observations are assumed to be independent across DSOs, there could be correlation between yearly observations for the same DSO.

Main results

Table 2: Fixed effects regression on the relationship between BEV stock (log_ev) in a DSOs operational area and DSO costs (log_tot)

	(1)	(2)	(3)	(4)	(5)	(6)
log_ev	0.013***	0.011	0.018**	0.019**	0.014*	0.019**
	(0.004)	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)
log_subscribe	0.383**	0.326	0.967	0.840	0.534	1.154
	(0.193)	(0.245)	(0.917)	(1.117)	(1.049)	(1.001)
log_voltline	0.291**	0.280*	1.698***	1.706***	1.526**	1.539**
	(0.147)	(0.146)	(0.628)	(0.635)	(0.713)	(0.726)
log_subscribe2			-0.036	-0.029	-0.019	-0.047
			(0.049)	(0.061)	(0.060)	(0.052)
log_voltline2			-0.131**	-0.132**	-0.114*	-0.118*
			(0.058)	(0.059)	(0.067)	(0.065)
log_ev2				-0.000		
				(0.001)		
_cons	5.594***	6.173***	-0.197	0.283	2.595	-0.546
	(1.616)	(2.217)	(4.310)	(4.908)	(4.392)	(4.558)
Year dummies	No	Yes	Yes	Yes	Yes	Yes
Removed outliers	No	No	No	No	Removed 3 largest DSOs	Removed 3 smallest DSOs
N	1070	1070	1070	1070	1040	1040
r2_within	0.200	0.276	0.291	0.291	0.299	0.289

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the first column we report the results where we only control for the size of the customer base and kilometers of high voltage line. The estimated effect of *log_ev* is positive, as expected, and significant at 1% level. This is the naivest regression model where we do not control for any time effects. We provide more controls by adding year dummies in column 2. The estimated coefficient for *log_ev* is similar to that in column 1, but is statistically insignificant.

In column 3 we add the squared terms *log_subscribe2* and *log_voltline2* as controls. There is a good theoretical argument for testing whether these cost elements display declining cost elasticities, as DSOs are expected to show increasing returns to scale. After all, they are regulated as natural monopolies. As expected, the squared terms are negative. Compared to column 2, this specification improves the explanatory power of the model (larger within R^2), but it also increases both the size and precision of the *log_ev* coefficient.

In column 4 we use the same model as in column 3, but we add the squared term *log_ev2* to see if the cost elasticity for BEVs change significantly with changes in BEV stock. The estimated coefficient for *log_ev2* is negative but close to zero, and highly insignificant. The size and precision of the coefficient for *log_ev* does not change much. We therefore proceed with column 3 as our preferred specification.

Finally, in column 5 and 6 we test if the preferred model is robust to the removal of outliers. In the former column we have removed the three largest DSOs in terms of annual costs during the period 2008-2017. In the latter column we have removed the three smallest DSOs in terms of costs. In the former column the coefficient becomes somewhat smaller and is only significant at 10% level. In the latter column both the point estimate and standard error remains largely unchanged. The confidence intervals for the coefficient in these models largely overlap with each other, and the original model. We can conclude that the original model is relatively robust to removal of outliers.

The point estimates from our preferred specification indicates that a 1 % increase in the number of BEVs in a DSOs area is associated with a 0.018 % increase in cost. In order to translate this into monetary value, we look at the median values for DSOs in 2017. The median values were 44 mill. NOK (about €4.4 mill.) in total costs for about 7300 customers with in total 78 registered BEVs. If this DSO experienced a 10% increase in BEVs in 2018 (8 cars), ceteris paribus, the model would predict about 80 000 NOK increase in costs. This would translate into a cost of about 10 000 NOK per BEV imposed on the DSO, which can be considered economically significant. However, if these estimates are applied to the DSO with the highest BEV stock in its area (the Oslo area), the cost per BEV is about 600 NOK. Such scale effects follow naturally from a log-log model with a coefficient between zero and one, as this implies a positive but declining marginal cost per BEV in absolute terms. However, a constant cost elasticity is a fairly strong assumption. We therefore investigate the heterogeneity in the effect from BEVs in different parts of the sample.

