

Online Appendix for

“CLIMATE POLICIES AND ELECTRICITY PRICES: WHY ABATE WHEN YOU CAN GENERATE?”

by Kathrine von Graevenitz and Elisa Rottner

Contents

S.1 Appendix A: Regulatory Background	S.3
S.1 How Electricity Network Charges in Germany Are Set	S.3
S.2 What Drives Network Charges	S.4
S.2 Appendix B: Data, Descriptives and Estimation Sample	S.8
S.3 Data Cleaning: The Manufacturing Census	S.8
S.4 The Estimation Sample: Assigning Network Charges to Plants	S.8
S.4.1 Network Operators	S.8
S.4.2 Tariff Groups	S.8
S.4.3 Voltage Levels	S.10
S.4.4 Resulting Assignment	S.11
S.4.5 Estimation Sample versus Full Manufacturing Census	S.11
S.5 Additional Summary Statistics	S.15
S.5.1 Dependent Variables	S.15
S.5.2 Network Charges	S.15
S.5.3 Electricity Cost	S.15
S.3 Appendix C: Additional Results	S.20
S.6 Reverse Causality	S.20
S.6.1 Summary Statistics: Grids and Manufacturing Users	S.20
S.6.2 Adjustments of Network Charges to Switches into Onsite Generation . . .	S.21
S.7 The Effect of Electricity Prices on Onsite Generation	S.22
S.8 The Effect of Network Charges on Never Generators, Ever Generators, and Switchers	S.22
S.9 The Implications of Switching into Onsite Generation for Competitiveness	S.23

S.10 The Implications of Switching into Fossil Onsite Generation	S.24
S.11 Onsite Generation, ETS Regulation, and Surrendered Allowances	S.25

S.1 Appendix A: Regulatory Background

S.1 How Electricity Network Charges in Germany Are Set

The following section draws on the report from the Federal Network Agency Federal Network Agency (BNetzA) (2015), the regulatory authority overseeing network charges.

Regulatory periods, costs, and revenue caps

Network charges reflect the costs of operating, maintaining, and expanding electricity grids. The BNetzA reviews audited accounts to establish each network operator's cost base and then sets a revenue cap for a five-years regulatory period. The revenue cap determines the operator's maximum allowable income – and therefore its budget – for the period. The cap is adjusted annually to account for inflation, exogenous cost changes, and grid expansion. Differences between actual revenues and the cap are recorded in an adjustment account and corrected in the next regulatory period, so operators do not bear a volume risk.

Marginal and peak load prices by voltage level

Costs are allocated across voltage levels using standardized rules. Operators first calculate the cost per megawatt of peak load in the highest voltage level, reflecting that peak demand drives grid dimensioning. This cost is then divided into marginal and peak-load components using the *simultaneity function*.

To construct this function, each grid user is assigned a probability that their peak load coincides with the grid's annual peak. This probability equals the user's load divided by their own peak load at the moment of the grid's peak. Plotting these probabilities against users' annual hours of use produces a scatter plot that is approximated by two straight lines with a kink at 2,500 hours. The slope and intersect of each segment defines the marginal and peak load price components in the respective customer group.

Using the resulting price components, expected revenues for the highest voltage level are calculated and subtracted from that level's costs. Any uncovered costs are passed down to the next lower voltage level and added to its own costs. The procedure continues level by level until the lowest voltage tier, which absorbs all remaining costs.

Billing practices differ by customer type. Small users typically pay network charges through all-inclusive contracts with electricity suppliers, with monthly advance payments reconciled annually. Large industrial and commercial customers with registered load metering usually settle charges directly with their distribution system operator. If the peak load varies over the billing year, charges are adjusted retroactively to the maximum peak load.

S.2 What Drives Network Charges

Network charges depend on the cost for grid operation encountered by DSOs. In its report (2015), the BNetzA highlights five key drivers:

- Low utilisation of the grid: Low population densities (especially in Eastern Germany as well as in rural areas more generally) lead to an underutilisation of the electricity grid which, in the presence of fixed operating costs, translates into high network charges.
- Renewable energy expansion: The decentralised feed-in of renewables (mostly solar installations in South Germany, wind installations in Northern Germany) requires the expansion of electricity grids and extensive feed-in management measures. As Heim *et al.* (2020) stress, renewables increase rebalancing expenditures because they depend on unpredictable weather, increasing the risk of grid instability.
- Age of electricity grids: Relatively older grids (predominately in Western Germany) have lower residual values which lowers depreciation cost as compared to newer electricity grids.
- Quality of electricity grids: The BNetzA benchmarks DSOs against each other, and better performing grids are allowed to charge a higher markup.
- Cost of the upstream network: Onshore (and partially offshore) network expansion, re-dispatch or the cost for reserve power plants increase the cost of network operators at the transmission level and are passed on to DSOs.

We test the strength of the correlation of these drivers with network charges empirically by running two regressions, exploiting cross sectional variation in our base year 2009 (S.1), and exploiting the time variation within DSO (S.2):

$$nc_{j,k} = \beta_{0,k} + \sum_c \beta_{c,k} \times X_{c,j} + \epsilon_{j,k} \quad (\text{S.1})$$

$$nc_{j,k,t} = \beta_{0,k} + \sum_c \beta_{c,k} \times X_{c,j,t} + \mu_{j,k} + \gamma_{t,k} + \epsilon_{j,k,t} \quad (\text{S.2})$$

The dependent variable is the log of price component k (marginal or load) in grid j and year t .¹ On the right hand side of the equation, X represents a vector of c drivers collected at the grid level. We measure grid utilisation by the number of connection points to the grid (in 1000s) and the load extracted from the grid (in GWh), retrieved from ene't. We measure the renewable

¹We show regressions for the network charges that apply to customer group 2 of the medium voltage level as this is the tariff that applies to most plants in our estimation sample, but note that similar results hold for other customer groups and voltage levels.

energy expansion by the (renewable) generation capacity in the grid area (in GW), collected from the MaStrR.² As a proxy for older grids in Western Germany and as a proxy for the differing cost of upstream networks, we include a dummy for a grid location in the North-east of Germany.³ Lastly, we proxy the quality of electricity grids by transmission losses (in %), taken from ene't.

Results are shown in Table S.1. In line with the 2015 BNetzA report, we find that areas with higher grid utilisation in 2009, on average, charged lower network prices.⁴ The newer and oversized grids in North-eastern Germany translate into a network charges premium of 40% for marginal prices, and 21% for load prices in 2009. We also find a positive correlation between installed wind power capacity and network charges, providing support for the renewable energy expansion increasing the cost of grid operation. Results are qualitatively similar for the panel regressions. Within DSO, we confirm that increasing grid utilisation (i.e., increasing the load extracted from the grid), is associated with decreasing network charges; and each additional GW of wind power capacity, on average, raises load prices by 7%.

These results support the intuitions provided by the BNetzA (2015), but are correlational in nature. The price increasing effect of wind turbines, e.g., need not be causal if wind turbines are strategically built in areas with low and declining population densities. In a last step, we provide evidence that the renewable energy expansion has a causal impact on network charges. To do so, we follow Germeshausen *et al.* (2025) and instrument the installed capacity of wind power with spatial-temporal variation in the profitability of wind turbines owing to adjustments in a federal German subsidy program. The instrument relies on the geographically varying feed-in-tariffs for wind power. In Germany, areas with lower wind potential receive higher subsidies, reducing cross sectional differences in the profitability of wind turbines. The subsidy rates changed over the years. We exploit the variation in installed wind power that comes through these – arguably exogenous – subsidy driven shifts in investment incentives for wind turbines. The first stage of the IV regresses the installed wind turbine capacity in each grid and year

²The Marktstammdatenregister (MaStrR) is available online: <https://www.marktstammdatenregister.de>. The data set provides a snapshot of the currently existing installations. We transform the data set to a panel leveraging information on the start of operation of each individual installation. Since the MaStrR reports the grid to which each installation is connected, we can merge the information directly via grid IDs to the ene't data.

³The North-east of Germany comprises the following federal states: Berlin, Mecklenburg-Vorpommern, Sachsen-Anhalt, Brandenburg, Sachsen, and Thüringen.

⁴Several determinants, among them, extracted load and connection points, display opposite signs in the regression for marginal and peak load prices, reflecting the negative correlation between price components: A factor that decreases the slope of the simultaneity function reduces marginal prices and, hence, by construction raises its intersect and thereby load prices. In terms of magnitude, however, the effect of high demand dominates. Grids with a higher load and more users, on average, charge lower prices.

