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Do Manufacturing Plants Respond to Exogenous Changes in Electricity Prices? Evidence From Administrative Micro-Data

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Do Manufacturing Plants Respond to Exogenous Changes in Electricity Prices? Evidence From Administrative Micro-Data

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Abstract

Climate change is the result of global market failure and remedying the situation requires effective policy action. Climate policies often increase energy prices thereby affecting all actors in the economy. Concerns about competitiveness impacts of unilateral policies hamper the development of effective policies. We provide causal evidence on how industrial plants respond to electricity price increases. Our research design uses exogenous variation in German electricity prices in combination with detailed administrative data on German manufacturing plants. We find that rising electricity prices led German manufacturing plants to significantly reduce their electricity procurement with an own-price elasticity of -0.4 to -0.6 on average and substantial variation across procurement levels. They also induced industrial users to replace electricity procurement by electricity generated onsite contributing to a decentralization of electricity generation. We find no statistically significant negative effects on competitiveness indicators.

Keywords: Electricity Use, Firm Performance, Climate Policy

JEL-Classification: D22, L60, Q41, Q48

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1 Introduction

Climate change is one of the starkest examples of market failure of our times. The negative effects of greenhouse gas emissions are not internalized in market prices leading to too little abatement across the globe. As the urgency grows, policy makers are increasingly implementing market-based as well as command and control regulation to correct this market failure, in tune recommendations by economists (Baumol, 1972; Gillingham and Stock, 2018; Hahn, 1989; Nordhaus, 1977; Pigou, 1923; Reguant, 2019). Most climate policies have one thing in common: They raise energy and electricity prices (Fabra and Reguant, 2014; Gerster and Lamp, 2022; Hintermann, 2016; Reguant, 2019; Sato *et al.*, 2015; Wolverton *et al.*, 2022).

Through their effect on electricity prices, climate policies indirectly affect all actors in the economy. Electricity serves as a vital input for industrial production.[1] Reguant (2019) emphasizes the impact of climate policy cost passthrough on reducing demand for energy. Firms are flexible in how to deal with electricity price increases. They might, e.g., adjust their energy mix, and replace electricity by primary energy carriers, or shift towards other production factors. Potentially, firms respond in a way unintended by policy makers and outsource the most energy intensive intermediates.

Estimating the effects of rising electricity prices requires isolating how electricity prices alter the behavior of firms from confounding macroeconomic conditions and other policies. Predicting the effects of electricity price increases is difficult because firm level abatement cost curves are not observed. In this paper, we estimate the causal effects of electricity price increases on German manufacturing plants. We thereby provide evidence on both the environmental and economic consequences of all regulations that increase electricity prices.

While indispensable, electricity is of minor importance in manufacturing firms' total cost. On average, energy accounts for roughly 2% of revenues in industry (Ganapati *et al.*, 2020; von Graevenitz and Rottner, 2023). How strongly (policy-induced) price changes in such a minor cost component affect the environmental and the economic performance of manufacturing plants is an empirical questions that we address using the rich administrative micro-data from the German Manufacturing Census.

[1] For a description of how energy and electricity are used in US manufacturing, see Ganapati *et al.* (2020).

To guide our analysis and highlight relevant adjustment margins of firms, we present a simple model of production. In the model, firms can either procure electricity from the grid or generate electricity onsite which is cheaper at the margin, but requires a fixed investment cost. Small policy-induced increases in electricity procurement prices lead firms to reduce output. Larger increases in electricity procurement prices, however, lead firms to incur the fixed cost to start or expand onsite generation. The access to cheap electricity generated onsite can in consequence even lead to production expansion.

Exploiting exogenous changes in electricity prices in Germany, we find that rising electricity procurement prices cause manufacturing plants to buy less electricity from the grid. We estimate a short run own price elasticity of electricity procurement of -0.4 to -0.6 on average. Effects are heterogeneous, with plants at the lower end of the electricity procurement distribution displaying larger price elasticities than those at the upper end. Between 2009 and 2017, the elasticity of response has decreased. This finding could be indicative of increasing marginal abatement cost. It is also consistent with onsite generation acting as an insurance against increases in procurement prices and reducing plant responsiveness to continued price increases.

In line with our theoretical framework, we find evidence that plants expand onsite electricity generation (both at the intensive and extensive margin) in response to rising electricity procurement prices. Onsite generating plants using fossil fuels reduce electricity procurement the most, while plants using renewables show a somewhat weaker response. The intermittent nature of renewable energy makes it less attractive as an "insurance" since it is less dispatchable than fossil fuel generation. The electricity price changes we study did not decrease competitiveness, measured by sales and employment. Plants generating electricity onsite even increase their revenues, hours worked and capital stocks.

Our results show that over the past years, electricity price increases have contributed to a decentralization of electricity generation.[2] Reguant (2019) discusses the potential of leakage due to onsite generation in the context of model-based simulations. We show that this concern is real, but find that the electricity price-induced increase in fossil onsite gen-

[2]In the US, less than 1% of manufacturing plants generate electricity onsite, producing rather constantly around 11-12% of total industrial electricity consumption since 2002 (EIA, 2021). In Germany, this share increased substantially from roughly 14% in 2003 to 25% in 2017 (von Graevenitz and Rottner, 2023). The number of onsite-generating German industrial plants more than quadrupled from 1,188 in 2005 to 5,823 in 2017.

eration largely occurred in firms regulated under the EU's emissions trading scheme (EU ETS) and was mirrored by an increase in surrendered allowances. The decentralization, thus, did not negatively affect the EU's climate performance. It could nevertheless have broad and potentially long-lasting consequences. These include potential repercussions on grid stability, energy security (if industry increasingly relies on (certain) fossil fuels), as well as equity concerns (if, due to onsite generation, a declining number of users has to bear the fixed cost of the electricity grid). The rise in industrial electricity generation might also have long-lasting implications for how manufacturing firms will respond to future electricity price increases and climate policy measures.

Our estimates can be used to quantify the indirect effects of regulations increasing electricity prices. We give two examples using electricity price increases through the EU ETS as well as the Renewable Energy Surcharge used to subsidise renewable energy providers. The ETS reduced emissions from the German manufacturing sector through electricity price induced reductions in the demand for electricity. A back of the envelope calculation suggests, that without the electricity price increases induced by the EU ETS, (scope 1 and 2) carbon emissions in German manufacturing would have been 34 million tonnes higher over the complete period from 2005 to 2017. This corresponds to about 1% of total (scope 1 and 2) annual emissions from manufacturing. As the power sector is subject to the cap, these do not constitute actual EU-wide emissions reductions, but only a shift of emissions away from German manufacturing. In our second example, the Renewable Energy Surcharge, we use our estimates to quantify the demand effect in terms of excess allowances in the EU ETS. In earlier phases of the EU ETS, the cap was not adjusted to reflect emission reductions due to additional (national) policy measures. This led to a "waterbed effect" as emission reductions in one country or sector were offset by increases elsewhere within the EU ETS. A back of the envelope calculation suggests that we should have retired in total 125 million allowances between 2010 and 2017 to cancel the demand effect of the Renewable Energy Surcharge on carbon emissions in manufacturing.

Our paper contributes to several streams of literature. First, we contribute to the literature on the effects of electricity and energy prices on firm behavior (Bardazzi *et al.*, 2015; Boyd and Lee, 2016; Cox *et al.*, 2014; Marin and Vona, 2021). Our study stands out by using plant level data instead of the commonly used sector level data, and by exploiting an exogenous source of variation in electricity prices to address electricity price endogeneity. For identification, we rely on electricity network charges. Network charges are arguably exogenous due to regulation through the Federal Network Agency which results in single plants not being able to influence network charges. They also vary strongly both on a spatial and a temporal scale. This variation allows us to estimate causal effects at the plant level and to recover a credible estimate of the own-price elasticity of electricity.

Second, we contribute to the growing literature on the effects of climate policies on manufacturing firms. Much of this literature has focused on emissions trading as a prime example for pricing greenhouse gases (see e.g. Colmer *et al.* 2023, Naegele and Zaklan 2019 or Martin *et al.* 2016 for an overview). As many climate policy measures such as the EU ETS as well as compensation measures of climate policies feature a size threshold (20 MW installed capacity for inclusion in the EU ETS), much existing research focused on the largest and most energy intensive plants and firms (e.g., Colmer *et al.* 2023, or Gerster and Lamp 2022). While internal validity in these studies is high, external validity may be called into question as abatement options are likely to differ from those of an average plant.

We complement this literature by providing evidence on the effects of climate policies both on the environmental and the economic outcomes of a broader and more representative sample of plants than prior research. Our paper is also complementary to this literature as we focus on the indirect effects of climate policies through their impact on the derived energy carrier electricity. These indirect effects are considered in general equilibrium models, but causal micro-econometric evidence using recent data and current policy contexts is scarce. The elasticity estimates we provide can be used as an input to model, e.g., the emission pathways under policy scenarios for climate models. They are a current alternative to the off-the-shelf parameter values without a micro foundation commonly used in past research (Finkelstein-Shapiro and Metcalf, 2022; Heutel, 2012). Moreover, we complement existing literature by explicitly linking the relationship between climate policies and the inputs of fossil fuels and electricity. This way, we investigate the between sector leakage channel discussed by Reguant (2019). Climate policies could, by rising electricity prices, shift electricity production from the power sector generally covered by climate policies to the manufacturing sector in which coverage is not complete.[3,4]

Finally, we contribute to the literature by studying effect dynamics. Specifically, we investigate how the response to rising electricity prices has changed over a nine year period. We can assess how adjustments such as a shift towards onsite generation or technical progress affect the responsiveness to price increases.[5] We provide evidence that over time, plants require larger changes in electricity prices to take the next abatement step. Marginal abatement cost are increasing non-linearly.

2 Background on electricity prices and networks

2.1 Electricity prices and price components in Germany

Total electricity prices in Germany comprise three components: (1) the cost of generation and supply; (2) taxes, levies and surcharges; and (3) network charges. Figure 1 depicts their development between 2007 and 2017 for different consumption bands. The importance of taxes and surcharges has grown substantially, making up approximately 40% of final electricity procurement prices towards the end of the study period. This strong increase is mostly rooted in the development of the renewable energy surcharge imposed at the federal level, which financed the guaranteed feed-in tariffs for renewables and was in place from 2000 to 2022. Network charges – varying at the network level – account for up to 30% of final electricity prices and also tend to increase over the study period. In

[3]To the best of our knowledge, the trade-off between buying and generating electricity in the industrial sector has not been studied except for the work by Curtis and Lee (2019). While fuel switching seems an obvious response to changing relative energy prices, previous literature has either focused only on the effects of electricity prices on performance measures such as output or employment (e.g., Wolverton *et al.* 2022 or Cox *et al.* 2014), or on aggregate energy prices and consumption, which by construction masks substitution effects between energy carriers (Marin and Vona 2021 or Hille and Möbius 2019).

[4]Our result that high electricity prices increase onsite generation is similar in spirit to Borenstein and Bushnell (2022) and Borenstein (2017) who find that high retail prices render solar installations more attractive, focusing on residential consumers.

[5]Much of the previous literature has focused on estimating short-run effects of climate policy and energy prices. One exception is the work by Marin and Vona (2021); however, due to data availability, they define long-run as effects ranging over a three-year period only, which is substantially shorter than the time window we consider.

contrast, the generation and supply component is gradually decreasing. This decline is likely driven at least in part by the expansion of renewable energies with zero marginal cost in the German electricity mix.

Germany constitutes one electricity market such that identical wholesale prices apply to all users (price component 1), and taxes and surcharges are generally charged at the federal level (price component 2). However, users still face different electricity prices. This variation stems from customers choosing different electricity providers (price component 1),[6] from exemptions and reduced rates applicable to specific groups (e.g. in the case of the renewable energy surcharge), and from variation in network charges at the regional level (price component 3). Due to exemptions and lower charges for large electricity users, prices are generally lower the higher the consumption level.

Final electricity prices faced by individual customers are unknown, as the choice of supplier in the retail market is unobserved. Due to the opportunity to choose and negotiate a contract, total prices would be endogenous even if observed. Wholesale prices and national taxes and levies are observable, but generally do not exhibit cross-sectional variation making it hard to distinguish effects of changing prices from general or sectoral time trends. In contrast, network charges are observable and vary both cross-sectionally and over time. Additionally, they are plausibly exogenous, as the next section will show.

2.2 Electricity networks and the exogeneity of network charges

The German electricity market has undergone notable changes over the last 20 years associated with unbundling of vertically integrated utilities. [7] In this process, the Federal Network Agency was established. One of its tasks is to regulate the fees electricity network

[6]The German retail market for electricity is competitive. In 2011 approximately 1,100 different electricity suppliers were active in Germany and 54% of the customers had chosen a supplier other than the local incumbent (Federal Network Agency (BNetzA) and Federal Cartel Agency (BKartA), 2013).

[7]Prior to 2005, the German energy sector was characterized by vertically integrated utilities (generation, transmission and distribution as well as retail and supply) with regional monopolies. Through the 2005 amendment to the Energy Act, electricity generation and network operation were unbundled. This process left network operation to four Transmission System operators (TSOs) that transport electricity around the country at the extra high voltage level, and to up to 900 Distribution System Operators (DSOs) that run the low, medium and high voltage networks and connect final customers to the electricity grid. Both transmission and distribution networks constitute natural monopolies.