Heterogeneity

As the example above illustrates, there is substantial heterogeneity among the DSOs. We will use the regressors from column 3 when investigating the heterogeneity in the results, which is shown in Table 3.

Table 3: Fixed effects regression on the relationship between BEV stock (log_ev) in a DSOs operational area and DSO costs (log_tot). Heterogeneity test with sample splits along 3 dimensions

	(1) (lower half customers)	(2) (upper half customers)	(3) (lower half BEV density)	(4) (upper half BEV density)	(5) (lower half costs per customer)	(6) (upper half costs per customer)
log_ev	0.036^{***}	0.005	0.032^{**}	0.008	0.015	0.032^{***}
	(0.012)	(0.009)	(0.014)	(0.011)	(0.009)	(0.011)
log_subscribe	0.408	2.576	0.445	2.333^{**}	0.011	1.779
	(2.247)	(1.729)	(1.882)	(0.965)	(1.093)	(1.877)
log_subscribe2	-0.002	-0.104	-0.018	-0.086^{*}	0.018	-0.078
	(0.140)	(0.084)	(0.112)	(0.050)	(0.056)	(0.113)
log_voltline	1.111	-0.628	1.920^{**}	0.798	2.049	1.086
	(1.075)	(2.207)	(0.930)	(0.913)	(1.424)	(0.987)
log_voltline2	-0.067	0.022	-0.135	-0.077	-0.166	-0.072
	(0.104)	(0.154)	(0.092)	(0.082)	(0.108)	(0.096)
_cons	2.828	-0.279	1.399	-4.839	3.287	-2.775
	(8.477)	(8.117)	(7.096)	(4.843)	(5.977)	(6.676)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	540	530	540	530	540	530
r2_within	0.315	0.314	0.287	0.333	0.264	0.343

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 3 we show split-sample heterogeneity in the regression results along the following dimensions; DSO size as measured by the number of customers, BEV density in DSO areas (average over the period of analysis) and cost per customer. We see that there is considerable heterogeneity in the results. The effect of BEV stock on cost seems to vary considerably between different parts of the sample, underlying our point earlier that a constant elasticity is a fairly strong assumption. If anything, the cost elasticity for accommodating BEVs seems to be declining.

We find effects of BEVs on cost that are statistically significant and with point estimates almost twice as large in the sample halves with the fewest customers, lowest BEV density and highest cost per customer, compared to the full sample. The strongest effect is found in the sample half with lower-than-median number of customers. However, it is worth noting that these 54 DSOs serve less than 7% of the total customers in the sample.

In the other halves of the sample the estimated coefficient are closer to zero and far form statistically significant. This could indicate that at the levels observed until now, the cost elasticity for accommodating BEVs may be declining rather than constant. Since a constant elasticity between zero and one already implies decreasing marginal costs in absolute terms, a declining elasticity implies that the marginal cost decreases even faster as the BEV stock increases.

Another possibility which has been mentioned in conversations with representatives from DSOs may complement the explanation that it is costlier for small, rural DSOs to accommodate BEVs. It could be costlier to accommodate BEVs in some rural areas where the need for investing in high capacity in all parts of the distribution grid has historically been relatively low. In such areas, if there is a need to upgrade parts of the old high voltage network or a distribution transformer to accommodate a few dozen BEVs, it may be a noticeable increase in total costs. We will look closer at this in the last part of this section.

Regressions for cost components

We now dig deeper into which cost components, through which EVs contribute to higher costs. This is shown in Table 4. The first five columns show the major cost components sorted from left to right according to their relative importance for total costs. Column 6 represents the reported stock of assets reported to the regulator from which they calculate annual capital cost for regulation. Column 7 represents the stock of co-paid assets, where the customer of the DSO pays for some or all of an increase in capital stock, e.g. a new substation to accommodate a fast-charging station for BEVs.