Table S.1: THE DRIVERS OF NETWORK CHARGES

	Marginal prices				Load prices			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Connection points	-0.0582*** (0.0177)	-0.0695 (0.0459)	0.0032 (0.0078)	0.0021 (0.0078)	0.0211** (0.0091)	0.0212* (0.0118)	0.0031 (0.0034)	0.0033 (0.0034)
Extracted load	0.0001** (0.0000)	0.0001* (0.0001)	-0.0000* (0.0000)	-0.0000* (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
Transmission losses	0.0261 (0.0373)	0.0210 (0.0334)	0.0136 (0.0132)	0.0137 (0.0133)	-0.0208 (0.0250)	-0.0209 (0.0206)	-0.0003 (0.0058)	-0.0011 (0.0058)
Northeast Germany	0.4013*** (0.0527)	0.3920*** (0.0481)			0.2127*** (0.0311)	0.2105*** (0.0294)		
Total power generation	0.3204** (0.1368)		0.0194 (0.0506)		0.0102 (0.1129)		0.0642*** (0.0225)	
Fossil generation		0.0102 (0.1591)		-0.0293 (0.1096)		-0.0078 (0.0880)		-0.0967** (0.0487)
Wind generation		0.1436 (0.0893)		-0.0336 (0.0659)		0.0507 (0.0494)		0.0721** (0.0293)
Solar generation		0.6473 (0.8567)		0.0427 (0.0981)		-0.0751 (0.4741)		-0.0437 (0.0435)
Other generation		-0.0048 (0.3635)		0.3691 (0.9652)		0.2090 (0.2011)		0.4715 (0.4284)
DSO FEs	NO	NO	YES	YES	NO	NO	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES	YES	YES
<i>N</i>	655	655	6,336	6,336	660	660	6382	6382
number DSOs	638	638	758	758	643	643	762	762

Notes: The regressions include observations for 2009 (Columns 1, 2, 5 and 6) or 2009–2017 (Columns 3, 4, 7 and 8). The dependent variable is the log of the network charges price components applying to a RLM customer connected to the medium voltage electricity grid in customer group 2. Standard errors are displayed in parentheses. Observation numbers differ as in some grids, the marginal price is equal to zero. Regressions are run at the DSO level except for DSOs with sub-grids in which they charge different prices. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.

on the expected revenue (in EUR 100,000) for a newly installed wind turbine in that area, following Germeshausen *et al.* (2025). For the instrument, we aggregate the municipality level profitability of wind turbines, provided by Germeshausen *et al.* (2025), to the grid level using averages.

Results are shown in Table S.2.

Table S.2: THE EFFECT OF WIND POWER ON NETWORK CHARGES

	Marginal prices (1)	Load prices (2)
<i>Second stage</i>		
Installed Capacity Wind	0.382 (0.794)	0.804** (0.376)
<i>First stage</i>		
Expected revenues	0.036** (0.016)	0.034** (0.016)
Ineligible	0.118*** (0.023)	0.117*** (0.022)
Ineligible $\times$ wind potential	-0.0000*** (0.0000)	-0.0000*** (0.0000)
DSO FEs	YES	YES
Year FEs	YES	YES
F statistic	10.97	10.91
<i>N</i>	6,066	6,116
number DSOs	780	784

Notes: The regressions include observations for 2009–2016. The dependent variable is the log of the network charges price components applying to a RLM customer connected to the medium voltage electricity grid in customer group 2. Standard errors are displayed in parentheses. Observation numbers differ as in some grids, the marginal price is equal to zero. Regressions are run at the DSO level except for DSOs with sub-grids in which they charge different prices. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.

The instrument is sufficiently strong with an F-statistic of around 10. Results are in line with expectations: Increasing the capacity of installed wind power, due to a higher profitability of wind turbines, leads to an increase of network charges through an effect on peak load prices. The IV point estimates are substantially larger than the OLS estimates in Table S.1 and indicate an increase of 0.8% in the peak load price for a 10 MW increase in wind capacity in the grid. This estimate represents an average effect over time after the start of operation of the wind turbines, and is silent on the exact timing of when network charges start to respond.

S.2 Appendix B: Data, Descriptives and Estimation Sample

S.3 Data Cleaning: The Manufacturing Census

In our analysis, we combine information from various modules of the Manufacturing Census (Amtliche Firmendaten für Deutschland – AFiD) provided by the research data centres of the German statistical offices. We clean the data using the following steps:

We exclude all observations that report a negative energetic fuel use and observations where total energy use is below zero. We calculate total energy use subtracting conversions losses for fossil fuels as in Rottner and von Graevenitz (2024).⁵ Moreover, we drop firms in which one plant reports energy use for all plants within the firm. We cannot properly allocate these firms' energy use at the plant level. We drop all observations where the electricity share from our calculated measure of total energy use exceeds unity, and all observations that report electricity self-generation from fossil fuels while at the same time reporting no consumption of fossil fuels. We also drop outliers in terms of fuel and electricity use, which we define as plants with an extreme variation in fuel or electricity use, respectively (i.e., a within-plant standard deviation exceeding 100 times the median).

S.4 The Estimation Sample: Assigning Network Charges to Plants

S.4.1 Network Operators

We assign network operators based on the plant's location (municipality and postal code). In several areas of Germany, this assignment is not unique. There can be several network operators within the same postal code and municipality code. Figure S.1 shows the areas we lose because of ambiguous assignment.

S.4.2 Tariff Groups

Given the network operator, network charges depend on voltage level and customer group. There are three customer groups: standard load profile (SLP, below 100 MWh electricity use),

⁵This step is necessary to translate energy inputs (which assume a 100% efficiency in converting fossil fuels to heat and/or electricity) to the actual usable energy. We apply fuel-specific heat conversion factors for manufacturing plants not generating electricity, and sector- and year-specific average conversion factors for electricity generating plants that account for the prevalence of CHP and fuel mixes. For details, see Rottner and von Graevenitz (2024).

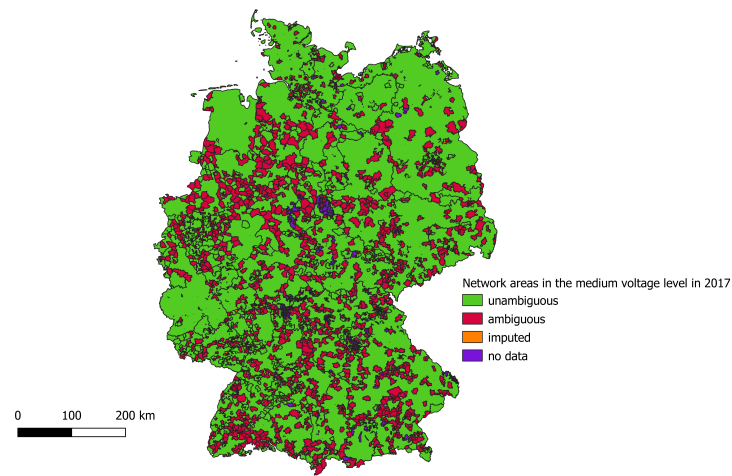


Figure S.1: Unique Assignment of Medium Voltage Level Network Areas to Municipalities in 2017

Notes: The Figure depicts areas in which there is a single network operator only (in green) versus areas in which multiple network operators are present (in red). Areas without any network operator (municipality free areas) are denoted in purple. Where there is no information at the municipality-postal code combination available, we fill in data at the municipality level. These are marked in yellow. The map shows this assignment for the year 2017 and for the medium voltage level. Information are based on data from ene't.

interval metered (RLM) customer group 1 (less than 2,500 operating hours a year), and RLM customer group 2 (more than 2,500 operating hours a year).

We classify plants as SLP customers connected to the low voltage level if their annual electricity purchases are below 100 MWh throughout the study period.⁶ We classify all other plants as RLM customers. For all RLM customers, we distinguish plants above or below the threshold in annual operating hours (2,500 hours) by using information on shift work. 2,500 hours of use are achieved by plants operating 6 days a week and 8 hours a day all year round (52 weeks), so that manufacturing plants with regular double shifts (16 hour work days) will exceed 2,500 annual operating hours, whereas plants with a single shift and a 40 hour work week will not.

Exemptions from paying full network charges exist for plants with atypical usage, or high purchase levels (above 10 GWh annually). These plants still pay at least 20% of the full network charge. We have gathered data on the exempted plants but do not use it in the analysis because the data is incomplete with regard to the timing and duration of the exemption. We use the information available for plausibility checks in our assignment of plants to voltage levels and to assess the potential for bias in our analysis. Within our study period, there are up to 5,000 exemptions annually across all sectors of the economy, less than half of which are in manufacturing. Most exemptions are granted based on atypical usage which does not systematically vary with purchases. Plants exempt due to their purchase levels are also eligible for exemptions from the RES and tend to benefit from both schemes. These plants are captured by the RES dummy to a large extent. Our analysis cannot account for the exemptions due to atypical usage, which leaves some scope for (classical) measurement error.

S.4.3 Voltage Levels

To assign manufacturing plants to voltage levels, we exploit technical standards of transformer and cable capacity that lead to users with higher peak loads having to be connected to the grid at higher voltage levels. Users with an annual peak load of less than 100 kW, e.g., tend to be connected to the low voltage level, while users with an annual peak load of more than 5 MW tend to be connected to the high voltage level, etc. Specifically, we use the following thresholds that we gathered from personal communication with several DSOs: ≤ 100 kW: low voltage level; > 100 and ≤ 300 kW: transformation level low to medium voltage; > 300 kW and ≤ 4 MW: medium voltage level; > 4 MW and ≤ 5 MW: transformation level medium to high voltage; > 5 MW: high voltage level. Relying on these threshold values leads to some degree of error: The

⁶There are a number of manufacturing plants that fluctuate around the threshold of 100 MWh. To prevent misclassifying these plants, we remove them from our sample.

decision at which voltage level to connect a user is subject to the individual situation of the DSO and the respective user, projections about future developments and the technical equipment of the DSO. Assignment based on the thresholds mentioned yields a reasonable approximation given our data.