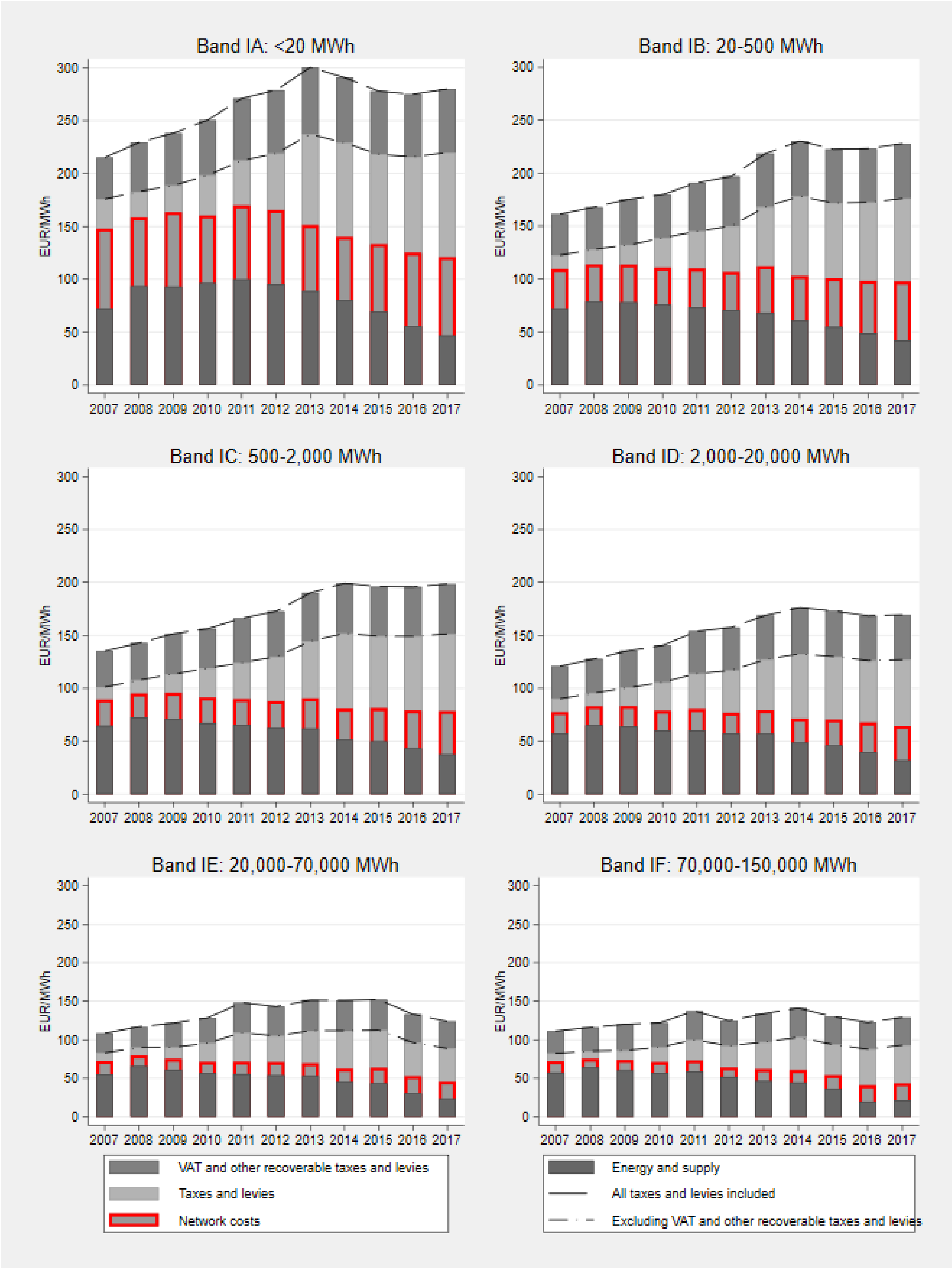


Figure 1: The development of electricity prices for different consumption bands

The figure shows the average development of different electricity price components between 2007 and 2017 for industrial consumers in different consumption bands. Network charges are marked by the red frames. Source: Eurostat time series nrg_pc_205 and nrg_pc_205_c.

operators charge their customers so as to reduce monopoly profits and inefficiencies in network operation.

To that end, since 2009, the Federal Network Agency benchmarks network operators against each other.[8] The result of this procedure is combined with information about the network operators' levels of (in the short-run) unalterable cost. These two components together serve as a basis for assigning a revenue cap to each individual network operator. Revenue caps are set for regulatory periods of five years, but adjusted annually to take into account price developments or unexpected infrastructure investments and restructuring of the grids. Network operators can only set network charges in accordance with their revenue cap. The revenue caps are translated into a marginal and a fixed/peak-load-dependent price component following a specific procedure also regulated by the Federal Network Agency.[9]

This regulation leads to network charges varying over time (where prices that will apply in the next year are published in October), and over space between the different DSOs.[10] The spatial variation is depicted in the left panel of Figure 2 which shows the average network charges that a hypothetical chemical plant connected to the medium voltage level would have had to pay in different areas in Germany in 2018. In Figure 1, that plant would belong to consumption band IC. Higher network charges apply to many of the states belonging to the former Eastern Germany.[11] However, there is substantial variation at a small spatial scale. The right panel of Figure 2 shows the average annual growth in average network charges for the same hypothetical chemical plant over the regulatory period from 2014 to 2018.[12] Clearly, there is substantial variation both over

[8]Before this so-called incentive regulation was established in 2009, starting in 2005 the TSOs, and in 2007 the DSOs were under a cost-plus regulation in which they were allowed to recover their costs plus a regulated markup through the network charges. Due to the regulatory change, our analysis is limited to the years from 2009 onwards.

[9]The setting of revenue caps and individual network charge components across different voltage levels is described in more detail in Appendix A.

[10]There are 800-900 DSOs at the low voltage level and a bit fewer at the medium voltage level. At the high voltage level the number of DSOs declines to 60-70 across Germany. Correspondingly, there is less spatial variation in network charges at the high voltage level.

[11]This is due to several factors including the young age of the grid in Eastern Germany and related high depreciation cost, the lower population density in rural areas, as well as the high number of renewable (wind) installations in the North of Germany which had to be connected to the grid.

[12]Figure 11 in Appendix B shows the variation over time in terms of growth rates.

time and space. Network charges have generally increased substantially. In other voltage levels, the development is similar.

Network charges faced by individual plants vary by grid operator, the voltage level at which a plant is connected to the grid, and customer group. There are three main customer groups: standard load-metered (small plants procuring less than 100 MWh per year) and interval-metered customers with annual operating hours below (gr.1) or above (gr.2) 2,500 hours. For each customer group in each voltage level there are specific load-based and marginal prices, where the load-based price component depends on the peak load for interval-metered customers. More details can be found in the Appendix. Drivers of variation in network charges across DSOs include grid-level variation in a variety of cost components, among them cost for network operation (maintenance, infrastructure investments and connection of new plants and installations), system support services (such as re-dispatch), and transmission losses. von Graevenitz and Rottner (2022) study drivers of network charges and find that much of the variation both across and within DSOs can be explained by the renewable energy expansion that required connecting new generation sources to the grid and likely increased the level of system support services needed.

Due to this regulation, network charges in Germany do not suffer from the same endogeneity concerns typically encountered when analysing electricity prices. Broadly, these challenges concern selection – users endogenously choose their supplier; endogenous price-setting – users might be able to negotiate tariffs with their suppliers; and reverse causality – the very outcomes researchers are studying affect the prices users are paying (which is prominently the case in block tariff systems as studied in Ito 2014). The same concerns do not apply to network charges for the following reasons.

First, selection is not an issue as for each electricity consumer in Germany, the location completely determines the relevant DSO. Once users are located in a certain area, the network operator is fixed. While in principle manufacturing plants could actively select into cheaper network areas, we make use of plant fixed effects and hence use the within-plant variation in network charges over time for identification; therefore, endogeneity concerns due to selection are minimal.[13]

[13]Limiting the sample to manufacturing plants that were already operating prior to 2005 (and hence prior to the Federal Network Agency even being established and prior to today's DSOs existence) does

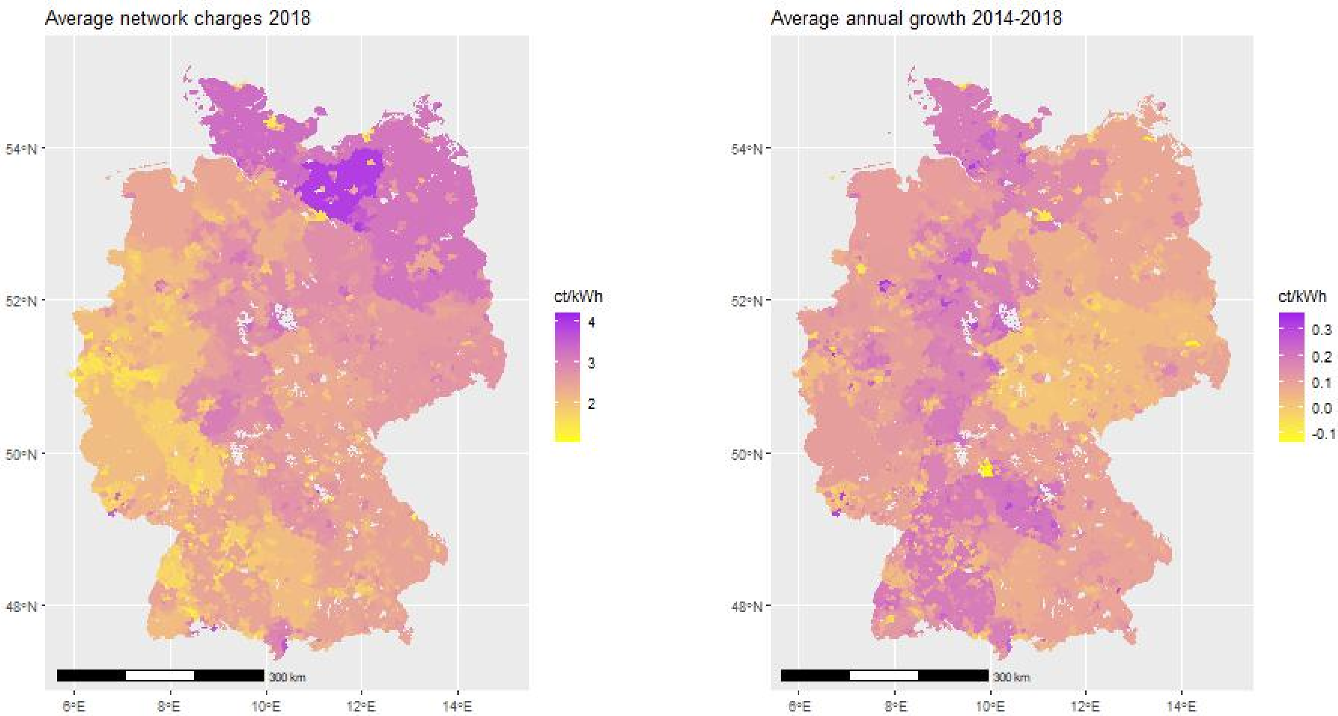


Figure 2: Left: Average network charges of a hypothetical chemical plant in 2018; right: Average annual growth in average network charges for the same plant between 2014 and 2018

Notes: Source: Own calculations, based on ene't data. Average network charges are calculated in cents per kWh for 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.*

Second, price negotiations and strategic behaviour are ruled out in the case of network charges: Local DSOs are not free to set network tariffs due to regulation through the Federal Network Agency. There is no scope for negotiations with single users, nor can DSOs strategically set network charges to attract and retain industrial plants. Regulation of the DSO's revenue cap and the translation of the cap into individual price components is very detailed and leaves little leeway.

Third, reverse causality is ruled out by the timing of network charge determination and demand responses: Network charges for a given year based on the (adjusted) revenue cap of a regulatory period are set and published in October of the previous year. Hence, they are fixed prior to potential demand responses of the industrial sector. Additionally, note that in general, reverse causality seems unlikely, as our identification uses within-plant variation and only requires changes in network charges to be exogenous (as opposed to levels).[14] Entry or exit of large manufacturing plants do not pose a threat to identification since we use within plant variation. For the incumbents a change in network charges due to a change in the composition of the customers would arguably be exogenous. For an entrant, the change in network charges in the grid area induced by the entry is not used for identification due to the use of plant fixed-effects.[15]

The exogeneity of (changes in) network charges allows us to recover causal effects that extend to electricity prices. A large share of manufacturing plants pay network charges on a monthly basis directly to their DSO. Given that network charges are salient for industrial consumers, it seems plausible that industrial users respond in the same way to an increase in electricity charges due to network charges as to increases rooted

not change the results, as shown in Figure 5. This suggests selection of DSOs via site location does not play a major role.

[14]This means, e.g., that the fact that network charges are higher in certain areas such as the north-east of Germany should not bias our findings. It would only constitute a violation of exogeneity if changes in the demand behaviour of industry affected the development of network charges. Network charges depend on a variety of factors including re-dispatch, maintenance and expansion of the grid. In addition, the consumption behaviour of lots of (large) electricity users outside manufacturing (e.g., warehouses, hospitals, movie theatres, and households) are also taken into account. The German system, which does not involve nodal pricing, makes the link between individual plant behaviour and network charges much weaker than it is, e.g., in the US.

[15]Nevertheless, we estimate effects on a balanced panel of plants in a robustness check to exclude that our findings are driven by plant entry (or exit). This does not qualitatively alter results.

in other (non-fuel) price components.[16] In reduced form regressions, we proxy unknown and endogenous electricity prices by the exogenous electricity network charges faced by manufacturing plants. In the next section we describe a simple conceptual framework for our analysis.

3 Conceptual Framework

As electricity constitutes an input factor in a manufacturing firm's production process, changing prices affect firm-level decisions and have an impact along different dimensions. To see this, consider the example of a simple Cobb-Douglas production function with two inputs, labour L and electricity E:[17]

$$q_i(L_i, E_i) = E_i^{\alpha} \times L_i^{\beta} \times \omega_i \tag{1}$$

ω represents factor-neutral productivity. Each plant i sells its product at market price p and accordingly pays market prices for its input factors, i.e. wage rate w and electricity price c_{elec}. Plants maximise profits given by:

$$\pi_i = p \times q_i(L_i, E_i) - w \times L_i - c_{elec} \times E_i \tag{2}$$

Standard profit maximisation implies that plants choose their optimal electricity input as:

$$E_i^* = c_{elec}^{\frac{1-\beta}{\alpha+\beta-1}} \times \alpha^{\frac{\beta-1}{\alpha+\beta-1}} \times p^{\frac{-1}{\alpha+\beta-1}} \times w^{\frac{\beta}{\alpha+\beta-1}} \times \beta^{\frac{-\beta}{\alpha+\beta-1}} \tag{3}$$

Under diminishing returns to scale (which are necessary for the profit maximum to be defined), the optimal input quantity decreases with electricity price increases. The profit maximizing input ratio, given by

$$\frac{E^*}{L^*} = \frac{w}{c_{elec}} \times \frac{\alpha}{\beta} \tag{4}$$

shifts towards more labour input in response. Similarly, optimal plant-level production is a function of input prices, so an increase in electricity prices not only changes the allocation across input factors, but leads to a decline in production:

$$q_i(L_i^*, E_i^*) = c_{elec}^{\frac{\alpha}{\alpha+\beta-1}} \times \alpha^{\frac{-\alpha}{\alpha+\beta-1}} \times p^{\frac{-\alpha-\beta}{\alpha+\beta-1}} \times w^{\frac{\beta}{\alpha+\beta-1}} \times \beta^{\frac{-\beta}{\alpha+\beta-1}} \tag{5}$$

[16] Appendix A gives further information on the billing procedure of network charges.
[17] The model is restricted to two input factors for convenience, but generalizes to more.