Table 4: Fixed effects regression on the relationship between the number of BEVs registered in a DSOs operational area and 5 different cost components and capital stock

	(1) log_opex	(2) log_cap	(3) log_cens	(4) log _depres	(5) log_ eloss_cost	(6) log_regulat _assets	(7) log_copaid _assets
log_ev	0.020*	0.011	0.024	0.017	-0.026*	0.011	-0.031
	(0.011)	(0.012)	(0.032)	(0.013)	(0.015)	(0.012)	(0.050)
log_subscribe	2.790**	-0.216	-2.184	0.294	2.261	-0.216	-6.594
	(1.303)	(1.226)	(3.497)	(1.399)	(1.699)	(1.226)	(4.332)
log_subscribe2	-0.138**	0.022	0.137	-0.009	-0.058	0.022	0.299
	(0.065)	(0.064)	(0.170)	(0.076)	(0.086)	(0.064)	(0.262)
log_voltline	2.101**	0.044	6.063**	2.167	1.844	0.044	5.856
	(1.016)	(1.064)	(3.025)	(1.369)	(1.338)	(1.064)	(3.593)
log_voltline2	-0.181*	0.036	-0.453*	-0.175	-0.116	0.036	-0.408
	(0.094)	(0.097)	(0.257)	(0.128)	(0.113)	(0.097)	(0.279)
_cons	-9.309	7.462	-4.251	0.497	-14.087**	10.061	24.231
	(6.231)	(6.443)	(15.417)	(7.004)	(6.697)	(6.443)	(16.960)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1070	1070	1070	1070	1070	1070	1070
r2_within	0.163	0.833	0.127	0.513	0.199	0.686	0.416

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In column 1 we run the model with operational costs as the dependent variable. Here BEVs have a positive and significant relation (at 10% level) with DSOs operational costs. We also find a positive relationship between EVs and capital costs in column 2, but this is not significant at the 10% level. Given the operational costs share of total costs (see Table 1), it looks like it would be through this component where BEVs would have the strongest impact on total cost. We are a bit surprised that BEVs would have a stronger effect on operational costs than capital costs on average, but it matches the experience of one of the DSOs with whom we have talked[8]. This is a relatively small DSO on the west coast of Norway, and they have had a few incidents over the last few years where they have upgraded their infrastructure more than they would otherwise have, because of BEVs. In some of these incidents they have received co-payments from customers for the hardware to upgrade the infrastructure, but all other costs (in particular labor costs) were registered as operational costs. Our model may also have problems picking up the impact BEVs have on capital costs, as the size and timing of investments may not match the growth in BEV stock in a given year. In Appendix B we regress the difference in cost on the difference in BEV stock between the end of the sample period and the start of the period. This model seems to pick up a stronger relationship between BEV growth and growth in capital costs but it is still not statistically significant.

In column 3 and 4 we also find small positive but highly non-significant effects on *log_depres* and *log_cens,* respectively. The results in column 5 may require some more explanation. Here we find a negative and significant (at the 10% level) relationship between EVs and grid energy losses. A drop in energy losses for DSOs with many EV owners in their operational area could be consistent with the DSOs upgrading their infrastructure faster, meaning a faster upgrade from 230 Volts grid to a 400 Volts grid. The energy losses are lower in an electric grid with higher voltage (Haugen, Haugland, Vingås, & Jonhnsen-Solløs, 2004).

In column 6 we look at the relationship between EVs and the size of the regulatory asset base, and find, as expected, the exact same relationship as with capital costs used for regulation. In column 7 we look at the relationship between BEVs and the capital investments that are wholly or partially paid for by consumers [in Norwegian: *anleggsbidrag*]. It could be the case that if more EVs drive up costs for DSOs, the EV owners are actually paying for it themselves. However, we find only a highly non-significant relationship between *log_EV* and *log_copaid_assets*.

Alternative specifications

We test some alternative specifications of the model in order to assess the robustness of our findings. We show this in Table 5.

[8] In total we have had discussions with representatives from six DSOs; two relatively large, and four relatively small. Only one of them, one of the small ones, could confirm that BEVs had caused noticeable costs.