Plant level peak loads are not publicly available. As the peak load price provides incentives to "flatten the curve" we instead use plant level average loads. Average loads are calculated by dividing electricity purchases by annual operating hours.⁷

S.4.4 Resulting Assignment

Our assignment procedure leads to patterns very similar to what we can observe in the applications for reduced network charges which is the only data source we have on manufacturing users' voltage levels. Table S.3 shows the result of our assignment procedure of manufacturing plants to voltage levels and tariff groups. Our estimation sample is dominated by plants connected at the low to medium voltage levels. Generally, there are more manufacturing plants exceeding 2,500 annual operating hours, especially at higher voltage levels. While there is substantial heterogeneity across sectors, energy intensive industries like chemicals or coke and petroleum tend to be connected at higher voltage levels, whereas less energy intensive industries like repair and installation of machinery are often connected to the low voltage level.

This assignment of manufacturing plants to different tariff groups and voltage levels involves some measurement error. We have no reason to believe that this error is systematically correlated with outcomes of interest in our analysis. With classical measurement error, our estimates are subject to attenuation bias and should be considered a lower bound on an effect.

S.4.5 Estimation Sample versus Full Manufacturing Census

Through the assignment procedure, we lose a large share of plants in the Manufacturing Census. Table S.4 shows how many observations we lose in each step. Column (1) shows the number of observations for the full German Manufacturing Census. Column (2) shows the observations

⁷For annual operating hours, we use different values for plants with or without shift work: For plants without shift work, we assume annual operating hours of 2,288 (which is the average between operating the full year 8 hours per day and 5 or 6 days per week, respectively). For plants with shift work, we assume annual operating hours of 7,064 and 6,419 in sectors that generally display longer or shorter operating hours, respectively. These values represent the expected values given the share of plants that operate by night and/or on Sundays and/or in shifts. The expected values are calculated from the year 2001 in which plants were surveyed about operating during the night, on Sundays, and in shifts (while in later years, they were only required to report shift work). Since the connection to a voltage level is physical in nature and does not change over time, we use a manufacturing plant's median electricity purchases over our complete observation period, and drop plants that switch into/out of shift work for the calculation of the (hence time-invariant) average loads that underly the assignment to voltage levels.

Table S.3: NUMBER OF MANUFACTURING PLANTS ASSIGNED TO DIFFERENT TARIFF GROUPS AND VOLTAGE LEVELS IN 2016

Voltage level	Tariff group	Number
Low	SLP	493
Low	RLM 1	327
Low	RLM 2	742
Low to medium	RLM 1	721
Low to medium	RLM 2	993
Medium	RLM 1	507
Medium	RLM 2	1,812
Medium to high	RLM 1	14
Medium to high	RLM 2	130
High	RLM 1	47
High	RLM 2	423

Notes: The Table shows the assignment of manufacturing plants in the estimation sample for the year 2016 to different network charges tariff structures and voltage levels described above. Tariff groups are SLP (less than 100 MW of annual procurement), RLM 1 (RLM, less than 2,500 hours of annual use of the grid) and RLM 2 (RLM, more than 2,500 hours of annual use of the grid).

which reported at least once in the structure of earnings survey since 2010. In column (3), we have dropped observations that fluctuate around the 100 MWh threshold of electricity purchases over the years. In column (4), we drop observations that change their work mode over time, i.e., switch into/out of conducting shift work. Lastly, in column (5), we drop all observations that are located in ambiguous network areas. This last column represents our baseline estimation sample.

Table S.4: OBSERVATIONS LOST IN THE ESTIMATION SAMPLE IN 2016

	Full sample	Structure of earnings	No switchers 100 MWh	No switchers shift work	No ambiguous DSOs
Total number of plants	42,897	10,959	9,577	8,966	6,095

Notes: Column (1) shows the full sample from the German Manufacturing Census on which information on electricity procurement is available. Moving from left to right shows how our sample changes when imposing the necessary constraints. Column (5) describes the baseline estimation sample.

Despite the fact that we lose many observations, the estimation sample remains fairly similar to the full census. Figure S.2 shows the distribution of electricity use in the full sample (left) and our estimation sample (right) in 2017.

The estimation sample is also similar to the full Manufacturing Census in terms of the sector composition, as can be seen from Table S.5. Nevertheless, larger manufacturing plants are overrepresented. Figure S.3 shows the share of electricity use (about 40%) and employment (about 35%) that the estimation sample covers. Overrepresentation of large plants is due to the sampling procedure used for the Structure of Earnings Survey. A reduction in the sample size

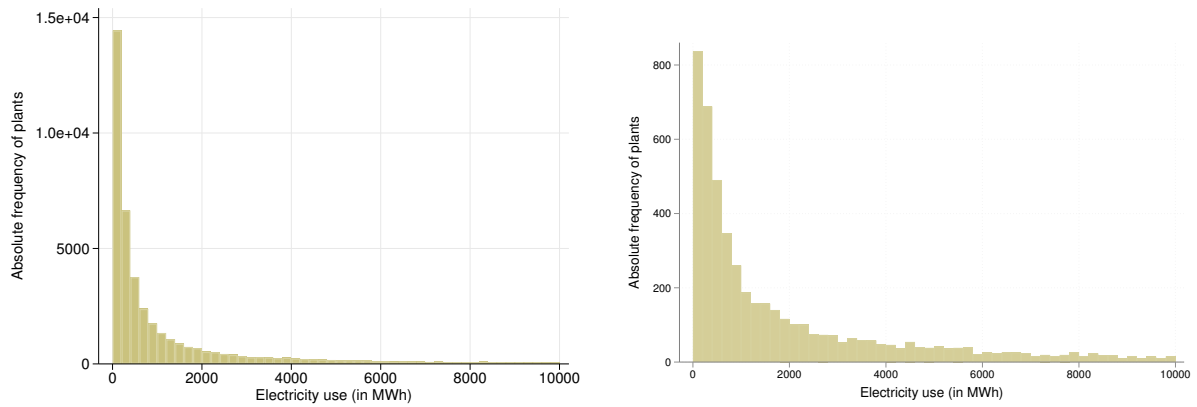


Figure S.2: Distribution of Electricity Use in 2017 in the Full Sample (left) and the Estimation Sample (right)

Notes: The distribution is capped at 10 GWh to improve readability of the figure. Larger users remain in the sample. Source: Own calculations, based on the Manufacturing Census.

for the Structure of Earnings Survey between 2001 and 2014 is also the reason why the number of plants decreases over the years of our sample

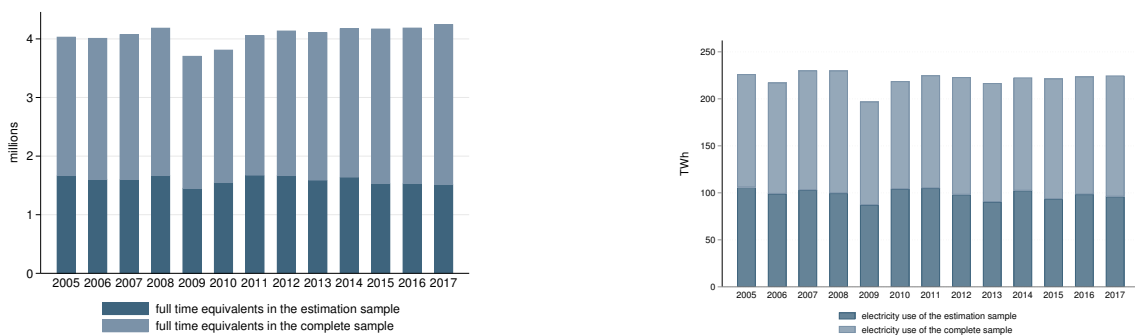


Figure S.3: Coverage of Key Variables of the Estimation Sample as Compared to the Full Manufacturing Census

Source: Own calculations based on the Manufacturing Census (AFiD).

Table S.5: SECTOR COMPOSITION IN % IN THE FULL SAMPLE VERSUS THE ESTIMATION SAMPLE IN 2016

Sector		Full sample	Estimation sample
10	Food products	12.3	11.5
11	Beverages	1.2	2.4
12	Tobacco products	0.1	0.2
13	Textiles	1.6	3.5
14	Wearing apparel	0.6	1.5
15	Leather and related products	0.3	0.7
16	Wood and products of wood and cork, except furniture	2.6	3.3
17	Pulp, paper and paper products	2.1	4.3
18	Printing and reproduction of recorded media	3.0	3.7
19	Coke and refined petroleum products	0.2	0.5
20	Chemical products	3.6	5.1
21	Basic pharmaceutical products and pharmaceutical preparations	0.8	1.7
22	Rubber and plastic products	7.4	6.3
23	Other non-metallic mineral products	6.5	6.1
24	Metal production and processing	2.4	4.2
25	Fabricated metal products	17.8	8.4
26	Computer, electronic and optical products	4.3	5.3
27	Electrical equipment	5.0	5.3
28	Machine manufacturing	14.0	8.4
29	Motor vehicles	3.0	4.8
30	Other transport equipment	0.7	1.8
31	Furniture	2.3	3.3
32	Other manufacturing	3.8	4.3
33	Repair and installation of machinery and equipment	4.7	3.5
Total number of plants		44,853	6,095

Notes: Based on the manufacturing census.