Manufacturing plants have two possibilities to cover their electricity demand: They can procure electricity from the grid, or they can generate it onsite. Effectively, the electricity price c_{elec} can take on different values:

$$c_{elec} \in (c_{proc}, c_{os}) \tag{6}$$

The cost for electricity procurement from the grid is denoted c_{proc}, while the (marginal) cost for (fossil) onsite generation is given by c_{os}. In the German context, these prices depend on fuel prices, emissions trading and taxes and charges to differing extents:

$$c_{proc} = c_{proc}\left(\frac{n}{F_G}, \tau, \kappa, \rho_{ETS}, X_G\right) \tag{7}$$

$$c_{os,i} = c_{os,i}\left(\frac{n}{F_i}, \rho_{ETS}, X_i\right) \tag{8}$$

Procurement prices depend on the cost of generation in the power sector (price component 1 in Section 2), i.e. a combination of fuel cost, n, and efficiency F (kWh of electricity generated per fuel input) in the power sector G. The component τ reflects taxes (such as the renewable energy surcharge, component 2 in Section 2) and κ captures grid charges (component 3 in Section 2). As past research has shown evidence of pass-through of emission allowances to the final customer in the power sector (Hintermann, 2016; Fabra and Reguant, 2014), procurement prices also depend on carbon prices ρ_{ETS}, and the emission factor reflecting the fuel mix used X.

The cost for onsite generation also depends on fuel prices and efficiency. In contrast to procurement prices, electricity generated onsite is largely exempt from taxes, levies and grid charges.[18,19]

We assume that prices of fossil fuels do not vary between the power sector and the manufacturing sector (n is the same). In consequence, our model is focused on changes

[18] The model is stylized, as regulation is fairly complicated and has been amended over time. Electricity generated in installations for onsite generation operating prior to 2014 is completely exempt from the renewable energy surcharge. The 2014 amendment of the Renewable Energy Act made onsite generation from installations built after 2014 subject to a reduced surcharge. Network charges in general are not charged for electricity generated onsite when the grid is not used. Further, we here assume that all onsite generation is regulated under the EU ETS, while in reality, this only applies to installations exceeding the threshold of 20 MW. For smaller installations the terms related to emission trading in c_{os} drop out.

[19] The power sector in Germany has not been eligible for free allowances since 2013. In Hintermann (2016), cost pass-through is found despite free allocation to the power sector suggesting that the incidence of the ETS fell completely on final consumers even prior to auctioning.

in electricity prices that are not induced by changes in the price of fossil fuels. Manufacturing plants may be less efficient in generating electricity (F_G is high compared to F_i).[20] Nevertheless, for any manufacturing plant, onsite generation is likely cheaper at the margin due to the exemptions from levies, taxes and grid charges. It however requires a fixed cost of investing into the necessary equipment, space, skilled workers as well as acquiring permits from local authorities and navigating other regulation such as emissions trading or regulation concerning local pollutants. These fixed costs can differ across plants.[21] Therefore, manufacturing plants will only switch to onsite generation, if the expected net present value of doing so is positive:

$$\mathbb{E}\left[\sum_{t=0}^{N} \frac{\pi_i(p, \frac{n}{F_i}, w, r) - \pi_i(p, c_{proc}, w, r)}{(1+r)^t}\right] \geq FC_i \tag{9}$$

Assuming that other input prices are fixed, the decision to generate onsite or continue to procure electricity from the grid depends on the potential gains from switching in terms of increased profits, and the fixed cost associated with establishing/expanding onsite generation, FC. Since future fuel cost and electricity prices (including regulation) are unknown to the manager, this decision depends on expectations.[22]

The impact of an increase in the price for electricity procurement, c_{proc}, will differ across plants. While increases in prices for electricity procurement generally make onsite generation a more attractive option, for some plants, the associated fixed cost will be too high. Consequently, according to the model, they experience an increase in c_{elec} and will respond by adjusting their input mix and reducing electricity consumption as well as output. This is depicted in Figure 3 by the upward shift in the marginal cost curve from MC_{proc} to MC'_{proc}, and the switch in production quantities from q_{proc} to q'_{proc}. For other

[20]The use of CHP in industry means that in terms of total energy output, including heat, industrial onsite generation might be more efficient than in the power sector. This is however unlikely to be the case for electricity separately.

[21]The fixed cost can be a (weakly) increasing function of onsite generation, e.g. a step-function, such that more onsite generation also potentially comes with an increase in fixed cost. In that case, manufacturing plants do not decide between either only procuring electricity from the grid or only generating electricity onsite, but might optimally choose a mix of the two options.

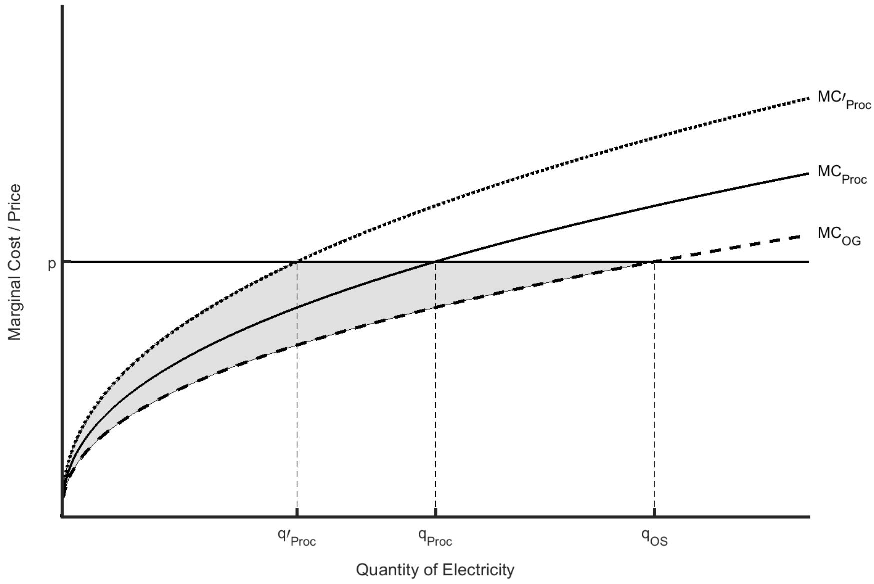
[22]The same type of model could be used to show that investments in energy efficiency would be undertaken if the expected savings exceed the fixed cost of investment. Past research (e.g. Colmer *et al.* 2023) has shown that investments in energy efficiency play a role in abatement. Here we focus on the much less studied channel of substitution between onsite generation and electricity procurement.

plants, an increase in the prices c_{proc} makes it profitable to incur the fixed cost to start generating electricity onsite. As onsite generation is cheaper than electricity procurement (c_{os} is smaller than c_{proc}), this is equivalent to shifting the marginal cost curve downwards. The savings from that shift are represented by the shaded area. Hence, onsite generators will be able to expand output (to q_{os}), and increase demand for production inputs.[23] Plants that already generate electricity onsite will not respond to increases in c_{proc}, as their capacity to generate their own electricity effectively insulates them. The exception is procurement price changes that are rooted in fuel price increases n which would also affect onsite generators. With this simple model in hand, we argue that responses to changes in individual price components such as network charges can be interpreted as equivalent to responses to price increases for other reasons – except those rooted in general fuel price developments.

In our empirical analysis, we show that indeed, rising electricity procurement prices have contributed to a trend towards more industrial electricity generation in the manufacturing sector. Plants that never generate electricity onsite respond significantly differently to increases in the prices for electricity procurement with respect to their demand of input factors (electricity use, fuel use, labour input and capital) as well as output (measured by revenues) as compared to onsite generators. We also discuss implications in terms of carbon emissions.

[23] Effectively, manufacturing plants most likely will not substitute all of their electricity procurement by onsite generation. In that sense, they actually face a price c_{elec} that constitutes a weighted average of c_{proc} and c_{os}. In Figure 3, this means that marginal cost curves do not shift down all the way to MC_{os}. However, as long as c_{os} is smaller than c_{proc}, the new marginal cost curve will lie strictly below MC_{proc}. Improvements in energy efficiency will have a similar effect.

Figure 3: Marginal cost curves and produced quantities under varying electricity prices



4 Empirical Strategy

4.1 Research design

Given that we treat changes in network charges over time as exogenous to manufacturing plants, our regression analysis is very straightforward. In a first step, we estimate panel regressions as shown in equation (10). Due to the use of plant fixed effects μ_i, identification comes from within-plant variation in network charges over time.

$$y_{it} = \beta \times avgnc_{ijt} + \alpha \times \mathbf{1}_{RES,it} + \tau \times CT_{ijt} + \pi_{st} + \mu_i + \epsilon_{ijst} \tag{10}$$

y_{it} denotes the log outcome variable of plant i in year t, including electricity procurement and carbon emissions as well as competitiveness indicators such as sales or employment. Our main explanatory variable of interest is denoted $avgnc_{ijt}$: the average network charges per kWh of electricity procured applying to plant i at time t given its location in network area j.[24] The average is calculated by dividing the total network charge

[24] We use current and not lagged network charges because network fees for the next year are already published in October of a given year. Hence, the development of network charges is already known to manufacturing plants prior to the actual change so that an immediate instead of delayed response can be expected. However, Figure 15 in the Appendix contains additional results from estimating distributed lag-models showing that, while network charges tend to have an effect also in the following year, most of the effect unfolds immediately in year t.

consisting of the marginal price component (charged per kWh of electricity procurement) and the fixed price component (charged as a fixed price for small customers, and based on the peak-load for customers larger than 100 MWh) by the electricity procured.

We control for plants being exempt from paying the full renewable energy surcharge (RES_{it}) (Section 2). Moreover, as network charges differ on a spatial scale similar to the level at which commercial tax rates vary, we also control for the commercial tax rate at the plant location, CT_{ijt}.[25] Plant-level fixed effects μ_i control for all time-invariant plant-specific factors that might affect dependent variables, like the location. π_{st} represents sector by year fixed effects at the four-digit level and capture sector-specific demand shocks, or the development of electricity wholesale prices and national levies and surcharges. In further specifications we interact network charges with an indicator for onsite generators to allow effects to vary for plants that have the possibility to evade higher procurement prices by expanding onsite generation.

A few clarifications are in order. Note that we use average network charges as an explanatory variable. Hence, plant behaviour is explained by a weighted average of changes in the load-based and marginal price component. We abstain from using the individual price components as regressors for two reasons. First, they exhibit strong negative correlation, i.e., if marginal prices increase, peak load prices tend to decrease. This correlation is grounded in the way in which the revenue cap is translated into price components as explained in further detail in Appendix A. The strong correlation makes it difficult to back out separate effects of marginal and peak load prices. Second, the weight on marginal and peak load price components in the plant's total network charges differs substantially across manufacturing plants. For users with high peak loads, the load-based price component constitutes the lion's share of total network charges, while the marginal price component is more important for smaller customers. Due to this heterogeneity, estimating average effects of each of the different price components does not properly take into account their relative importance. Average prices by construction take this issue into account.[26]

[25](Fuest *et al.*, 2018) show that changes in commercial tax rates have an effect on plant behaviour, e.g., in terms of wages.

[26]Standard neoclassical theory would suggest that plants optimize on marginal prices. Ito (2014) however shows empirically that households in the US respond to average rather than marginal prices. We empirically test the importance of the peak load price component by additionally running regressions

Identification is achieved by using the year to year variation in network charges. Regression results capture short-run responses. Given that a single elasticity of response is estimated for the whole time period, the coefficient β constitutes a weighted average of the potentially varying responses over time. As discussed by Burke and Emerick (2016), the weights depend on how long a given elasticity is valid and when adjustments occur that lead to changes in the elasticity.

To assess whether the elasticity of response changes over time, we reformulate the model in long differences in equation (11):

$$\begin{aligned}
\Delta y_{ij} &= \beta_{t1}\, NC_{ijt1} - \beta_{t0}\, NC_{ijt0} + ... \\
&= \beta_{t1}\, NC_{ijt1} - \beta_{t0}\, NC_{ijt0} + \beta_{t1}\, NC_{ijt0} - \beta_{t1}\, NC_{ijt0} + ... \\
&= \beta_{t1}\, (NC_{ijt1} - NC_{ijt0}) + (\beta_{t0} - \beta_{t1})\, NC_{ijt0} + ... \\
&= \beta_{t1}\, \Delta NC_{ij} + \Delta\beta\, NC_{ijt0} + ...
\end{aligned} \tag{11}$$

We take long differences, but allow β to change across start and end period. We add and subtract the product of end period elasticity and start period network charges, $\beta_{t1}\, NC_{ijt0}$. Rearranging yields that the change in the outcome variable is a function of the change in network charges over the observation period and the change in the elasticity of response to changing network charges. As we observe both the change in network charges over time and base period network charges, we can estimate both β_{t1} and $\Delta\beta$ and learn about the direction and size of a potential change in manufacturing plants' response to rising electricity prices.[27] In all regressions, standard errors are clustered at the county-level to account for spatial correlation of observations.[28]

in which we include marginal instead of average network charges. Results are reported in Table 14 in Appendix C. As Ito (2014), we find that responses to changes in marginal prices are weaker than to average prices.

[27]In taking long differences, we make two adjustments: First, we do not use the first year available, 2009, as a starting point, since that year was characterized by a strong recession in German industry. Second, as suggested by Burke and Emerick (2016), we use average values from several years over which differences in dependent and explanatory variables are taken. Considering the length of our panel, we use average values from 2010 and 2011 as a starting and values from 2016 and 2017 as an end point.

[28]In principle, it would be more appropriate to cluster standard errors at the level of grid areas. As grid areas frequently change over time, e.g. due to mergers or acquisitions of DSOs, we refer to the more stable counties as an approximation. Counties are more similar in size and thus more likely to capture shared regional shocks than grid areas, which can vary from a neighbourhood in a city to an

4.2 Data

Data on electricity network charges combined with the German Manufacturing Census and data on exemptions from the renewable energy surcharge and commercial taxes form the basis of our research.