Table 5: Alternative specifications on fixed effects regressions on the relationship between BEV stock in a DSOs operational area and DSO costs

	(1)	(2)	(3)	(4)	(5)
log_ev	0.039*	0.018**	0.018**	0.018**	0.018**
	(0.023)	(0.008)	(0.008)	(0.008)	(0.008)
log_subscribe	0.338	0.969	0.955	1.050	0.994
	(1.196)	(0.920)	(0.899)	(0.886)	(0.921)
log_subscribe2	0.000	-0.037	-0.038	-0.042	-0.039
	(0.065)	(0.049)	(0.048)	(0.047)	(0.049)
log_voltline	1.533**	1.693***	1.713***	1.651**	1.677***
	(0.649)	(0.631)	(0.624)	(0.630)	(0.629)
log_voltline2	-0.117*	-0.131**	-0.131**	-0.128**	-0.130**
	(0.061)	(0.058)	(0.058)	(0.058)	(0.058)
log_ev x log_voltline	-0.003				
	(0.003)				
wintertemp		0.001			
		(0.005)			
event			0.004**		
			(0.002)		
log_hh_inc				-0.431	
				(0.334)	
log_substation					0.025**
					(0.012)
_cons	2.869	-0.182	-0.056	5.344	-0.336
	(5.682)	(4.295)	(4.260)	(6.486)	(4.328)
Year dummies	Yes	Yes	Yes	Yes	Yes
N	1070	1070	1070	1070	1070
r2_within	0.292	0.291	0.294	0.293	0.291

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In column 1 we investigate whether we can find support for the hypothesis that the marginal cost of accommodating more BEVs is higher for small DSOs in rural areas with little grid capacity (here measured as km with high voltage line) compared to larger city areas, that usually have invested more in capacity. We add an interaction term between *log_ev* and *log_voltline*. Here we see that the marginal cost of more BEVs is decreasing in the amount of high voltage line (though not statistically significant), supporting that more capacity makes it less costly to accommodate more BEVs. This corroborates our interpretation of the main results and heterogeneity tests, and also the conversations with representatives from a handful DSOs.

We add the control variable *wintertemp,* a measure of average winter temperature in a given year at county level[9], in column 2. We expect lower winter temperatures to drive DSO costs upwards, and perhaps capture some of the costs per BEV, as lower average temperatures would generally require more electricity for heating, and more electricity for an average BEV-km. However, the control variable is highly statistically insignificant. A lot of the variation over time is captured by the year dummies. As for the coefficient for *log_ev*, it has become slightly larger and slightly less precise, but still significant at 5% level.

After conversations with representatives from a handful of DSOs we have also decided to include extreme weather events as a control variable[10], as many spikes in costs for different DSOs at different times can be attributed to such events. We see in column 3 that *event* has a statistically significant impact on DSO costs, but adding this variable does not bring much change to the coefficient for *log_ev*, nor its p-value.

It is worth discussing whether variations in BEV growth could be correlated with variations in an underlying growth in power usage and demand for modern appliances that require more power capacity, like induction stoves and heat pumps. If this is true, then our estimated coefficients for *log_ev* would be biased upwards, overstating the effect. Ideally, we would like to control for household ownership of modern appliances and their power usage from these appliances, but it is reasonable to expect that this should correlate with income. Figenbaum and Kolbenstvedt (2016) show at least that most BEV buyers until now have generally higher-than-median income. We therefore want to control for income. In column 4 we introduce average household income as a control variable. The income variable is aggregated from municipal level data, retrieved from Statistics Norway. This is a variable that does not display much variation over time during the sample period, and some of the variation over time is also captured by the year dummies. The coefficient for income is not statistically significant and the coefficient for *log_ev* and its standard error is unaffected.

Finally, in column 5 we introduce the variable *log_substations*. As discussed in Section 3, substations are an important part of regulators DEA calculation, but it is potentially a bad control when trying to estimate the impact of BEVs of cost. Compared to the preferred model, the coefficient for *log_ev* is largely unchanged and the p-value is almost the same. There still may be a theoretical argument for leaving *log_substations* out of the regression, but it does not seem to make much difference in practice.