S.5 Additional Summary Statistics

S.5.1 Dependent Variables

Manufacturing plants are very heterogeneous and these heterogeneities persist across onsite generation status. Figure S.4 shows the distribution of different variables by group. *Never generators* tend to be the smallest plants, on average. *Switchers* are larger, but are, in turn, smaller than *ever generators*. There is, however, a lot of overlap in all variables across groups.

S.5.2 Network Charges

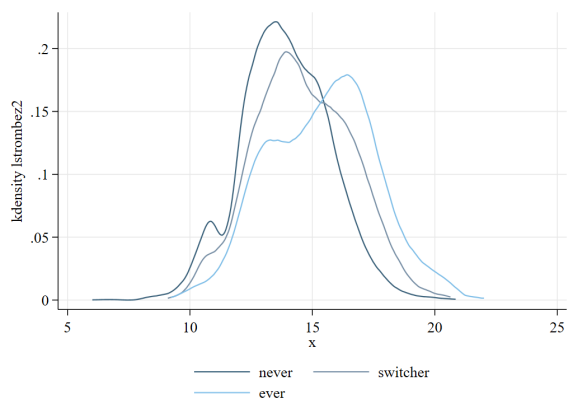
In the main text, we show regional patterns in how network charges changed between 2009 and 2017 for a given plant. Figure S.5 shows boxplots of the annual change in network charges across all manufacturing plants in our sample. The horizontal line shows the median of the changes for each plant between year t and $t - 1$. Median changes are generally above 0, indicating that network charges increase for most manufacturing plants. The whiskers for the 25th and 75th percentile reveal, however, significant variation: The price components decrease, as compared to the previous year, for a substantial share of observations each year. Variation tends to grow toward the end of the regulatory period (i.e., 2013 and 2017) before the revenue cap is reset.

In the main text, we show changes in network charges between 2009 and 2017 for a hypothetical plant. Figure S.6 shows network charges for the same plant in 2009 and 2017.

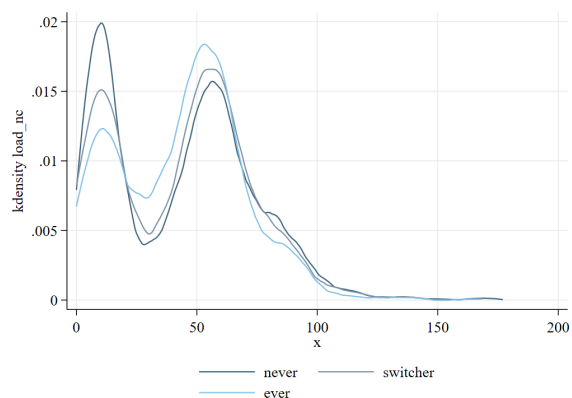
S.5.3 Electricity Cost

To verify that changes in network charges are reflected in changing electricity cost, we use information on firm level electricity expenditures available for a subset of firms in the years 2010 and 2014. We calculate per unit cost based on expenditures and purchases. Figure S.7 depicts the distribution of this unit cost over time. We regress the unit cost on network charge components including year and firm fixed effects. The results are shown in Table S.6.

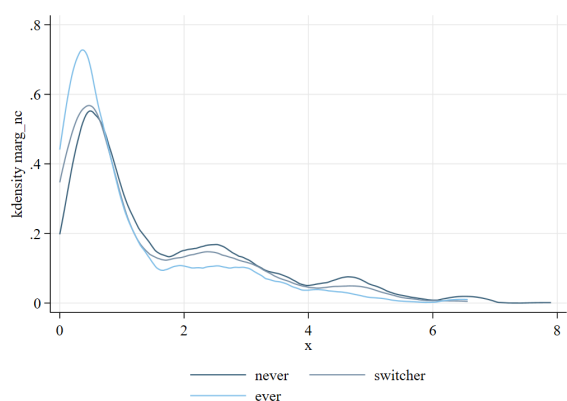
As network charges vary at the plant level, we only use information on single plant firms in the first two columns. In columns (3) and (4), we include multi plant firms, using the network charge information from the plants for which we have information available (i.e., implicitly assuming that network charges developed similarly in the plants for which we are lacking information). This introduces a margin of error, but adds additional observations to the regression. We find that a one euro increase in the marginal network charge is associated with a similar sized increase in the average electricity price. In the specification including multi-plant firms, load prices are also positively and statistically significantly associated with average electricity prices. Reassuringly, the coefficient on the RES exemption lies between 4.1 and 5.5 cents per



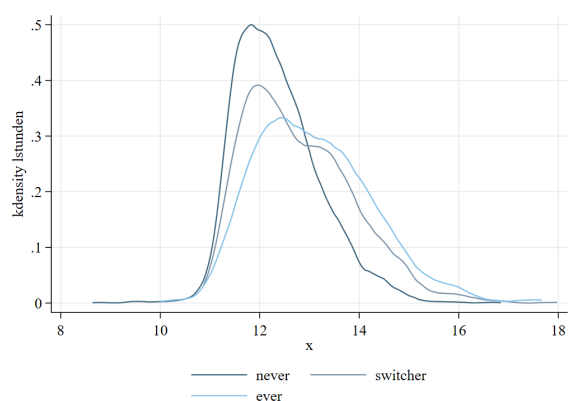
(a) Electricity Purchases



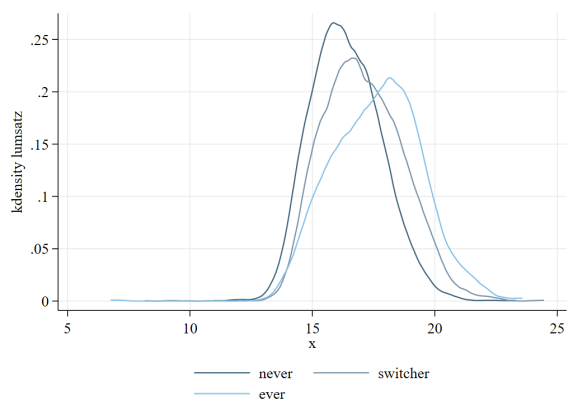
(b) Load-based network charges



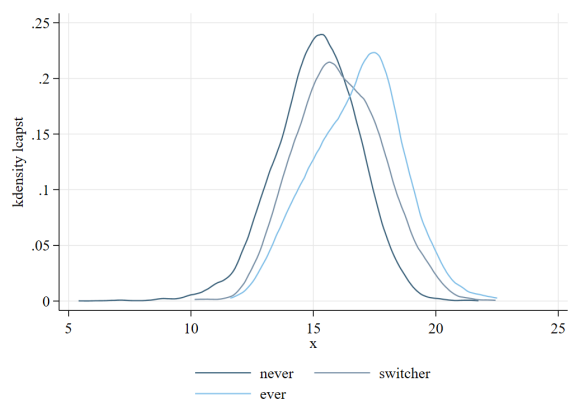
(c) Marginal network charges



(d) Employment



(e) Sales



(f) Capital stock

Figure S.4: Distribution of key variables for never generators, ever generators, and switchers in 2009

Source: Own calculations, based on the Manufacturing Census.

kWh across specifications: the RES grew from 2.05 to 6.24 cents per kWh between 2010 and 2014.

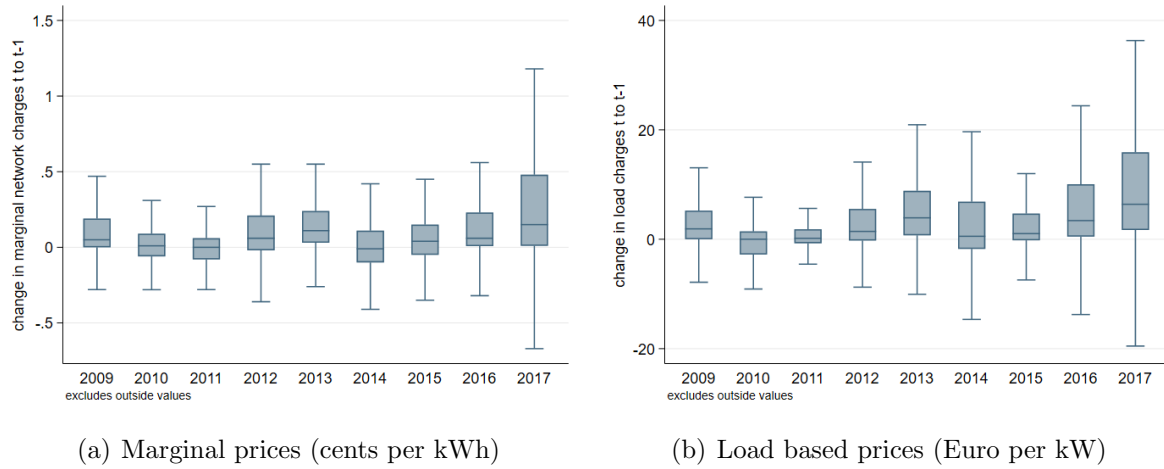


Figure S.5: Year on year variation in network charges in the estimation sample

Notes: The figure shows the distribution of the annual change in network charges for manufacturing plants in our sample. The horizontal line shows the median of the changes for each plant between year t and $t - 1$. The whiskers denote the 25th and 75th percentile. Source: Own calculations.