Data on electricity network charges was purchased from the ene't GmbH. This data provider compiles the information that DSOs are legally required to publish annually. The data set contains information on the network charges price components in different voltage levels and tariff groups for each DSO. We merge that information to the Manufacturing Census using a combination of municipality and postal codes.[29] In certain years, some municipality-postal code areas are divided between multiple DSOs. Since we do not know a manufacturing plant's exact location within a municipality-postal code, we drop those observations from our estimation sample. Such ambiguities frequently occur in cities so that our final estimation sample somewhat underrepresents manufacturing plants in urban areas.[30]

For information about plant-level economic indicators as well as electricity use and onsite generation, we refer to the German Manufacturing Census. This confidential administrative data set contains different modules and covers all German manufacturing plants with more than 20 employees. Participation in the respective surveys is mandatory. Responses are back-checked by the Federal Statistical Offices of the Bund and the Länder. We drop some observations with implausible reporting as described in Appendix B. Our study period comprises the years 2009-2017.

The Manufacturing Census contains information on manufacturing plants' locations (municipality and postal codes). We also use information on their electricity consumption, procurement and generation, measured in kWh per year. Furthermore, the Census covers manufacturing plants' revenues, hours worked, and investments. These variables are

area spanning almost an entire federal state. For robustness, we also cluster at the firm-level to allow for correlation between different plants within a firm. This does not change inference. Results are available from the authors upon request.

[29]In rural areas postal codes may be larger than municipalities and vice versa in urban areas. We use the intersection of the two polygons to match DSOs to plants with as much accuracy as possible.

[30]Figure 12 in Appendix B depicts the grid areas that are contained in our estimation sample in 2017 ("unique") and the areas we lose due to an ambiguous DSO assignment. Overall, we lose roughly 30% of observations in the sample for that reason. However, our results are robust to including these ambiguous network areas (Figure 5 and Table 20 in Appendix C).

available for the full sample of plants with more than 20 employees, except for hours worked which is available for plants with more than 50 employees. To assign and calculate average network charges we need information on the plant's annual operating hours and peak loads. Information on manufacturing plants' shift work derives from the Earnings Structure Survey, a stratified sample of manufacturing plants reporting every four years which constrains our final sample. Our estimation sample consists of all manufacturing plants that report their shift work at least once in 2006, 2010, or 2014 and can be assigned unambiguously to a network area. This amounts to approximately 20% of the full sample of plants.

A detailed description of the individual steps and assumptions made to calculate average network charges is given in Appendix B, Section 8.6. Table 7 in Appendix B gives an overview over the number of observations we lose in the different steps. We conduct several plausibility checks for our measure of average network charges as reported below.

Commercial tax rates derive from the Federal Statistical Office and exemption information on the renewable energy surcharge from the Federal Office of Economics and Export Control.[31] Information on regulation status under the EU ETS at the plant-level comes from the EU Transactions Log.[32] To obtain carbon emissions at the plant-level, we multiply fuel consumption with appropriate emission factors from the Federal Environmental Agency. For indirect emissions from electricity, we use an emission factor reflecting the German electricity mix and incorporating transmission losses. Finally, capital stocks are computed using the perpetual inventory method following Lutz (2016).

4.3 Sample statistics

The estimation sample consists of 7,396 individual plants (approximately 20% of the plants contained in the census), and covers 30-50% of the Census' full-time equivalents, employees, energy and electricity consumption (see Appendix B, Section 8.5). We work with an unbalanced panel of plants, but verify that results hold up in a balanced panel. Figure 4 shows the distribution of plants in our sample by electricity use. Clearly, our sample includes a lot of small manufacturing plants that have not been subject to previous

[31]We thank Andreas Gerster for generously sharing his list of exempt plants with us.

[32]We thank Andreas Gerster, Jakob Lehr, and Ulrich Wagner for generously sharing this data with us.

research on the causal effects of climate policy.[33] Further, our estimation sample is similar to the complete Manufacturing Census with respect to sector composition.

Table 1 contains summary statistics on calculated average network charges, electricity consumption and electricity procurement for the estimation sample. Procurement differs from consumption in that the latter variable adds onsite generation of electricity an subtracts electricity sales. Energy and electricity consumption have increased over time across the 10th, 50th and 90th percentile of the plant distribution between 2010 and 2016. Average network charges for most manufacturing plants in our estimation sample do not exceed 6-7 cents per kWh and have generally increased. These numbers are well in line with averages from the Federal Network Agency's monitoring report (Federal Network Agency (BNetzA) and Federal Cartel Agency (BKartA), 2021) for commercial (50 MWh) and industrial (24 GWh) users. They report values that range between 4.99-5.85 and 1.43-2.06 cents per kWh in the time period from 2009 to 2017.

Table 1: Summary statistics of key variables in 2016 (top panel) and 2010 (bottom panel)

	energy use (MWh)	**electricity use (MWh)**	**employees**	**average network charges (Ct/kWh)**
2016				
p10	322	147	31	1.45
p50	2,668	1,346	110	2.60
mean	62,400	16,300	321	3.10
p90	51,200	23,500	574	5.37
N	6,037	6,037	6,033	6,014
2010				
p10	307	140	29	1.02
p50	2,462	1,246	96	2.04
mean	49,700	14,500	272	2.35
p90	43,500	20,300	509	4.33
N	7,163	7,163	7,158	7,111

In Appendix B, we report additional statistics on the relationship between network charges and firm-level electricity expenditures for single-plant firms in the years 2010 and 2014 (see Tables 10 and 12). Calculated network charges account for 10-18% of total electricity expenditures for single-plant firms between the 25th and 75th percentile of the distribution in our sample consistent with the statistics from Eurostat displayed in

[33] Figure 14 in the Appendix displays the according histogram for the full sample for comparison.

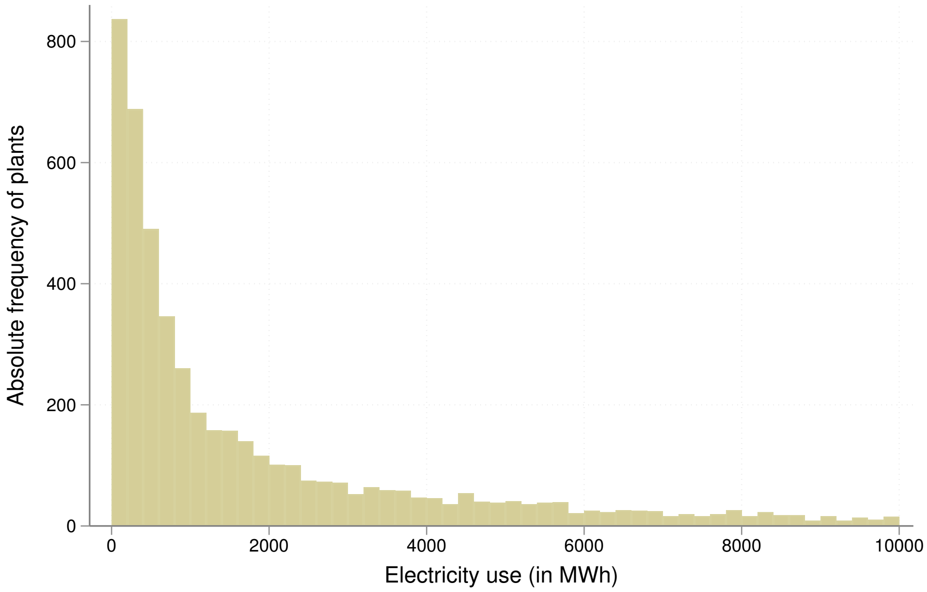


Figure 4: Distribution of manufacturing plants in the estimation sample with respect to their electricity consumption in 2017

Source: Own calculations. The distribution is capped at 10 GWh to improve readability of the figure. Larger users remain in the sample. Details on the census modules used and according DOIs can be found in the Appendix.

Figure 1. Within-firm regressions of average electricity prices on average network charges (controlling for year fixed effects and RES exemptions) show that on average, a one cent increase in average network charges is associated with an increase in electricity prices of 88 cents. The estimated effect is statistically significant at the 5% level and we cannot reject a coefficient of 1. In Table 13 in Appendix B, we also show the distribution of manufacturing plants in our sample in terms of voltage levels and tariff groups.

5 Results

5.1 Network charges and electricity procurement

Table 2 summarizes the results on the effects of average network charges on electricity procurement, electricity use, fuel consumption and the accompanying carbon emissions, obtained by estimating equations 10 and 11. Panel A contains short-run effects from the panel regression, while panel B decomposes long-difference effects into a change in network charges and a change in the elasticity of response.[34]

First, focus on the direct impact of network charges on electricity procurement (column (1)). As can be seen in Panel A, we find highly statistically significant negative effects of average network charges on electricity procurement. A one cent increase in average network charges on average reduces manufacturing plants' electricity procurement by 3.3 percent in the short-run.[35]

To put this effect into perspective, note that a one cent increase is substantial given the mean of average network charges of around 3 cents per kWh in our sample. In terms of overall electricity costs, a one cent increase amounts to a change of about 5-7%.[36] Assuming that manufacturing plants respond in the same way to electricity price

[34]Results on electricity procurement, split by two-digit sector, can be found in Table 15 in Appendix C.

[35]In fact, this effect constitutes an average of the effects of a given price shock over multiple periods. Figure 15 in Appendix C shows results from estimating a distributed lag model. It can be seen that in the year of the price change, the effect is actually somewhat larger, followed by a weaker response in the following year.

[36]Table 11 in Appendix B shows average electricity costs in our estimation sample for the years 2010 and 2014, calculated by dividing total electricity expenditures by electricity consumption. As electricity expenditures are available only at the firm-level while electricity consumption is available at the plant-level, statistics include single-plant firms only.

Table 2: The effects of average network charges on German manufacturing plants

	Electricity procurement	**Electricity consumption**	**Fuel consumption**	**Indirect emissions**	**Direct emissions**	**Total emissions**
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: panel regression			
Average network charges	-0.033***	-0.032***	-0.014	-0.033***	-0.012	-0.014**
	(0.011)	(0.010)	(0.009)	(0.011)	(0.009)	(0.006)
N	57,589	57,589	55,634	57,589	55,634	57,589
number plants	7,460	7,460	7,283	7,460	7,283	7,460
			Panel B: long-differences			
Delta network charges (β_{t1})	-0.023**	-0.021**	-0.018	-0.023**	-0.021	-0.010
	(0.011)	(0.011)	(0.015)	(0.011)	(0.014)	(0.009)
Lagged network charges ($\Delta\beta$)	0.023***	0.014**	-0.003	0.023***	-0.003	0.011**
	(0.006)	(0.006)	(0.008)	(0.006)	(0.008)	(0.005)
Start period (2009/10) elasticity (β_{t0})	-0.046***	-0.036***	-0.015	-0.046***	-0.018	-0.021*
	(0.014)	(0.014)	(0.019)	(0.014)	(0.018)	(0.011)
N	5,722	5,722	5,494	5,722	5,494	5,722
number plants	5,722	5,722	5,494	5,722	5,494	5,722

*Notes: The regressions include observations from 2009–2017. Dependent variables are log-transformed. All regressions are run within-plant, controlling for commercial taxes, exemption from the RES, and with 4-digit sector time trends. Standard errors are clustered at the county-level and displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.*

increases in general, our results imply an own-price elasticity of electricity of -0.4 to -0.6. This estimate lies comfortably within the range of estimates from other quasi-experimental studies on more specific subsets of manufacturing firms: Gerster and Lamp (2022) find an elasticity of -0.2 for (electricity-intensive) German manufacturing plants consuming between 1 GW and 10 GW of electricity, while Martin *et al.* (2014) report a substantially higher (tax-induced) elasticity of between -0.84 and -1.51 for UK plants in selected energy intensive industries.[37]

Panel B decomposes effects into changing network charges and a changing elasticity of response. Results show that the elasticity of response is decreasing over time. It takes on negative values both in the base period 2010/2011 and the end period 2016/2017. However, the statistically significant effect of base period network charges implies that the response is getting weaker over time. Point estimates suggest that a one cent increase in average network charges led to a decrease in electricity procurement of approximately 4.5% on average in 2010/2011, but only of 2.2% in 2016/2017.[38] The implied own-price elasticity decreased in absolute terms from -0.7 – -0.9 to -0.3 – -0.5. This result would be in line with marginal abatement costs increasing at a growing rate such that in later years, larger electricity price changes are necessary to induce the same abatement response. However, as the implied elasticities at base and end period are not statistically different from each other, this evidence should be taken as suggestive.[39]

Effects on electricity consumption (including onsite generation) are virtually identical to the ones on electricity procurement in the panel. The long-differences results, however, suggest that the decrease in the responsiveness to rising electricity prices over time is less pronounced in the case of electricity consumption than procurement consistent with an increase in onsite generation. Due to the decrease in electricity use, rising network charges lead to lower indirect emissions from electricity procurement. Electricity is the

[37]Reassuringly, the RES exemption studied by Gerster and Lamp (2022), which is included as a control variable in our analysis, enters with a statistically significant positive coefficient into the regression of electricity procurement, in line with the results of Gerster and Lamp (2022).

[38]As $\Delta\beta$ is defined as the difference between β_{t1} and β_{t0}, β_{t0} can be computed as the difference between the estimate of β_{t1} and of $\Delta\beta$.

[39]Running the panel regression from equation 10 with an interaction term between network charges and regulatory period also leads to the conclusion that the response elasticity has been higher in the regulatory period from 2009 to 2013 as compared to the regulatory period from 2014 onwards. Results are reported in Table 16 in Appendix C.

most important energy carrier in German manufacturing, making up on average 51% of plants' energy mix. Total emissions decline by on average 1.4% in response to a 1 cent increase in average network charges taking potential fuel mix adjustments into account.

The sample we study is very heterogeneous as can be seen from the summary statistics in Table 1. Effects might be very different for small manufacturing plants that use little electricity, as compared to large plants in sectors that rely heavily on energy in their production processes. To assess this heterogeneity, we exploit the fact that our sample spans all types of electricity users across all industrial sectors, and estimate equation 10 using quantile regression. We follow recent advances in the literature that allow the inclusion of fixed effects in quantile regression (Machado and Silva, 2019), and apply a split-panel jackknife bias correction to deal with the incidental parameters problem (suggested, e.g., by Hahn and Newey 2004).[40] The result is reported in Table 3.