5 Discussion

The results of our preferred model specification show that an increase in the BEV stock in the operational area of a DSO is associated with an increase in local grid costs. This finding is robust to the addition of several controls and removal of outliers. The estimated cost increases are also economically significant, as they imply additional costs

[9] Retrieved from https://www.yr.no/klima/

[10]. County-level data on extreme weather events according to the definition from the Norwegian Meteorological Institute: https://no.m.wikipedia.org/wiki/Liste_over_ekstremvær_i_Norge [In Norwegian. Last accessed October 1st 2019]

of several thousand NOK per BEV when the BEV stock is low. With a constant cost elasticity of 0.018, the per-BEV cost becomes relatively low when the stock has reached the higher levels in the sample.

The results indicate that there is fairly large heterogeneity in the effect of BEVs on DSO costs. In particular, the effect is a lot smaller for DSOs that have a higher-than-median number of customers, and over the period has had a higher-than-median BEV density. We tried to test whether the effect of BEVs could be higher in areas with less installed capacity, usually rural areas. The point estimates gave some support to this, but they were not very precise.

Because of this heterogeneity, it seems like including EVs as a variable in NVE's regulatory calculations would be premature. Adding BEVs to NVE's analysis could simply lead to more noise without strengthening the analysis with any certainty. And if it is the case that the cost imposed from more BEVs is increasing but at a decreasing rate, then any cost differences between DSOs stemming from more BEVs will be decreasing over time as the stock of BEVs continues to grow nationwide.

The heterogeneity also indicates that costs imposed on DSOs by BEV owners, is not a problem that will affect a large number of consumers. The half of the sample with largest DSOs serve over 93% of the customers in the entire sample. The effect of BEVs on costs in that sample half is a lot smaller than the full-sample estimate, and statistically insignificant. If BEV owners are imposing pecuniary externalities in the incomplete local grid market, these externalities do not seem to be very large for most Norwegians. A minority of unlucky DSO customers may have to bear some cost as their DSOs seem to have a hard time accommodating BEVs.

The analysis in this paper should be revisited in later years as the stock of BEVs in Norway continues to grow. In this dataset the highest level of BEVs in any of the DSOs operational area amounts to 8.3 per 100 customers. Even though the cost of an additional BEV seems to be positive but decreasing up until now, it could be that when we reach substantially higher levels in a matter of years we would detect larger cost impacts, unless measures are put in place. A recent analysis from DNV GL and Pöyry Management Consulting (2019) estimates investment costs up to 15 bn NOK by 2040 in local grid components nationwide unless a significant amount of BEV charging can be pushed to off peak hours. It has gone relatively painless so far, as the current BEV stock – the most concentrated in the world – has not yet substantially stress-tested the local grid in most places. In Section 2 we referred to NVE stress-test that found that if 70% of the residents charge their EVs simultaneously during peak hours, they would expect overload for more than 30% of the current transformers. Norway is not there yet.

It is worth noting a few caveats at the end. The main caveat is that our model applies for analyzing the statistical relationship between DSO costs and the number of BEVs *registered* in the DSOs area. We do not have data on the charging behavior of the BEV-owners, or what kind of equipment they have installed. In addition, the number of registered BEVs in one DSO operational area does not need to correspond completely to where the BEV charging is taking place. There could be cases where DSOs experience costs from BEVs charging, but these are not BEVs registered in their area. This could e.g., apply to municipalities with many cabins, which typically lie in areas where the local grid is not dimensioned for high capacity[11]. Our model would not be able to pick up any of that cost if it is there. However, to include cabin owners with BEVs to the analysis could be an interesting venue for future research, when more data is available.

6 Summary and conclusions

In this paper, we have used a complete dataset of Norwegian DSOs outputs, costs and registered BEVs in their operational area over the time period 2008-2017 to analyze the effect increasing BEV numbers have on DSO costs. We have also investigated through which mechanisms, i.e. cost components, do we see this effect.