Table S.6: THE EFFECTS OF NETWORK CHARGES ON ELECTRICITY UNIT COST

	Electricity unit cost			
	(1)	(2)	(3)	(4)
Marginal network charges	0.691 (0.450)	0.983** (0.489)	1.092* (0.617)	1.651** (0.663)
Load based		0.022 (0.015)		0.043** (0.019)
RES exemption	-4.108*** (0.739)	-4.071*** (0.739)	-5.518*** (0.929)	-5.504*** (0.928)
N	2,104	2,104	2,700	2,700
number plants	1,052	1,052	1,350	1,350

Notes: The table depicts results from a regression of firms' electricity unit cost (annual electricity expenditures divided by electricity purchases) on their network charges. Columns (1) and (2) only use single-plant firms, where column (1) uses only marginal network charges as explanatory variable, and column (2) adds load based network charges. Column (3) and (4) show the equivalent regressions, adding multi plant firms. The regressions are run with firm fixed effects and year fixed effects. It includes observations from 2010 and 2014. Source: Own calculations based on AFiD.

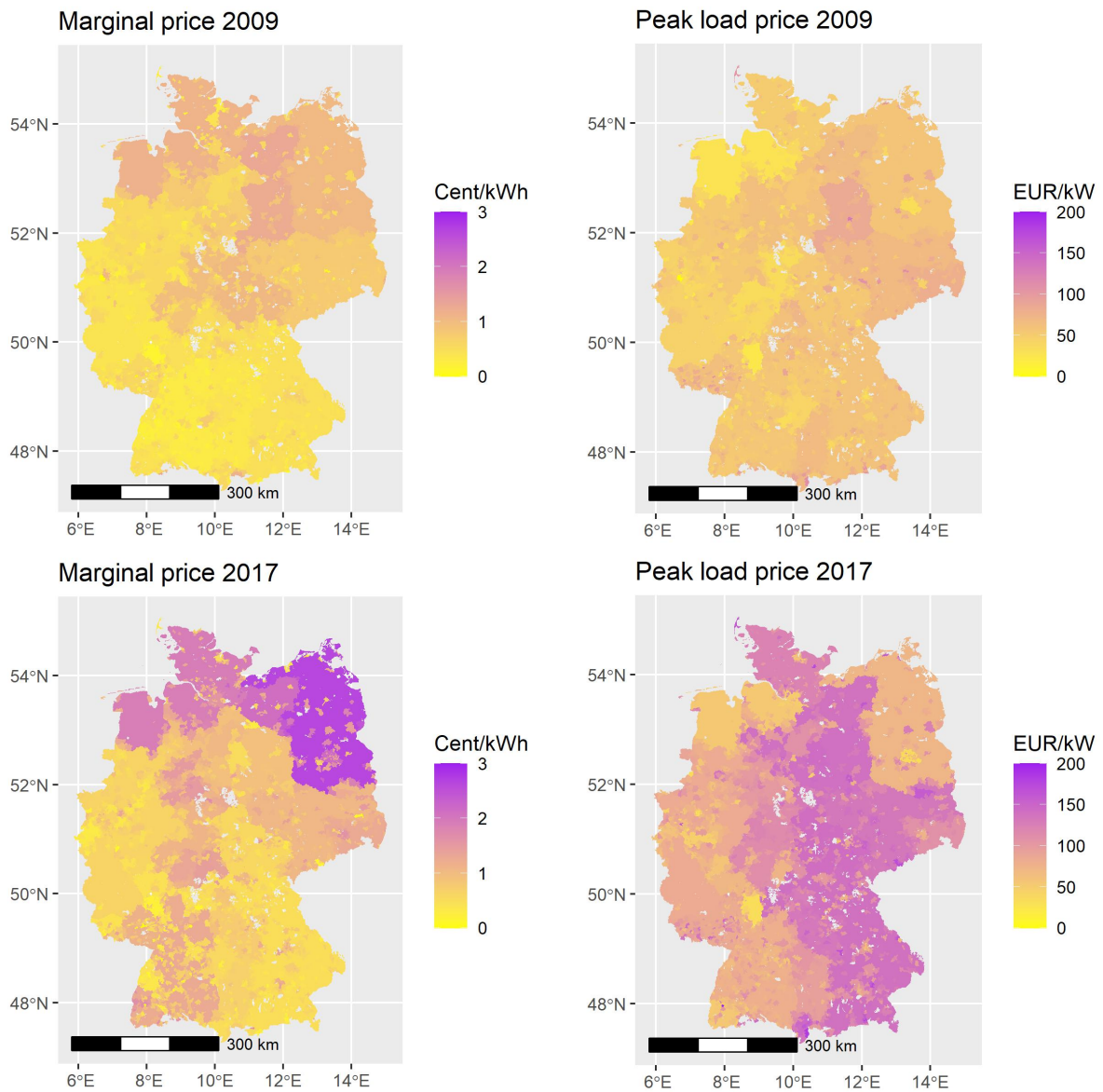


Figure S.6: Marginal and load-based network charges for a manufacturing plant in 2009 and 2017

Notes: The prices apply to a hypothetical chemical plant consuming 950 MWh per year with a peak load of 152 kW and shift work (annual operating hours > 2,500) in different network areas of Germany. The plant is connected to the medium voltage level. Areas without inhabitants and without an electricity grids (e.g., mountains, lakes) are left blank. Source: Own calculations, based on ene't data based on ene't data and GeoBasis-DE / BKG 2019 (data processed).

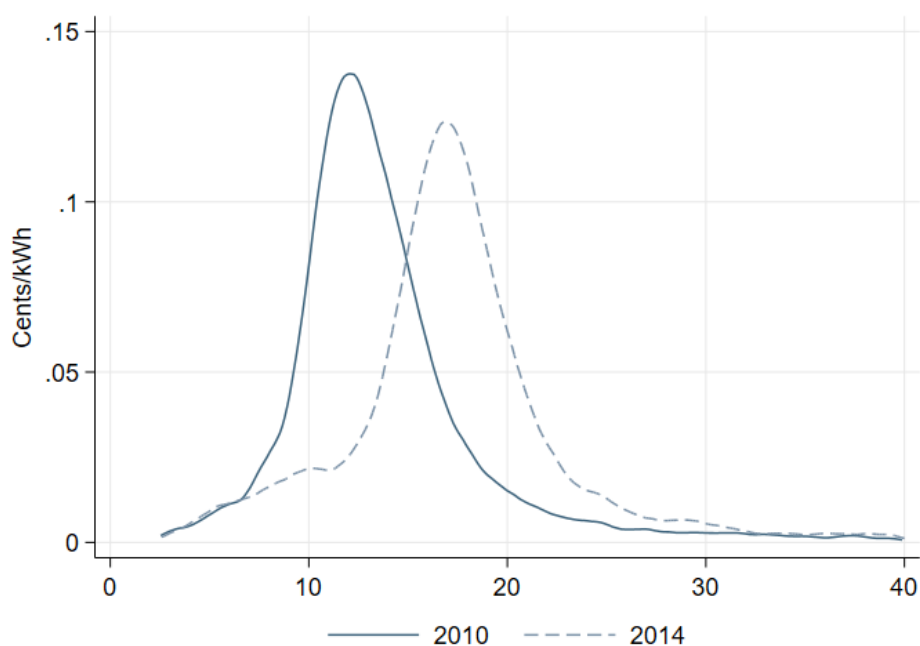


Figure S.7: Electricity Price Distribution of Manufacturing Firms

Notes: The figure shows the distribution of electricity unit cost for a sample of roughly 10,000 manufacturing firms in 2010 and 2014. Source: Own calculations, based on Manufacturing Census.

Table S.7 provides statistics on the share of network charges from these total electricity cost as described in the main text.

Table S.7: SHARE OF NETWORK CHARGES FROM ELECTRICITY EXPENDITURES FOR SINGLE-PLANT FIRMS IN 2014 (COLUMN (1)) AND 2010 (COLUMN (2))

Share of network charges from electricity costs (%)	2014 (1)	2010 (2)
p10	7.4	7.5
p25	9.8	10.1
p50	12.8	13.7
p75	18.1	18.4
p90	24.4	24.8
N	2,104	2,444

Source: Own calculations based on AFiD.