As evidenced by the positive scale parameters and the estimates at the different quantiles, manufacturing plants at the lower end of the distribution with respect to electricity procurement generally respond more strongly to rising network charges as compared to those at the upper end – both in terms of magnitude and statistical significance. At the 75th percentile of the electricity procurement distribution, the effect of network charges is only marginally statistically significant. At the median, the effect is in the same order of magnitude as the average reported in Table 2. The same general pattern holds for electricity consumption.[41] Given that users procuring less electricity on average pay higher prices (see Figure 1), a 1 cent increase in network charges translates into a smaller percentage change in electricity prices at the 25th quantile (i.e., roughly 6-8%, depending on the year) than at the median (7-9%) or the 75th percentile (9-11%). Our estimates imply that the own-price elasticity of electricity is substantially larger for plants procuring and using less electricity.

One potential explanation for our findings is that larger users are more dependent on electricity in their production processes and face higher abatement costs in consequence.

[40]The issue at hand is that we observe each plant only for a limited number of periods. The bias is especially large if the ratio of observed units to time periods is large, as in our case.

[41]Note that the plant at a given quantile in the procurement distribution can be different from the plant at the same quantile in the consumption distribution, especially if plants in the right tail of the consumption distribution produce parts of their electricity use onsite. Therefore, quantile regression effects estimated for different variables are not directly comparable.

Table 3: The effect of network charges along the electricity (procurement) distribution

	Electricity procurement	**Electricity consumption**
	(1)	(2)
Location parameter	-0.027**	-0.029***
	(0.011)	(0.010)
Scale parameter	0.013**	0.011*
	(0.006)	(0.006)
Q25	-0.041**	-0.041***
	(0.017)	(0.015)
Q50	-0.026***	-0.028***
	(0.009)	(0.010)
Q75	-0.013*	-0.017***
	(0.007)	(0.007)
N	57,744	57,744
number plants	7,529	7,529

*Notes: The regressions include observations from 2009–2017. Dependent variables are log-transformed. All regressions are run within-plant and with 4-digit sector time trends. Standard errors are clustered at the county-level and displayed in parentheses. The split-sample jackknife bias correction by Machado and Silva (2019) is applied to all estimates. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.*

From a data perspective, results could be explained by measurement error for larger electricity users: Exemptions from paying full network charges apply for a subset of manufacturing users with electricity procurement larger than 10 GWh and annual hours of use of the grid above 7,000. The presence of these plants in the upper tail of the distribution might bias estimates downwardly for higher quantiles, as we cannot identify them. However, most of these plants will also be exempt from the renewable energy surcharge, which we do control for limiting the resulting bias.

5.2 Robustness

How robust are these results? In this section, we discuss potential threats to identification and present results of various robustness checks we conducted to address these concerns. Results are shown for estimating equation (10) on electricity procurement in Figure 5.[42] The first row shows the estimate from the main specification of the last subsection.

One concern could be that (certain types) of manufacturing plants might actively select into certain types of network areas. If this was the case and was causing bias, results should be different when limiting the sample to plants that were already in operation prior to 2005. This is the year the Federal Network Agency was established. Prior to that year, network charges did not exist in the way they do today. In consequence, manufacturing plants could not have chosen their location based on network charges. As the second row of Figure 5 shows, however, results are virtually identical.

Relatedly, readers might still be concerned about reverse causality. Specifically, could the opening up or the closing down of a large industrial user affect network charges leading to endogeneity? We run our analysis with a balanced panel of manufacturing plants, shutting down any variation coming from entering and exiting plants in the estimation. This does not substantially alter results, as is shown in the third row.

Figure 2 shows the strong regional patterns in network charges (e.g., higher network charges in the north-east of Germany). Federal state boundaries are discernible, at least in the map of the level of network charges. Could the development of other policies at the regional level be responsible for the effects we find? We include additional federal

[42]Equivalent results for estimating equation (13) on electricity procurement are shown in Table 20 in the Appendix.

state-by-year fixed effects to capture state-specific developments. Results are shown in row (4) and are qualitatively unchanged.

Similarly, could our results be explained by different types of plants (e.g., with respect to size) following different trends as they are subject to different types of shocks? We include additional tariff group-by-year and voltage level-by-year fixed effects in row (5). Effectively, we are allowing for different time trends for plants whose electricity procurement and operating hours fall in different ranges. If anything, this slightly increases estimates.

On the data side, one might be concerned that our main sample constitutes a selected sample with limited external validity. Specifically, our sample underrepresents urban areas since it is more difficult to assign a unique DSO to a given manufacturing plant in urban areas. We carry out two robustness checks: We include all plants in areas where the assignment is always ambiguous, using average values from all network operators present in the area in row (6). In row (7), we exclude all plants located in areas that are ambiguous at some point over the study period. Our findings are robust to both changes in the sample.

Despite our efforts to assign network charges precisely to plants some measurement error may remain. This is because we cannot identify manufacturing plants subject to exemptions from network charges (among them, many larger electricity users), but also because we do not directly observe a manufacturing plant's operating hours as well as its peak load. We approximate these variables based on the available data to assign manufacturing plants the appropriate network tariffs. If measurement error is classical, our estimates constitute a lower bound. Note however that measurement error is not an issue for plants below 100 MWh. For them, a simplified tariff applies such that we do not require information on voltage levels, operating hours or peak loads for assigning them correct network charges. Therefore, it is reassuring that in the quantile regression shown in Table 3, results hold qualitatively along the complete distribution, also at the 25th percentile, i.e., among the small plants without measurement error. Extending the sample to include all plants procuring below 100 MWh (and not only those that report in the structure of earnings survey used to approximate operating hours), increases our estimated effect (see row (8)).

Finally, note that the regression results are also robust to using more aggregated sector-by-time fixed effects (rows (9) and (10)).

5.3 Onsite generation, and carbon emissions

Our conceptual framework emphasized the incentives to switch to onsite generation. Over the period under study, onsite generation increased from 17 % in 2009 to approximately 25 % of total electricity use in manufacturing in 2017. In Tables 4 and 5, we re-estimate the panel regression with interaction terms for plants that generate electricity onsite at some point during our study period. Table 4 shows results differentiating between plants with and without onsite generation in general, whereas Table 5 goes further and disentangles effects by plants using fossil fuels versus renewables for onsite generation.[43]

Table 4: The effects of average network charges on German manufacturing plants – onsite generators

	Electricity procurement	**Electricity consumption**	**Fuel consumption**	**Indirect emissions**	**Direct emissions**	**Total emissions**
	(1)	(2)	(3)	(4)	(5)	(6)
Average network charges	-0.019*	-0.036***	-0.025***	-0.019*	-0.028***	-0.015**
	(0.012)	(0.011)	(0.010)	(0.012)	(0.009)	(0.007)
Network charges	-0.076***	0.022**	0.064***	-0.075***	0.093***	0.004
* Onsite generator	(0.013)	(0.010)	(0.016)	(0.013)	(0.018)	(0.009)
Effect onsite generators	-0.095***	-0.014	0.039**	-0.094***	0.065***	-0.011
	(0.015)	(0.011)	(0.016)	(0.015)	(0.018)	(0.009)
N	57,069	57,069	55,134	57,069	55,134	57,069
number plants	7,396	7,396	7,221	7,396	7,221	7,396

*Notes: The regressions include observations from 2009–2017. Dependent variables are log-transformed. The variable Onsite generator is a dummy variable taking the value one if the plant generates electricity onsite and zero otherwise. All regressions are run within-plant and with 4-digit sector time trends. Standard errors are clustered at the county-level and displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.*

[43] Plants are only classified as onsite generators using renewables if they exclusively use renewables for generation. If they both use fossil fuels and renewables, they are classified as fossil fuel generators.

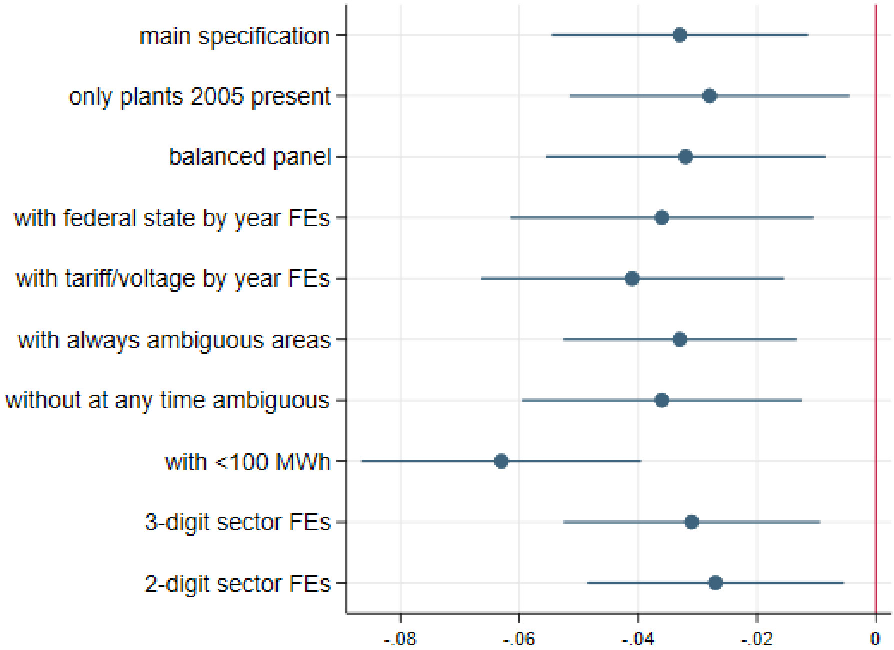


Figure 5: Estimated coefficients and confidence intervals for electricity procurement

Notes: The regressions include observations from 2009–2017. The dependent variable is the logarithm of electricity procurement per plant. All regressions are run with plant, and sector-by-time (generally at the 4-digit level) fixed effects. Standard errors are clustered at the county-level. 95%-confidence intervals are displayed with the point estimate. Row (1) repeats the main specification. Row (2) shows results when plants not present in the Census data in 2005 are dropped. Row (3) shows results for a balanced panel. Row (4) adds federal state-by-year fixed effects. In row (5), tariff group-by-year and voltage-by-year fixed effects are added. Row (6) adds plants to the sample that are always located in ambiguous network areas. Row (7) drops all plants from the sample that are ever located in an ambiguous network area. In row (8), the sample is extended to additionally cover all plants with an electricity procurement always below 100 MW. Rows (9) and (10) show results when replacing 4-digit sector trends with 3- and 2-digit sector trends. A table of the results is available in the appendix.
Source: Own calculations.

Table 5: The effects of average network charges on German manufacturing plants – onsite generators by fuel type

	Electricity procurement	**Electricity consumption**	**Fuel consumption**	**Indirect emissions**	**Direct emissions**	**Total emissions**
	(1)	(2)	(3)	(4)	(5)	(6)
Average network charges	-0.020*	-0.036***	-0.024**	-0.020*	-0.027***	-0.015**
	(0.012)	(0.011)	(0.010)	(0.012)	(0.009)	(0.007)
Network charges * Fossil	-0.110***	0.032**	0.132***	-0.108***	0.174***	0.020
	(0.017)	(0.014)	(0.025)	(0.018)	(0.028)	(0.014)
Network charges * Renewable	-0.046**	0.013	0.002	-0.045**	0.016	-0.011
	(0.019)	(0.013)	(0.016)	(0.019)	(0.020)	(0.011)
Effect onsite generators						
-Fossil	-0.130***	-0.004	0.107***	-0.128***	0.147***	0.006
	(0.018)	(0.014)	(0.026)	(0.018)	(0.027)	(0.013)
-Renewable	-0.065***	-0.023	-0.022	-0.065***	-0.011	-0.026**
	(0.021)	(0.014)	(0.019)	(0.021)	(0.021)	(0.011)
N	57,069	57,069	55,134	57,069	55,134	57,069
Number of plants	7,396	7,396	7,221	7,396	7,221	7,396

*Notes: The regressions include observations from 2009–2017. Dependent variables are log-transformed. The variables Fossil and Renewable are dummy variables taking the value one if the plant generates electricity onsite using fossil or renewable energy sources, respectively, and zero otherwise. All regressions are run within-plant and with 4-digit sector time trends. Standard errors are clustered at the county-level and displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.*

Clearly, onsite generators react very differently to rising network charges (and in extension rising electricity prices) compared to the remaining manufacturing plants. Several differences stand out: First, manufacturing plants that at some point generate their own electricity respond more to rising prices for electricity procurement than plants that rely solely on electricity bought from the grid. Second, onsite generators do not significantly reduce their electricity consumption when network charges rise. These findings indicate that substitutability of electricity through other inputs seems limited, whereas onsite generation is a perfect substitute for electricity procurement.[44]

Correspondingly, consumption of fossil fuels rises among onsite generators – to the effect that total carbon emissions for onsite generators do not decline when network charges increase. The negative effect of increasing electricity prices on industrial carbon emissions is mostly driven by manufacturing plants that, in the short-run, are unable to evade high prices as they have no facilities to generate their own electricity.

Manufacturing plants that generate electricity onsite with renewable resources however do reduce their total carbon emissions in response to rising network charges. These manufacturing plants show a stronger response to price increases with respect to their procurement than non-generators, but a weaker response than plants using fossil fuels for generation. One reason may be, that plants with renewable generation tend to sell the electricity generated to the grid to receive (generous) feed-in-tariffs instead of using electricity generated as an input themselves. Another reason may lie in the intermittency of renewable electriticy generation, which reduces the extent to which renewable onsite generation can replace electricity procured from the grid.

The above results provide evidence that onsite generation has expanded in response to rising prices for electricity procurement. We next ask whether this expansion is driven by extensive margin effects as manufacturing plants start to generate electricity onsite, or whether it is an intensive margin effect among existing onsite generators. We estimate a linear probability model in long differences as the decision to invest in generation facilities is unlikely to be driven by the development of electricity prices over single years. Effectively, we analyse whether manufacturing plants that experienced larger increases

[44] The impacts of network charges on the input factors labour and capital are analysed in subsection 5.4.

in average network charges between 2010/2011 and 2016/2017 were more likely to switch their generation status. The model is given by:

$$\Delta onsite_i = \beta_{LR} \times \Delta avgnc_{ij} + \pi_s + \alpha \times \Delta \mathbf{1}_{RES,it} + \tau \times \Delta CT_{ij} + \epsilon_{ijs} \qquad (12)$$

In our sample, we have roughly 5,000 plants that never generate electricity onsite (88 %), about 80 that stop doing so (1 %), and approximately 600 that switch into onsite generation (11 %).