We use a fixed effects regression model and find that increases in BEV stock are associated with positive and statistically significant increases in DSO costs when controlling for other DSO outputs and applying year dummies. The point estimates also imply that the effect is economically significant. A 10% increase in BEV stock s associated with a 0.18% increase in DSO costs. This translates into over 10000 NOK (about €1000) per new BEV for the median DSO, but a little less than 600 NOK (about €60) per BEV for the DSO with the highest BEV density.

There is substantial heterogeneity in the results, with larger and effects for smaller DSOs and DSOs with the lowest levels of BEV density. For the other half of the sample, with larger DSOs and higher BEV densities, the effect is close to zero and is not statistically significant.

When looking closely at individual cost components, we see that increases in BEV numbers are associated statistically significant increases in operational costs, but statistically insignificant increases in other components. The exception is the cost component grid energy losses, where increases in BEV numbers are associated with cost reductions. Lower energy losses could stem from newer infrastructure in places with higher capital investments. Energy losses are in any case a relatively minor cost component (see Table 1), so this finding would not influence the impact on total cost much. The results indicate that BEVs impact DSO costs mainly through operational costs. We found this somewhat surprising, but it does corroborate the experiences of one of the DSO representatives that we have been in contact with in this project.

Already before we consider the cost impacts BEVs may have on the distribution grid, several papers have documented that the CO_2 abatement costs from policies that promote a shift from conventional to electric cars are fairly large (see e.g., Bjertnæs, 2016; Fridstrøm & Østli, 2017; Wangsness, 2018; Wangsness, Proost, & Rødseth, 2018). These costs may come in the form of higher costs for a given quality level of the car stock, a loss in government revenue that has to be funded by distortionary taxes elsewhere, and higher congestion levels in cities because of low energy costs and low tolls. Should we in addition to these costs worry about BEVs imposing higher costs

[11] https://www.distriktsenergi.no/artikler/2019/1/16/elbilene-gjor-at-stromnettet-i-hytteomradene-ma-oppgraderes/ [Electric cars leads to a need to upgrade the electric grid in cabin areas (Article from DistriktsEnergi in Norwegian, last accessed 05.12.2019)]

on the local grid and passing on the cost to all customers, and subsequently want the regulators to take action?

As many economists before us, we expect there to be efficiency gains if the regulator allowed for a well-designed peak pricing system. That would incentivize more efficient use of local grid capacity with regards to all electric appliances, including BEVs. And with a fast-growing number of BEVs, the gains from introducing such a pricing scheme would be even larger. Many BEV owners would probably respond by installing smart charging systems, which would ease the household cost minimization and ensure more efficient grid capacity utilization, even with small hour-to-hour price differences.

With regards to including "BEV stock" as a variable in the regulatory analysis, our cautiously optimistic interpretation of the findings suggest that this would be a bit premature. Although we find a statistically significant relationship between BEV stock and DSO costs, the marginal cost is positive but decreasing, and for the half of the DSOs that serve more than 93% of the Norwegian customers, the point estimates are actually quite close to zero. DSOs and regulators should keep an eye on developments, but for now grid costs stemming from higher BEV ownership rates do not need to be at the top of their list of worries.

7 Acknowledgements

We are thankful to Eivind Skjærven, Ole-Petter Kordahl and Roar Amundsveen at the Norwegian Water Resources and Energy Directorate for helping us compile cost and geographical data for DSOs, and helping us interpret the underlying variables. We also thank Knut Einar Rosendahl, Live Dokka, Tor Westby Stålsett, Kjersti Vøllestad and participants at the presentation at the 16th IAEE European Conference for comments and insights.

Funding: This work was supported by the Norwegian Research Council (NRC) and the Industry Partners Co-Financing NRC project 255077 (Energy Norway, Norwegian Water Resources and Energy Directorate, Ringeriks-Kraft AS, Norwegian Public Roads Administration and Statkraft Energi AS).

Declarations of interest: none.