S.3 Appendix C: Additional Results

S.6 Reverse Causality

Network charges depend on the cost of grid operation which, in turn, is influenced by the behaviour of grid users, such as manufacturing plants. As prices are set in advance of manufacturing plant responses, cope for reverse causality is limited. Here we provide additional supporting evidence why reverse causality is unlikely to drive our results.

S.6.1 Summary Statistics: Grids and Manufacturing Users

Table S.8 shows the share of extracted annual load due to individual manufacturing plants in their respective grid area. The number of plants is smaller than our estimation sample because information on extracted annual load is not available for all grids. For most plants, the share is below 2%.

Table S.8: SHARE OF ELECTRICITY PROCUREMENT FROM GRID LOAD AT THE PLANT LEVEL

Year	p10	p50	p90	Number of plants
2009	0.0000	0.0005	0.0195	6,372
2010	0.0000	0.0005	0.0182	6,212
2011	0.0000	0.0005	0.0184	6,378
2012	0.0000	0.0005	0.0214	5,803
2013	0.0000	0.0005	0.0190	6,016
2014	0.0000	0.0006	0.0214	6,281
2015	0.0000	0.0006	0.0180	6,043
2016	0.0000	0.0005	0.0175	5,753
2017	0.0000	0.0005	0.0170	5,610

Notes: The table shows the distribution of the share of electricity procurement of individual manufacturing plants from the extracted load for their grid in our sample. The number of plants is smaller than our estimation sample because information on extracted annual load is not available for all grids. Own calculations based on data from *ene't* in combination with the Manufacturing Census.

Despite manufacturing plants switching into onsite generation (and the expansion in residential PV), there was no decrease in the load extracted from the German electricity grids over our study period. Figure S.8 shows the distribution of extracted load in the low and medium voltage levels, respectively.

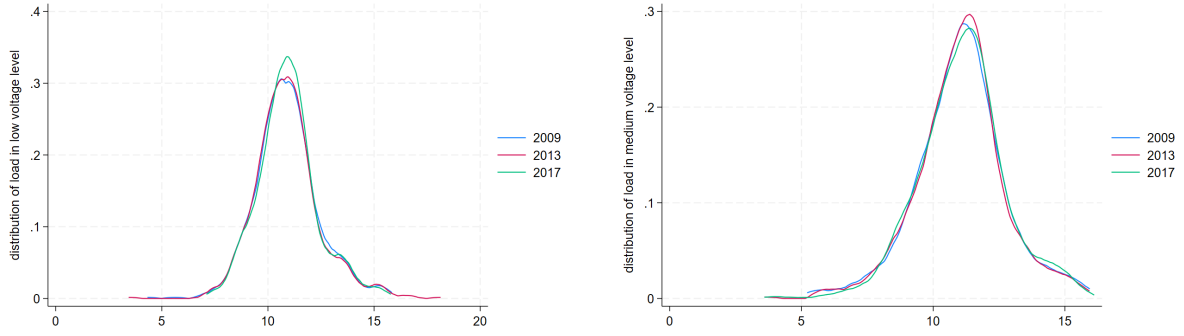


Figure S.8: Distribution of Load Extracted in the Low Voltage Level (left) and the Medium Voltage Level (right)

Notes: Extracted load is log transformed. Source: based on data from *ene't*.

S.6.2 Adjustments of Network Charges to Switches into Onsite Generation

To evaluate the potential for reverse causality, we estimate an event study as in the main text with the network charge components as dependent variables. This allows us to assess whether manufacturing plants that switch into onsite generation experience a divergent development in network charges prior to and after their switch. Results are depicted in Figure S.9.

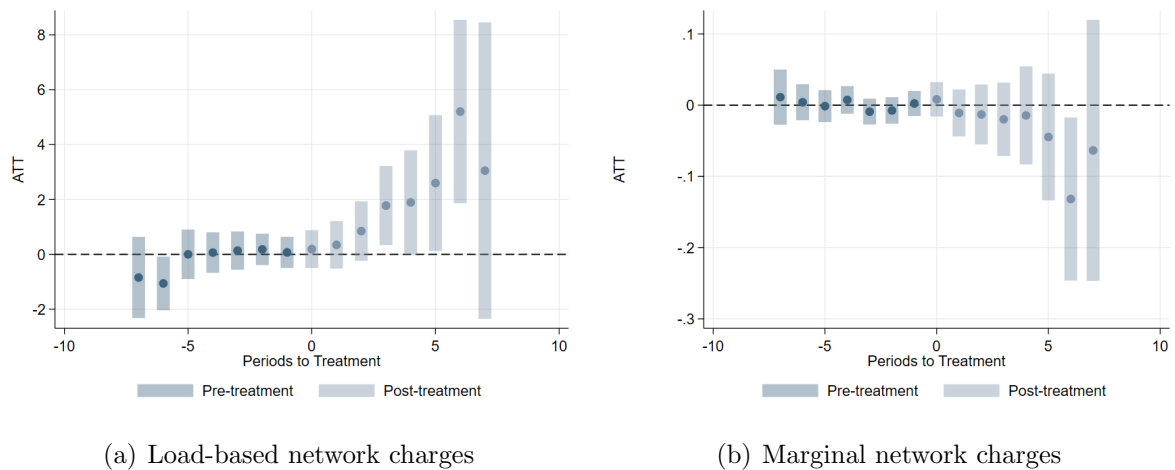


Figure S.9: Network Charges and Switches into Onsite Generation

Notes: The Figure compares the development for manufacturing plants that switch into onsite generation at $t = 0$ to never generators. The regressions control for commercial taxes, plant fixed effects as well as 4-digit sector by year fixed effects. Source: Own calculations, based on the Manufacturing Census and data from *ene't*.

Network charges do not adjust immediately after the switch. With a lag of 4 to 5 years, however, we see that peak load prices are higher for the switchers as compared to the never generators. Marginal prices follow an opposing trend. This development supports our reasoning

that network charges can only adjust to changing demand with a lag, and, hence, current network charges can be treated as exogenous. The opposing development of marginal and peak load prices reflects the construction of the simultaneity function as described in S.1 Appendix A.

S.7 The Effect of Electricity Prices on Onsite Generation

In the main text, we study the impact of network charges as well as electricity tax exemptions on the probability of onsite generation. We treat these price components as exogenous. In this section, we use this exogenous variation in a 2SLS IV regression to estimate the overall impact of rising electricity prices. Due to the limited availability of electricity expenditure data, these analyses are limited to the years 2010 and 2014. Given the limited power of these regressions, we only use plant and year fixed effects. The first stage results are depicted in Table S.6. Column (1) uses single plant firms only, Column (2) is extended to multi plant firms, potentially introducing measurement error.

Table S.9: THE EFFECTS OF NETWORK CHARGES ON ELECTRICITY UNIT COST

	P(Onsite Generation)	
	(1)	(2)
Average electricity price	0.039 (0.029)	0.008 (0.013)
F statistic	2.331	4.178
<i>N</i>	2,104	2,700
number plants	1,052	1,350

Notes: The table depicts results from a 2SLS IV regression instrumenting firms' average electricity unit cost (annual electricity expenditures divided by electricity purchases) by their network charges. Column (1) only uses single-plant firms, and column (2) shows the equivalent regression, adding multi plant firms. The first stage results are depicted in Table S.6. The regressions are run with firm fixed effects and year fixed effects. They include observations from 2010 and 2014. Source: Own calculations.

The analyses are underpowered, and the instrument, in consequence, is weak. Point estimates, however, are positive and similar to the results of the reduced form reported in the main text.

S.8 The Effect of Network Charges on Never Generators, Ever Generators, and Switchers

In the main text, we study plant outcomes following a switch to onsite generation, regardless for the reason of the switch. Here, we focus on the effect of network charges. We estimate a TWFE model, as in Equation (1), using the input and output choices of manufacturing plants

as dependent variables. We separate effects by never generators, ever generators, and switchers. We find that the only plants that consistently respond to network charges are the switchers. The effects of the switchers are, qualitatively, identical to what we find in the event studies: Switchers respond to network charges by reducing electricity purchases, increasing electricity use, increasing fuel use as well as capital stocks. This suggests that margins of adjustment are limited for those plants that cannot generate onsite. However, as we cannot separate intensive and extensive margin responses for lack of a suitable instrumental variable, these results remain suggestive.

Table S.10: THE EFFECTS OF NETWORK CHARGES ON GERMAN MANUFACTURING PLANTS

	Electricity purchases (1)	Electricity use (2)	Fuel use (3)	Capital stocks (4)
Marginal network charge	0.003 (0.006)	-0.010 (0.006)	-0.030*** (0.011)	-0.007 (0.007)
<i>effect switcher</i>	-0.073*** (0.017)	0.010 (0.014)	0.039 (0.024)	0.057*** (0.016)
<i>effect ever</i>	-0.006 (0.016)	-0.025* (0.014)	0.015 (0.023)	0.005 (0.017)
Load based network charge	0.001*** (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
<i>effect switcher</i>	-0.003*** (0.001)	0.001 (0.000)	0.001** (0.001)	0.001*** (0.000)
<i>effect ever</i>	-0.001 (0.001)	0.000 (0.000)	0.001 (0.001)	0.001** (0.000)
<i>N</i>	57,584	57,605	55,650	57,865
Number of plants	7,460	7,462	7,285	7,488

Notes: The regressions include observations from 2009–2017. Dependent variables are log-transformed. Sample sizes differ slightly due to zero values in the fuel consumption variable. All regressions include plant fixed effects, year by sector fixed effects at the 4-digit level, and control for commercial taxes and exemption from the RES. Standard errors are clustered at the county level and displayed in parentheses. Effects are differentiated between never generators, ever generators, and switchers. Source: Own calculations.