Results are shown in Table 6. Point estimates have the expected signs: Becoming exempt from the RES drastically reduces electricity prices and therefore makes plants less likely to start generating their own electricity. For network charges, the effect is the reverse, and statistically significant at the 10% margin: For each 1 cent increase in average network charges over the nine year period, the probability of becoming an electricity generator rises by roughly 1 percentage point.

Table 6: The effect of network charges on becoming an onsite generator

	Change in onsite generation status
	(1)
Δ network charges	0.011*
	(0.006)
Δ RES status	-0.025
	(0.024)
Δ commercial tax	0.000
	(0.000)
N	5,722
number plants	5,722

*Notes: All variables in the regression consist in long-differences between 2010/2011 and 2016/2017. The dependent variable is the change in the onsite generation status. All regressions are run with 4-digit sector fixed effects. Standard errors are clustered at the county-level and displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Regressions are run on the full estimation sample. Source: Own calculations.*

We take these estimates as indicative of an extensive margin effect, though the regression lacks statistical power.[45]

5.4 Effects on competitiveness

In the last subsection, we showed that rising network charges – and hence, electricity prices – lead manufacturing plants to significantly reduce their electricity procurement and consumption. In this section, we focus on whether these price increases have negative effects on competitiveness as measured by sales, employment, investments and capital stocks.[46]

Figure 6 shows the estimated coefficients with confidence intervals for revenues, hours worked, and capital stocks. We cannot identify any statistically significant negative impacts of network charges on any of these outcomes. On the contrary, estimates on hours worked tend to be significantly positive.[47] The effect on hours worked is driven by the plants with onsite generation, and especially those using renewable energies for generation.[48] Similarly, network charges do not adversely affect revenues in a statistically significant way. For plants with onsite generation revenues increase significantly. This increase is driven by the manufacturing plants with renewable generation and could be

[45] Another way to separate out the intensive margin effect from the extensive one is to re-estimatethe panel regression with an interaction term for onsite generators, excluding plants that switch into onsite generation. This reduces the number of plants counted as onsite generators by more than half. The estimation then contrasts the behaviour of non-generators with the behaviour of plants that generated electricity both in 2009/2010 and in 2016/2017 and respond along the intensive margin only. Generally, results are similar, albeit weaker: Onsite generators tend to respond more strongly to rising network charges with respect to electricity procurement, and less strongly with electricity consumption. They do not significantly decrease their fuel use, in contrast to non generators. Results are reported in Table 18 in Appendix C. The linear probability model together with the regressions without plants switching into onsite generation suggest that the manufacturing sector responds to rising network charges by increasing onsite generation both along the extensive and the intensive margin.

[46] We use hours worked as a measure of employment instead of the total number of employees. This is because strict labour laws in Germany make it more difficult to adjust the latter in the short-run as compared to the former. Correspondingly, hours worked exhibit a lot more variation than the number of employees.

[47] These conclusions hold at different moments of the distribution, as shown in quantile regressions reported in Table 17 in Appendix C.

[48] Results split across energy sources for onsite generation can be found in Figure 16 in Appendix C.

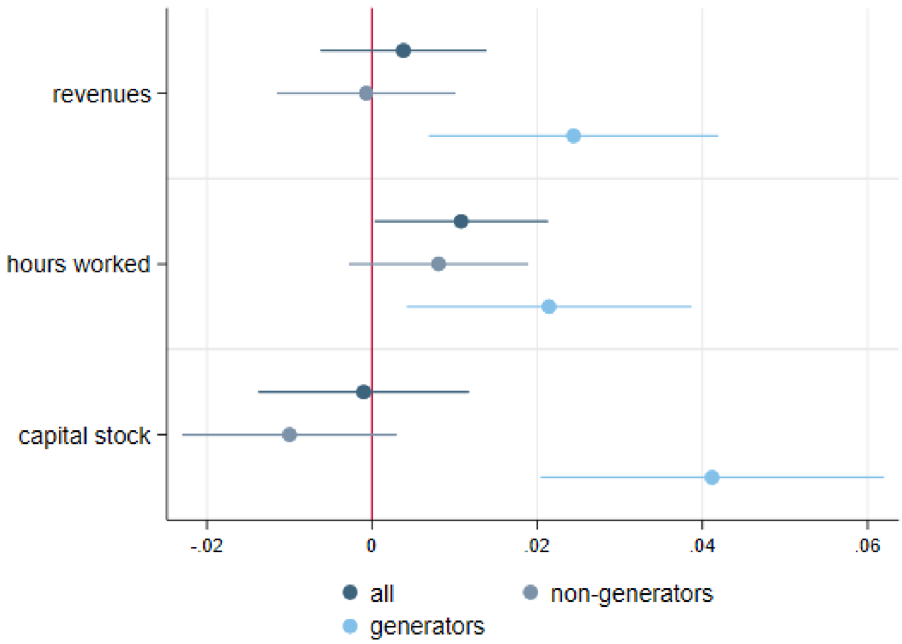


Figure 6: Estimated coefficients and confidence intervals for competitiveness indicators

Source: Own calculations.

driven in part by manufacturing plants selling part of the generated electricity to the grid, or expanding production consistent with the labor effects. Given that marginal costs of generating with renewables are zero, these findings are also consistent with our conceptual framework: For plants with renewable generation, marginal costs decrease more than for those with fossil fuel generation. In consequence, output and hours worked increase for these plants. Finally, we find evidence that onsite generators (no matter which energy carrier) react to increases in electricity prices by accumulating more capital stock. This finding is consistent with a fixed investment cost of expanding or initiating onsite generation.

5.5 Discussion

Rising electricity prices due to climate policies induce manufacturing plants to switch to onsite generation. Does that constitute leakage by shifting emissions from the electricity sector covered under the EU ETS to installations not covered? In this section, we put our findings into perspective in the context of the EU ETS as the foremost climate policy in the EU. We illustrate two applications of our estimates: 1) We quantify the effect of electricity price increases due to the EU ETS on emissions (the indirect effect of the EU ETS). 2) We calculate the demand effect of the RES to determine how many EU emission allowances should have been cancelled to avoid waterbed effects. Finally, we discuss whether our findings concerning competitiveness effects of electricity prices generalize to other circumstances such as the current energy crisis due to the Ukraine war.

We estimate that on average, industrial carbon emissions are reduced through rising electricity prices. Onsite generators, however, do not significantly reduce their emissions. The shift to onsite generation could, in principle, constitute a leakage effect in the sense that emissions are shifted from the fully regulated power sector to the incompletely regulated manufacturing sector. In the specific case of German manufacturing, we do not believe that to be the case because an increasing share of electricity generated by industrial plants is subject to a carbon price, just as in the power sector.

In 2016, 77% of electricity from fossil fuels in industry was generated by plants that were (at least partly) regulated under the EU ETS. This is shown in Figure 7 that depicts the amount of electricity generated onsite (net of generation with renewables) and the number of plants with onsite generation by regulatory status under the EU ETS.[49] While the number of manufacturing plants covered under the EU ETS is very low, these plants are responsible for the lion's share of electricity generated onsite in the more recent years. In fact, over our observation period, the share of electricity generated onsite at industrial facilities that are not subject to the EU ETS declined drastically, despite the fact that the number of non-ETS onsite generators increased substantially. The amount of electricity generated by non-ETS plants declined even in absolute terms. Figure 8 shows that the increase in fossil electricity generation in ETS-plants is accompanied by an increase in the allowances surrendered by those firms, making widespread leakage unlikely.[50,51]

Through their effects on electricity demand, climate policies have an impact on German manufacturing's emissions. ETS permit prices translated into electricity price in-

[49] We have data available on ETS regulation at the plant-level up to 2016.

[50] The increase in surrendered allowances between 2012 and 2013 is grounded in the third phase of the ETS starting, and several plants being subject to the ETS for the first time.

[51] The increase in surrendered allowances is important as our measure of ETS coverage is inaccurate: We only have data on regulatory status available on the plant-level. Hence, leakage could still occur when electricity generation takes place in a plant covered by the EU ETS, but not in the installation that is subject to emissions trading.

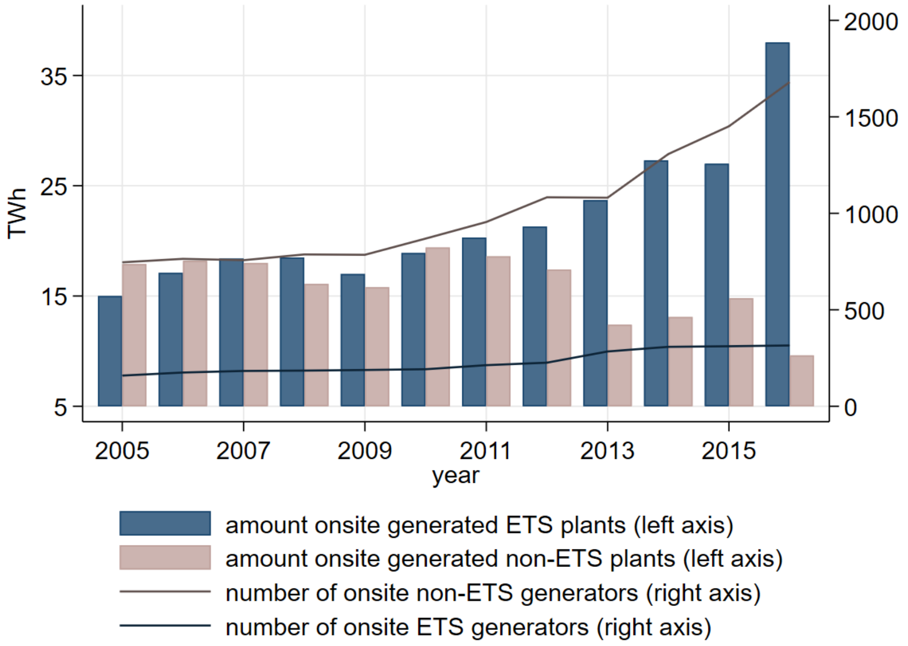


Figure 7: Non-renewable Electricity generation in German industry by ETS coverage

Notes: Source: Own calculations.

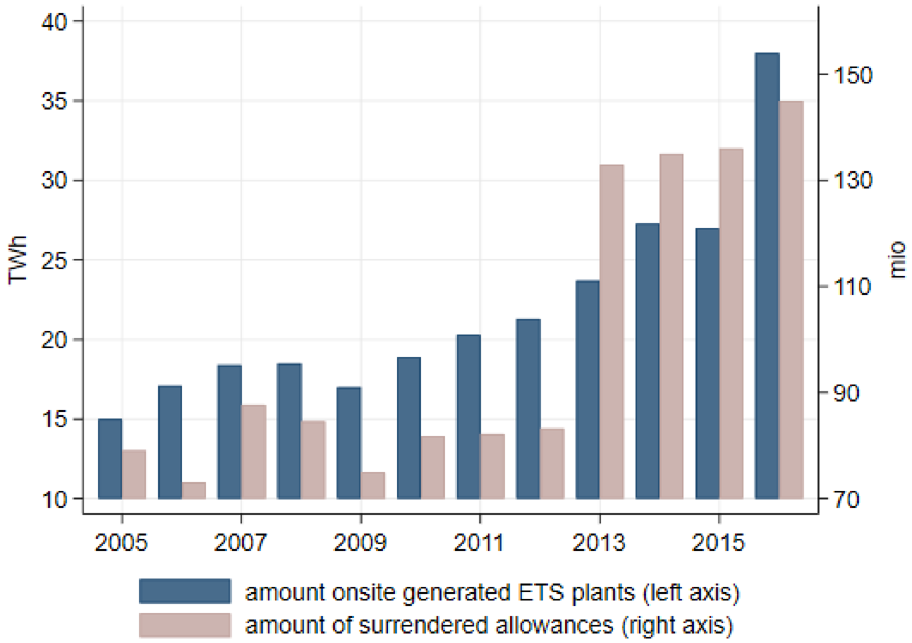


Figure 8: Electricity generation and surrendered allowances in ETS firms

Notes: Regulation status is at the plant level. Source: Own calculations.

creases in the range of 0.04 (in 2007) to 1.3 (in 2008) cents per kWh in our study period, assuming full pass-through.[52] In combination with our estimated emissions elasticity to electricity prices (-0.014) and total carbon emissions in German manufacturing, we calculate that carbon emissions in German manufacturing would have been about 34 million tonnes higher without the ETS induced price increases over the complete period between 2005 and 2017.[53] This amounts to 0.9% of average annual industrial carbon emissions, revealing the downstream effect of the EU ETS.

By quantifying the reduction in emissions due to the increase in electricity prices, our results can also help shed light on the impact of overlapping regulation in the first phases of the EU ETS. Since the beginning of the EU ETS, failure to adjust the cap for reductions due to (national) policy measures have contributed to the low ETS prices and reduced the efficiency of the scheme. A prominent example in Germany is the RES by which the generous feed-in tariffs for renewable energy providers were financed. At its peak, the RES accounted for up to 30% of final electricity prices.

Using our estimated emissions elasticity suggests that the German government should have retired in total 125 million allowances between 2010 and 2017 to cancel the effect of the RES in terms of reduced demand for carbon emissions in the energy sector.[54] We arrive at this estimate by considering the emissions of plants subject to paying the full RES (220-240 million tonnes annually), the size of the RES (2-7 Cents/kWh), and our estimated emission elasticity (-0.014).[55] In a counterfactual in which the German renewable energy expansion was financed through taxes and did not increase electricity prices (as is the case since July 2022), manufacturing emissions in Germany would have been 7-20 million tonnes higher each year. With an EU-wide cap under the EU ETS of roughly 2,050-2,080 million tonnes over the observation period, the cap should have been

[52] Average annual carbon prices under the EU ETS ranged between less than 1 Euro and roughly 22 Euros between 2005 and 2017. Estimated pass-through rates by Hintermann (2016) for Germany range between 80 and 110%. Estimates for Spain by Fabra and Reguant (2014) lie between 60 and 110%.

[53] Each year, emissions would have been around 0.1 and 2% higher. Total industrial emissions range between 280 and 300 million tonnes.

[54] This is a partial equilibrium estimate, since retiring allowances would have increased the ETS price lowering demand further.