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Appendix A: Regressions with a per-customer model

As discussed in section 3, there was a need to transform the data because of the very skewed distribution of DSOs. The log-log transformation was preferred because the dependent variable was closer to a normal distribution than was a per-customer-transformation. Still, a per-customer model can work as a robustness check. Table 6 below is the counterpart of Table 2, but with a per-customer transformation. The variable of interest is *EV_percent*, which is the number of BEVs per 100 customers.

Table 6: Fixed effects regression on the relationship between EV density in a DSOs operational area and DSO costs per customer (measured in 2015-NOK)

	(1)	(2)	(3)	(4)	(5) (removed 3 largest DSOs)	(6) (removed 3 smallest DSOs)
EV_percent	61.94**	52.40	42.45	23.00	24.80	39.48
	(30.46)	(44.27)	(46.74)	(98.96)	(48.85)	(47.55)
1000subscribers	-15.64***	-20.11***	-20.18***	-20.93***	-31.99**	-20.12***
	(4.36)	(4.98)	(5.18)	(4.62)	(12.76)	(5.35)
Meters of high voltage line per subscriber	42.35***	49.38***	6.69	5.95	-15.11	-3.95
	(15.58)	(15.55)	(54.61)	(54.93)	(48.16)	(53.99)
Meters of high voltage line per subscriber^2			0.27	0.28	0.46	0.32
			(0.37)	(0.37)	(0.30)	(0.36)
EV_percent2				3.68		
				(11.59)		
_cons	4453.49***	4034.52***	5431.13***	5471.29***	6044.53***	5818.63***
	(917.65)	(922.36)	(1826.46)	(1837.35)	(1761.20)	(1814.01)
Year dummies	No	Yes	Yes	Yes	Yes	Yes
N	1070	1070	1070	1070	1040	1040
r2_w	0.03	0.13	0.13	0.13	0.15	0.13

Standard errors clustered at DSO level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We find that the coefficient for *EV_percent* is positive under all specifications, just like we find with the log-log model. However, with the exception of the most naïve specification in column 1, we do not find any statistically significant effects from registered BEVs (per customer) on DSO costs (per customer). However, compared to the log-log model, the per-customer model does a worse job explaining the variation in the data. Given a choice between specifications, it is clear that the log-log model is preferable.

Appendix B: Aggregation over periods

Here we investigate whether we pick up a stronger relationship between BEV stock and capital costs when we look at the change over the entire sample period instead of year-to-year changes. We want to minimize the year-to-year noise in the data, so we take the average of the first three years of the sample (2008-2010) and the last three years of the sample (2015-2017). We then take the differences between these two averages and run regressions for total costs, capital costs and operating costs. The results are shown in Table 1Table 7.

Table 7: Regression on the relationship between over-period-differences in the number of BEVs registered in a DSOs operational area and the differences in the DSOs total costs, capital costs and operational costs.

	(1) diff_log_tot	(2) diff_log_cap	(3) diff_log_opex
diff_log_EV	0.045***	0.020	0.054***
	(0.012)	(0.022)	(0.018)
diff_log_subsciber	1.714	0.045	3.292*
	(1.279)	(2.339)	(1.883)
diff_log_subsciber2	-0.078	0.009	-0.166
	(0.073)	(0.133)	(0.107)
diff_log_voltline	2.361**	0.222	3.174*
	(1.162)	(2.123)	(1.710)
diff_log_voltline2	-0.196*	0.020	-0.284*
	(0.105)	(0.192)	(0.155)
_cons	-0.084*	0.203**	-0.207***
	(0.046)	(0.084)	(0.067)
N	107	107	107
r2	0.186	0.036	0.159

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In column 1 we see that the estimated coefficient for the effect of change in BEV stock is statistically significant and even larger than the coefficient estimated in our preferred model in Table 2. We also see that there is a relatively stronger and relation between differences in BEV stock and differences in capital costs relative to what we see in Table 4. However, it is not statistically significant. On the other hand, the relationship between over-period-differences in BEV stock and operational cost is stronger and more precise compared to what we found earlier. This model strengthens our conclusion that the relation between total DSO costs and BEV stock is significant and robust.