S.9 The Implications of Switching into Onsite Generation for Competitiveness

In the main text, we focus our attention on the implications of a switch into onsite generation on energy related outcomes. In Figure S.10, we extend the analysis to sales and employment. We do not find strong evidence that switching into onsite generation is associated with increasing sales and employment. While point estimates are positive and there does seem to be a small increase after the switch, all coefficients are insignificantly different from pre-switch levels. There are

moderate pre-trends. This is consistent with our heterogeneity analysis, where we found larger plants more likely to generate onsite.

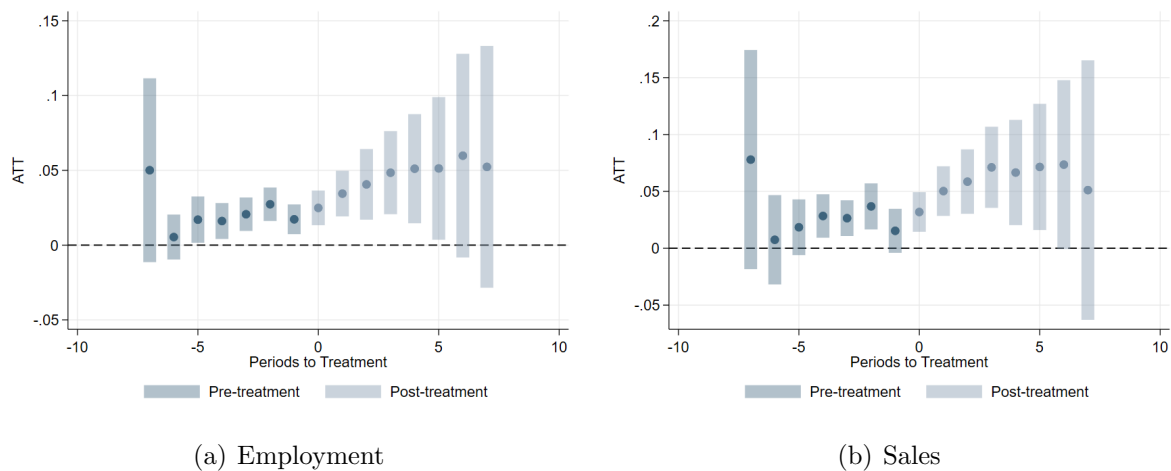


Figure S.10: The Implications of Starting to Generate Electricity for Competitiveness

Notes: The Figure compares the development of never generators to manufacturing plants that switch into onsite generation at $t = 0$. The regressions control for commercial taxes, plant fixed effects as well as 4-digit sector by year fixed effects. Source: Own calculations, based on the Manufacturing Census.

S.10 The Implications of Switching into Fossil Onsite Generation

In the main text, we estimate event-study models following Callaway and Sant’Anna (2021) to analyse plant outcomes before and after the start of onsite electricity generation. We show in the extensive margin regressions that adoption differs across fossil and renewable generators. Here, we run event studies comparing only fossil fuel generators to never generators. Fossil generators reduce electricity purchases by 35% after starting to generate electricity. Gas use increases by 34%.

Table S.11 suggests that in the German case, most manufacturing plants resorted to gas for fossil onsite generation. In accordance with that, Figure S.11 shows that a switch into onsite generation not only increases gas use, but also the probability of using any gas. We cannot identify significant changes in the probability of using other fuels around the switch.

Table S.11: THE IMPLICATIONS OF STARTING TO GENERATE ELECTRICITY

	Electricity purchases (1)	Electricity use (2)	Gas use (3)	Capital stocks (4)
Pre average	0.001 (0.006)	0.001 (0.006)	0.023 (0.016)	0.012*** (0.004)
Post average	-0.346*** (0.046)	0.035 (0.025)	0.336*** (0.068)	0.124*** (0.025)
<i>N</i>	49,067	49,067	35,841	49,067

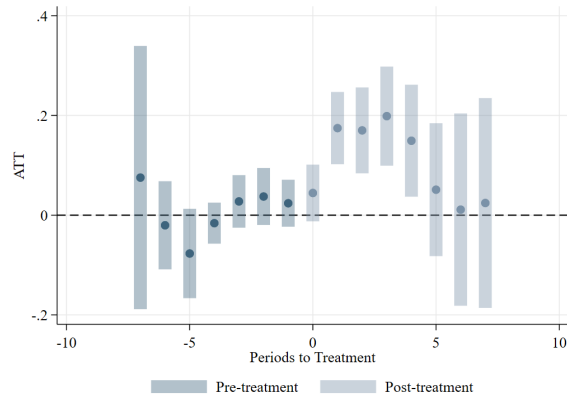
Notes: The Table compares the development of never generators to manufacturing plants that switch into fossil onsite generation ($t = 0$). It reports the average difference between never generators and switchers before the switch and after the switch. The regressions control for commercial taxes, plant fixed effects as well as 4-digit sector by year fixed effects. Source: Own calculations, based on the Manufacturing Census.

S.11 Onsite Generation, ETS Regulation, and Surrendered Allowances

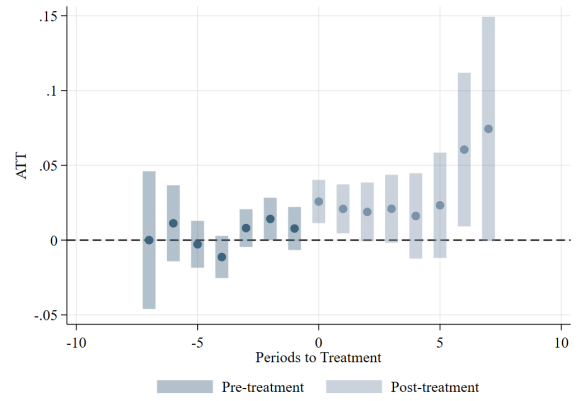
In figure S.12, we repeat our event study analysis, but restrict it to manufacturing plants switching into onsite generation which are not regulated under the EU ETS. It shows that our main results are, at least in parts, driven by unregulated switchers.

Figure 13(a) shows that there is substantial growth in electricity generated with fossil fuels by manufacturing plants not regulated under the EU ETS. Between 2005 and 2016, this unregulated electricity generation increased by 4.17 TWh, or 76%.

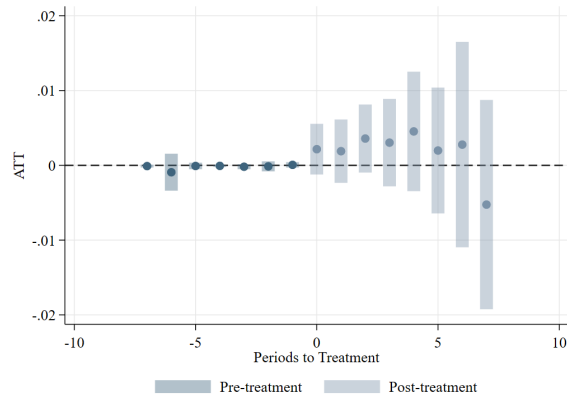
Figure 13(b) shows that even within plants regulated under the ETS, the increase in onsite generation goes (partly) unregulated. Since 2013, the ETS also includes process emissions. This change in the regulation led to an increasing number of manufacturing plants being regulated, but not because of their onsite generation facilities. In fact, Figure 13(b) shows that the fossil fuel onsite generation of the plants switching into regulation at the date of the regulatory change subsequently increased substantially (58% from 2013 to 2016), while the number of allowances submitted remained stable (allowances surrendered increased by 0.5 mio. over the 4 years, whereas emissions due to combustion increased by 1 mio. tonnes), suggesting that allowances of newly regulated plants were largely submitted for process emissions and not for the (increasing) combustion activities involved in onsite generation.