[55] By using the total emissions elasticity, this back of the envelope calculation is net of manufacturing plants' responses in terms of switching into onsite generation; it takes into account manufacturing's fuel mix as well as the prevalence of CHP.

reduced by 0.4-1% annually, given the electricity demand response to the RES of German manufacturing.[56]

We do not identify any negative competitiveness effects of rising network charges on German manufacturing plants. However, note that our identification relies on variation in electricity prices that is not driven by changes in fuel prices. Effects might be very different if prices for all energy carriers increase simultaneously, as under the current energy crisis due to the war in Ukraine. In such a situation, manufacturing plants do not have the outside option of cheaply generating their own electricity instead of buying it from the grid. Moreover, the price increases were several orders of magnitude larger and competitiveness effects could be severe. That being said, our findings are meaningful for the evaluation of climate policies in the period under study and for price increases in the order of magnitude typically induced by climate policies. Our results are consistent with the findings in Gerster and Lamp (2022): We too find that electricity prices do have a significant effect on manufacturing plants' electricity usage, but not on competitiveness indicators. We generalize these findings to a more representative sample of manufacturing plants and identify an important channel through which plants responded to electricity price increases in this period.

6 Conclusion

Climate policies like the EU ETS or the renewable energy surcharge in Germany tend to result in increasing electricity prices. Given that climate change regulation does not apply worldwide but remains a largely unilateral issue, concerns about job losses and decreases in international competitiveness have been raised. As the German manufacturing sector is both an important pillar of the German economy and export-dependent, it is of crucial interest to policy makers how manufacturing plants react to increasing electricity prices.

In this paper, we shed light on the responses of German manufacturing plants to exogenous variation in electricity prices using administrative micro-level data and detailed information on electricity network charges. Causal effects are obtained through the use of panel-estimation as well as in a long-differences designs.

[56]The cap should have been reduced even further if we take into account that emissions in the energy sector would have been higher in the absence of the feed-in-tariffs for renewables.

Exploiting the within-plant variation over time, we generally find negative effects of average network charges on manufacturing plants' electricity procurement. The estimates from our preferred panel regression imply a short-run own-price elasticity of electricity of roughly -0.4 to -0.6 on average. Elasticities are larger for plants procuring little electricity, and smaller for large electricity users. Evidence is suggestive that plant responsiveness towards rising electricity prices declined over the period from 2009 to 2017. This finding is consistent with marginal abatement cost increasing more than linearly such that larger price increases are necessary to induce the same absolute abatement response. It is also consistent with the increased use of onsite generation partially insulating plants from increases in the procurement price.

We find evidence that the decrease in electricity procurement is completely offset by an increase in onsite generation by the subgroup of manufacturing plants that own facilities to do so. For the remaining manufacturing plants, the response to price increases with respect to electricity procurement is weaker, suggesting that short-run improvements in energy efficiency are relatively costly. In the long-run, rising electricity prices increase the proprensity of manufacturing plants to start generating electricity onsite. As our analysis shows this is a non-negligible channel and should be taken into account by policymakers.

In total, rising electricity prices lead to a decrease in carbon emissions in German manufacturing despite the increase in onsite generation. Given that most of industrial electricity generation occurs in plants covered under the EU ETS, it is unlikely that the shift towards industrial electricity generation constitutes carbon leakage on a large scale.

Decreases in electricity demand due to climate policy induced electricity price increases constitute an important channel to achieve emissions reductions. We calculate that carbon emissions in German manufacturing would have been about 34 million tonnes higher without the ETS-induced price increases over the complete period between 2005 and 2017. By quantifying the reduction in emissions due to the increase in electricity prices, our results can also begin to shed light on the impact of overlapping regulation in the first phases of the EU ETS. Since the beginning of the EU ETS, failure to adjust the cap for reductions due to (national) policy measures have contributed to the low ETS prices. Our results indicate how emissions in Germany responded and suggests that we should have retired in total 125 million allowances between 2010 and 2017 to cancel the demand effect in manufacturing of the Renewable Energy Surcharge on carbon emissions already covered by the ETS.

We find no evidence of negative competitiveness effects of rising electricity prices. This finding is consistent with existing research that has focused predominantly on large and very electricity intensive plants. Despite facing higher electricity prices and having less access to relief measures such as the exemption from the renewable energy surcharge, smaller plants seem to get by without suffering negative consequences, while reducing their electricity use.

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7 Appendix A: Regulatory background

How electricity network charges in Germany are set

All information from the following paragraphs are based on the report from the Federal Network Agency (BNetzA) (2015).

The regulatory system: costs, revenue caps and fee system

Broadly speaking, network charges are based on a network operators' costs for operation, maintenance and expansion of electricity grids. Network charges (since January 1, 2009) are determined by the Incentive Regulation Ordinance which divides the regulatory regime into 5-year periods. Before each 5-year period, the cost basis of each network operator is newly determined. To do so, regulatory authorities review the audited annual accounts (made according to the rules of the Electricity Network Charges Ordinance – StromNEV) of network operators.

This cost basis then serves as the starting point for determining the revenue cap of network operators. The revenue cap constitutes the budget available to each network operator for the operation and maintenance of the grid during the 5-year period; however, it is annually reviewed and adjusted to take into account the development of costs that cannot be influenced on a permanent basis, consumer price indices, and the costs for network expansion. The revenue cap defines the maximum admissible revenues for network operators.

Following the rules of the StromNEV, the fee system determines how these admissible revenues are split onto different consumer groups (see next subsection). Network operators have to send their calculated network charges each year to the regulatory authorities. Potential differences between revenue cap and actual revenues are recorded in the so-called adjustment account. Excess or shortfall revenues compared to the revenue cap then are distributed at the beginning of the next regulatory period, so that network operators to not bear a volume risk: Planned and actual quantities are balanced.

Distributing network operators' costs on the users of different voltage levels

The costs of network operators are split onto users of the different voltage levels by means of cost type, cost centre and cost unit accounting (in accordance with the StromNEV): First, the costs incurred by a network operator in a specific period are assigned to different cost types (cost type accounting); then, the cost types are allocated to their sources, i.e. voltage levels (cost centre accounting); lastly, given this division of costs onto different voltage levels, it can be determined which part of total costs has to be covered by users of the different voltage levels (cost unit accounting).

This last step follows a top-down approach: Starting at the highest operating grid or transformation level, the specific annual costs (the "stamp") are calculated. These are given by dividing costs of the highest network level by its simultaneous annual peak load. This normalization is conducted because the peak load is considered the central cost driver determining the size of the grid. By means of the simultaneity function (also: G-function), these specific annual costs are converted into different price components (see next subsection). Given these network prices, direct revenues in the highest operated voltage level can be calculated and subtracted from the costs of this level. Remaining costs not covered by revenues are taken over to the next lower network level and added to the genuine costs of this level. Thus, total costs in the lower network level consist of the total original costs of this level plus the costs not covered by revenues from the higher network level(s) (see Figure 9). The lowest network level has to bear all remaining costs.

Getting from the stamp to actual network charges: marginal prices, peak load prices and the simultaneity function

The annual peak load of the electricity grid is a central cost driver for network operators since it determines the sizing of the electricity grid. The network charges fee system is designed to take this factor into account to fairly allocate costs onto different users of the electricity grid. Thus, individual users who have a high chance to contribute with their individual peak load to the annual peak load of the grid are supposed to pay a higher share of the peak load costs (by being charged higher peak load prices). This idea is captured by the G-function.

With the simultaneity or G-function, the network operator assigns each grid user a probability (the simultaneity degree) that the user's peak load contributes to the annual peak load of the whole network level. The G-function is modelled as a function of the number of hours of use of the grid with a kink at 2,500 hours. The kink defines the switching point between two different network tariffs. Hence, network charges differ depending on whether or not the number of hours of use of the grid exceeds 2,500 hours.

To derive marginal and peak load prices, the network operator calculates a simultaneity degree for each user of the grid. Grid users in this sense are both final consumers and downstream network operators. Simultaneity degrees are given by a user's ratio of load to individual peak load at the time of the simultaneous annual peak load of the grid. The single simultaneity degrees are then plotted in a scatter plot as a function of the number of hours of use of the grid and approximated by two straight lines which constitute the G-function. This is schematically depicted in Figure 10.

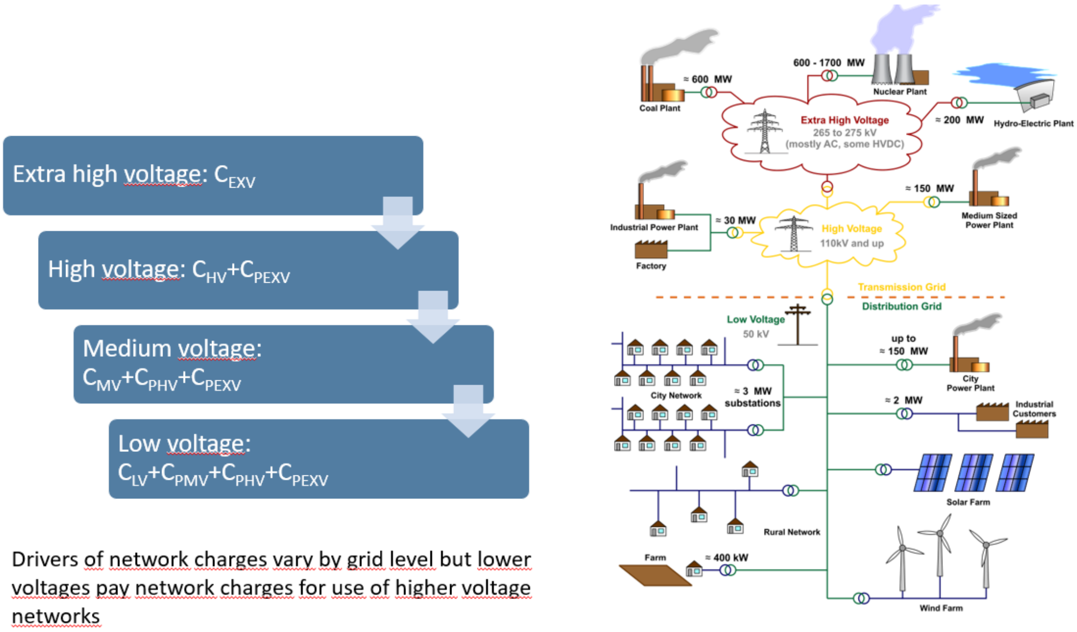

Figure 9: The structure of network charges

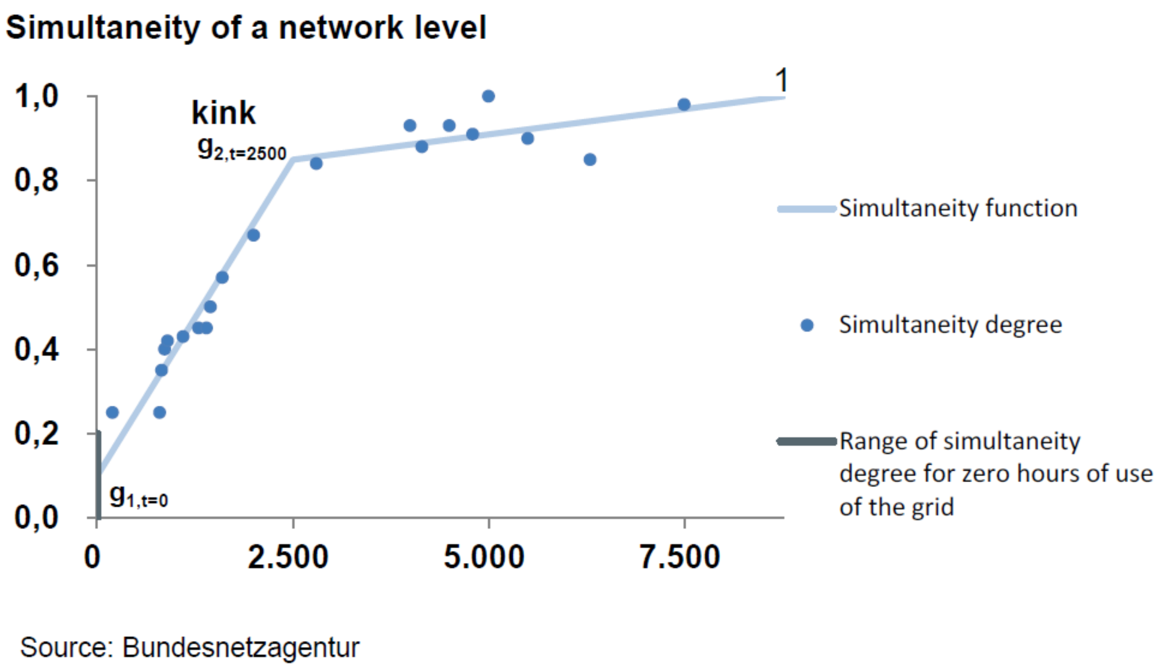

Figure 10: The simultaneity function

The G-function needs to satisfy the following properties:

- It has a kink at 2,500 hours of use of the grid.
- The simultaneity degree for zero hours of use of the grid has to lie in between 0 and 0.2.
- At a number of annual hours of use of the grid of 8,760, the simultaneity degree has to be equal to 1.

Multiplying slopes and intersects of the G-function with the stamp yields marginal and peak load prices that differ for users with more or less than 2,500 annual hours of use. The specification of the G-function thereby ensures that users with low numbers of hours of use of the grid pay a relatively low peak load price and a relatively high marginal price, while it is the other way round for users with high numbers of hours of use of the grid. For users without registered load metering (SLP customers), base and marginal price must be in an appropriate balance.

What does this imply for our analysis? This setting of network charges leads to a negative correlation in the developments of marginal and peak load prices: Because the G-function has to satisfy the requirements mentioned above, there is limited potential to shift the whole curve up- or downwards. This generates the tendency for one price component to decrease if the other one increases: If the slope gets higher and the curve steeper, the intersection is likely to decrease, and the other way round.

How electricity network charges in Germany are paid

The invoicing of network charges differs among different types of customers. Small electricity users generally have integrated "all-inclusive" contracts with their electricity suppliers. As such, they pay network charges as part of their general electricity bill to their respective electricity providers. These providers then transmit the network charges collected by their customers to the relevant DSOs under the framework of a grid usage contract between electricity provider and network operator. While integrated contracts are the default for users of the standard load profile (SLP, less than 100,000 kWh annual electricity procurement), in principle, these small customers can also choose to enter into their own contract with the respective DSO and pay network charges directly (and separately from the rest of the electricity bill) to the network operator.

For SLP customers, payments are customarily made on a monthly basis as advance payments, while the billing period comprises 12 months. Note that billing periods do not have to coincide with the calendar year; the respective begin of the billing period is set by the network operator. Potential differences between the sum of advance payments made and actual invoice amount after 12 months are balanced after the end of the billing period.