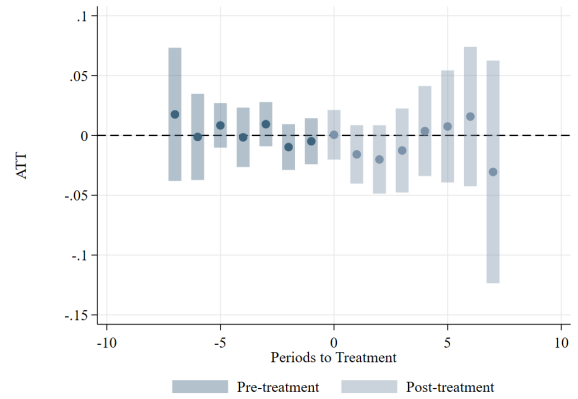
(a) Gas Use



(b) Dummy Gas Usage



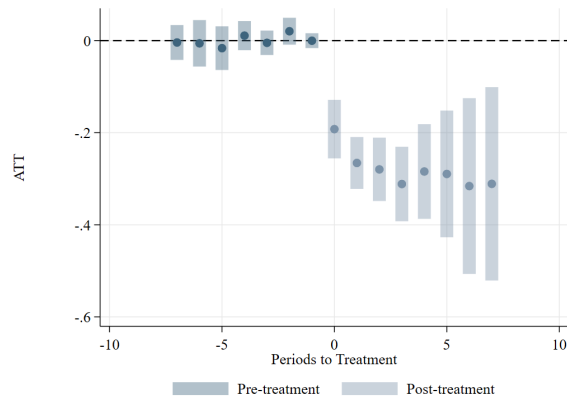
(c) Dummy Coal Usage



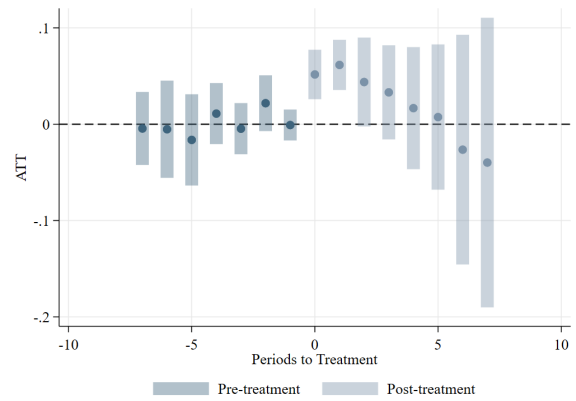
(d) Dummy Oil Usage

Figure S.11: Fuel Usage Patterns when Starting to Generate Electricity

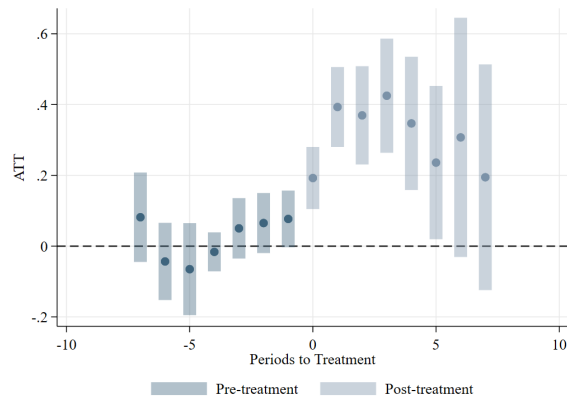
Notes: The Figure compares the development of never generators to manufacturing plants that switch into onsite generation ($t = 0$). The regressions control for commercial taxes, plant fixed effects as well as 4-digit sector by year fixed effects. Source: Own calculations, based on the Manufacturing Census.



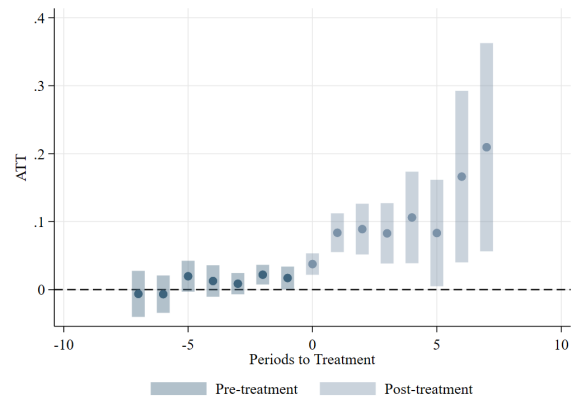
(a) Electricity Purchases



(b) Electricity Use



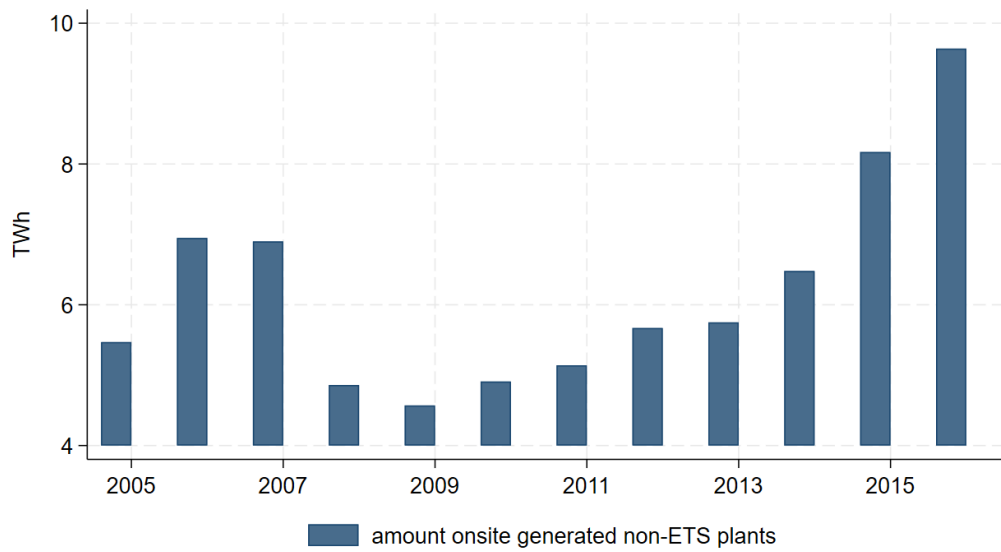
(c) Gas Use



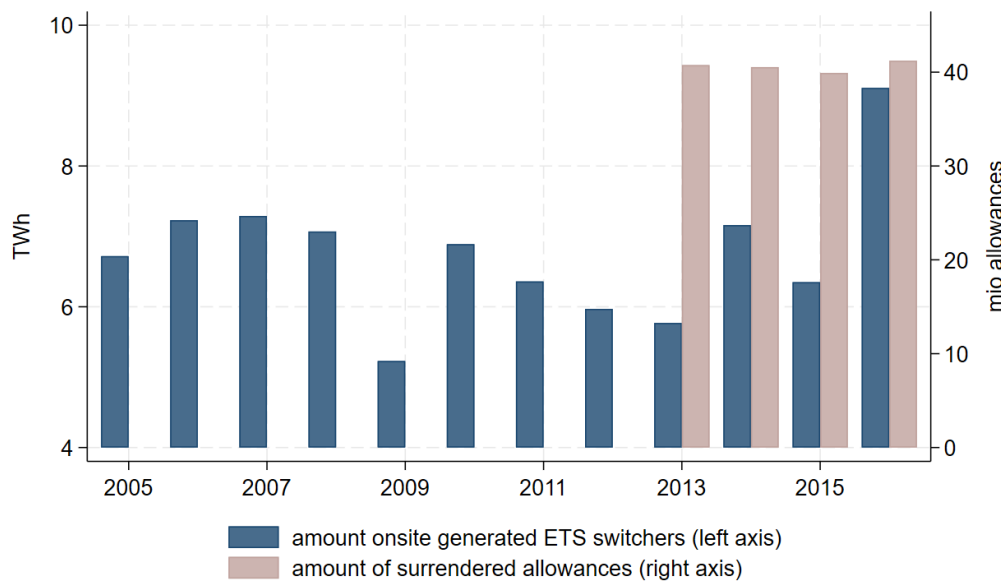
(d) Capital stock

Figure S.12: Starting to Generate Electricity Without ETS-Regulation

Notes: The Figure compares the development of never generators to manufacturing plants that switch into onsite generation at $t = 0$ and that are not regulated under the EU ETS. The regressions control for commercial taxes, plant fixed effects as well as 4-digit sector by year fixed effects. Source: Own calculations, based on the Manufacturing Census.



(a)



(b)

Figure S.13: Non-renewable Electricity Generation and Surrendered Allowances in German Industry by ETS Coverage

Notes: Regulation status is at the plant level. Regulation status is consistent over time. The figure depicts the onsite electricity generation from fossil fuels. Figure 13(a) shows electricity generation by all plants never regulated under the EU ETS (roughly 42,000 plants per year). Figure 13(b) shows electricity generation and surrendered allowances by all plants that switch into the ETS in 2013 (roughly 250 plants per year). Source: Own calculations.

References

- CALLAWAY, B. and SANT'ANNA, P. H. C. (2021). Difference-in-Difference with multiple time periods. *Journal of Econometrics*, **225**, 200–230.
- FEDERAL NETWORK AGENCY (BNETZA) (2015). *Netzentgeltsystematik Elektrizität*. Bonn.
- GERMESHUSEN, R., HEIM, S. and WAGNER, U. J. (2025). Support for Renewable Energy: The Case of Wind Power. *Journal of Public Economics*, **250**, 105468.
- HEIM, S., KRIEGER, B. and LIEBENSTEINER, M. (2020). Unbundling, regulation, and pricing: Evidence from electricity distribution. *The Energy Journal*, **41**.
- ROTTNER, E. and VON GRAEVENITZ, K. (2024). What Drives Carbon Emissions in German Manufacturing: Scale, Technique or Composition? *Environmental and Resource Economics*, **87**, 2521–2542.