Larger (industrial and commercial) customers with registered load-metering (RLM) generally have their own grid usage contracts with their network operators and pay network charges directly to them. However, these users too can choose to rather pay network charges to their electricity suppliers under the scope of the framework contracts of the suppliers (where suppliers then pass the network charges on to the DSOs, as for SLP customers).

For RLM customers, billing approaches have been quite heterogeneous across network operators until 2016. As of January 2016, a standardized grid usage contract by the Federal Network Agency has to be used, which was developed in a determination process starting in 2013. This standardized contract specifies that the billing period for RLM customers uniformly starts on January 1st. Customers are billed every month. Since network charges for RLM-customers depend on their annual peak-load – which is a priori unknown and can change in the course of the year –, retroactive billing becomes necessary in case a higher peak-load is reached in a given month as compared to the peak reached in the previous months of the billing cycle. This has been the customary procedure also before the standardization through the Federal Network Agency.

What does this imply for our analysis? This billing procedure of network charges has several implications for our analysis. First, it might introduce some measurement error into our analysis if billing cycles do not coincide with calendar years in the case of RLM customers before 2016. In these cases, we calculate an approximated peak-load based on electricity procurement information of a different period (the calendar year) than the billing period (which spans two calendar years). As long as there is no extreme variation in electricity procurement over the years, this is however unlikely to drastically affect approximated peak-loads and results.

Second, the fact that many manufacturing plants pay network charges directly to their DSO (RLM customers by default, SLP customers if they opt in) suggests that network charges are indeed sufficiently salient to induce manufacturing plants to adjust. Contrary to e.g. households for whom network charges just constitute one block of an aggregate bill, most manufacturing plants will be aware of price developments by virtue of paying them in a separate bill.

8 Appendix B: Data, descriptives and variable creation

8.1 Census modules and DOIs

In our analysis, we combine information from various modules of the Manufacturing Census.

Information on investments, employment, and sales are taken from the monthly reports (DOIs 10.21242/42111.2005.00.01.1.1.0-10.21242/42111.2016.00.01.1.1.0). In most analyses, we use information from the years 2009 ti 2016.

Information on electricity and fuel consumption as well as onsite generation of electricity for the same time period is taken from the energy use module of the Manufacturing Census (DOIs 10.21242/43531.2005.00.03.1.1.0-10.21242/43531.2016.00.03.1.1.0).

In most analysis, the sample is restricted to plants reporting at least once in the structure of earnings survey (DOIs 10.21242/62111.2014.00.03.1.1.0, 10.21242/62111.2010.00.03.1.1.0 and 10.21242/62111.2006.00.03.1.1.0).

8.2 Data cleaning for the Manufacturing Census

While the research data centres and the statistical offices conduct various quality controls with the data, the large amount of data makes it impossible to check every data point for inconsistencies and to correct all inaccuracies. Therefore, we adopt a separate data cleaning procedure:

We exclude all observations that report a negative energetic fuel use and those observations where our calculated measure of total energy use is below zero. We calculate energy use correcting fuel consumption for the occurrence of conversion losses, as in Rottner and von Graevenitz (2021). This step is necessary to get from energy inputs (assuming 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 (2021).

Moreover, we drop all firms in which one plant reports the energy statistics for several plants within the firm. While we can identify these cases at the firm-level, we cannot properly allocate these firm's fuel and electricity use across the associated plants. Furthermore, 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. Lastly, we drop outliers in terms of fuel and electricity use, which are defined as plants where one standard deviation of fuel or electricity use within the plant, respectively, is bigger than 100 times the median fuel use of the plant.

8.3 The growth of network charges in different areas

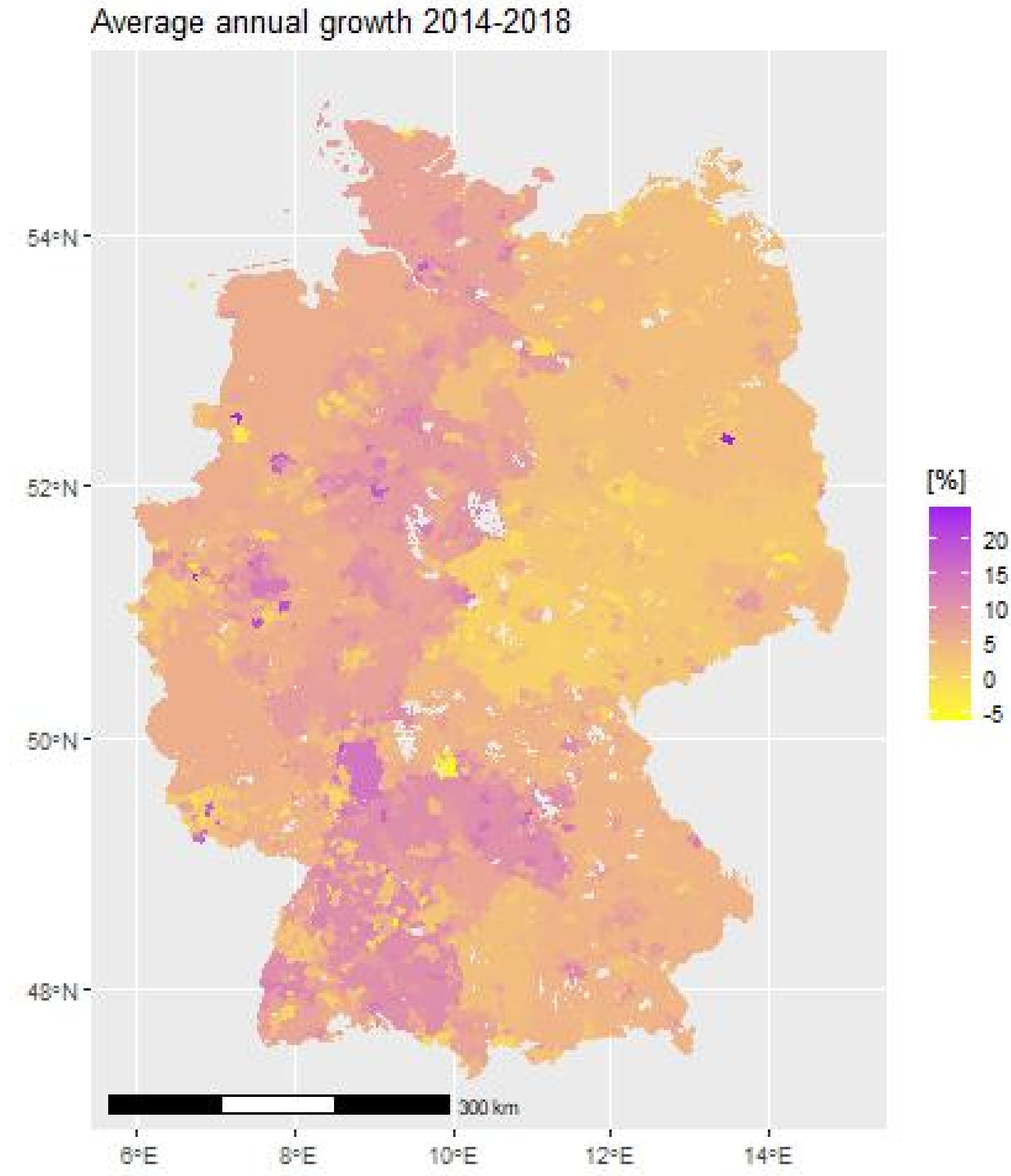

Figure 11: Average annual growth rate in average network charges for the same plant between 2014 and 2018

Source: Low voltage networks as defined by merging ene't data to municipality shape files.

Notes: Source: Own calculations, based on ene't data. Average network charges are calculated in cents per kWh for 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.*

8.4 Unique and ambiguous network areas

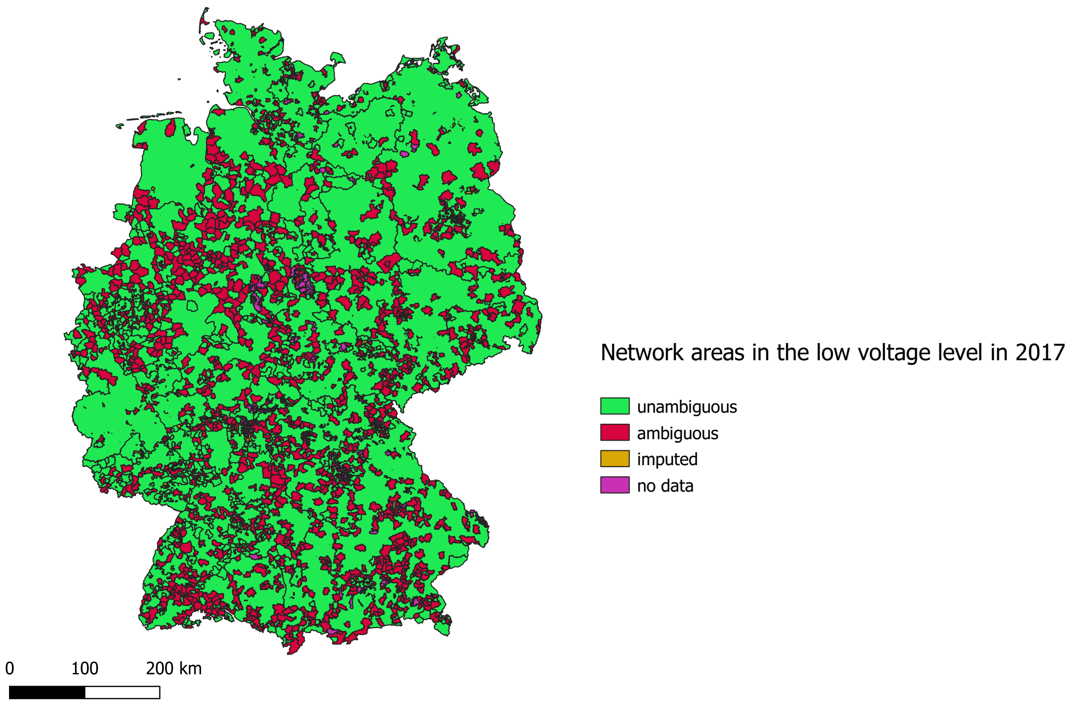

Figure 12: Unique assignment of low voltage level network areas to municipalities in 2017

Source: Low voltage networks as defined by merging ene't data to municipality shape files.

Notes: Source: Low voltage networks as defined by merging ene't data to municipality shape files. 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 exemplary for the year 2017 and for the low voltage level (where there are most ambiguities because the number of network operators is highest). Information are based on data from ene't.

8.5 Estimation sample vs. full sample

Table 7 shows how many observations are lost in the different steps of limiting the sample. Column (1) gives the observation numbers for the full sample from the German Manufacturing Census on which information on electricity procurement is available. Column (2) gives the number of observations which reported at least once in the structure of earnings survey since 2010. In column (3), observations are dropped that switch between procuring more or less than 100 MWh of electricity over the years. In column (4), additionally, plants are dropped that change their work mode over time, i.e. switch into/out of conducting shift work. Lastly, in column (5), all plants are dropped that are located in ambiguous network areas. This constitutes our baseline estimation sample.

Table 8 and Figure 13 contrast our estimation sample and the full German Manufacturing Census with respect to sector composition, full time equivalents and electricity consumption.

Table 7: Observation numbers in the full sample versus the estimation sample in 2016

Sector		**Full sample**	**Structure of earnings**	**No switchers 100 MWh**	**No switchers shift work**	**No ambiguous areas**
10	Food	5,274	1,212	1,075	1,024	692
11	Beverages	541	236	224	215	140
12	Tobacco	24	24	x	13	x
13	Textiles	700	399	350	329	215
14	Wearing apparel	240	172	139	127	92
15	Leather	124	97	75	61	44
16	Wood and wood products	1,109	333	297	264	198
17	Pulp, paper and paper products	889	415	370	357	256
18	Printing and reproduction	1,238	403	349	341	223
19	Coke and refined petroleum	65	54	x	42	x
20	Chemicals	1,528	542	489	472	310
21	Pharmaceutical products and preparations	346	221	188	156	103
22	Rubber and plastic	3,195	644	581	548	379
23	Other non-metallic minerals	2,828	593	534	512	365
24	Metal production and processing	1,028	433	413	381	251
25	Fabricated metals	7,614	861	761	736	508
26	Computer, electronic and optical products	1,839	665	527	480	325
27	Electrical equipment	2,119	631	508	475	321
28	Machine manufacturing	5,998	972	847	790	510
29	Motor vehicles	1,284	523	440	415	285
30	Other transport equipment	314	210	176	155	109
31	Furniture	985	329	288	267	196
32	Other manufacturing	1,632	496	400	373	260
33	Repair and installation of machinery	1,938	491	373	342	212
	Total number of plants	42,897	10,956	9,476	8,875	6,037

The "x" denote cases in which the number of observations is too small to be released for confidentiality reasons.

Table 8: Sector composition in % in the full sample versus the estimation sample in 2016

Sector		**Full sample**	**Estimation sample**	**Long differences sample**
10	Food products	12.27	11.48	11.32
11	Beverages	1.24	2.31	2.37
12	Tobacco products	0.06	0.18	x
13	Textiles	1.64	3.52	3.63
14	Wearing apparel	0.56	1.51	1.55
15	Leather and related products	0.29	0.73	0.71
16	Wood and products of wood and cork, except furniture	2.56	3.28	3.25
17	Pulp, paper and paper products	2.09	4.29	x
18	Printing and reproduction of recorded media	2.96	3.73	3.68
19	Coke and refined petroleum products	0.15	0.52	x
20	Chemical products	3.55	5.10	5.11
21	Basic pharmaceutical products and pharmaceutical preparations	0.8	1.72	1.69
22	Rubber and plastic products	7.38	6.22	6.31
23	Other non-metallic mineral products	6.51	6.01	5.97
24	Metal production and processing	2.43	4.17	4.25
25	Fabricated metal products	17.76	8.46	8.38
26	Computer, electronic and optical products	4.33	5.42	5.45
27	Electrical equipment	4.96	5.29	5.39
28	Machine manufacturing	13.99	8.43	8.53
29	Motor vehicles	3.01	4.74	4.82
30	Other transport equipment	0.73	1.80	1.82
31	Furniture	2.33	3.26	3.23
32	Other manufacturing	3.77	4.25	4.23
33	Repair and installation of machinery and equipment	4.7	3.56	3.25
	Total number of plants	44,853	6,158	5,812

The "x" denote cases in which the number of observations is too small to be released for confidentiality reasons.

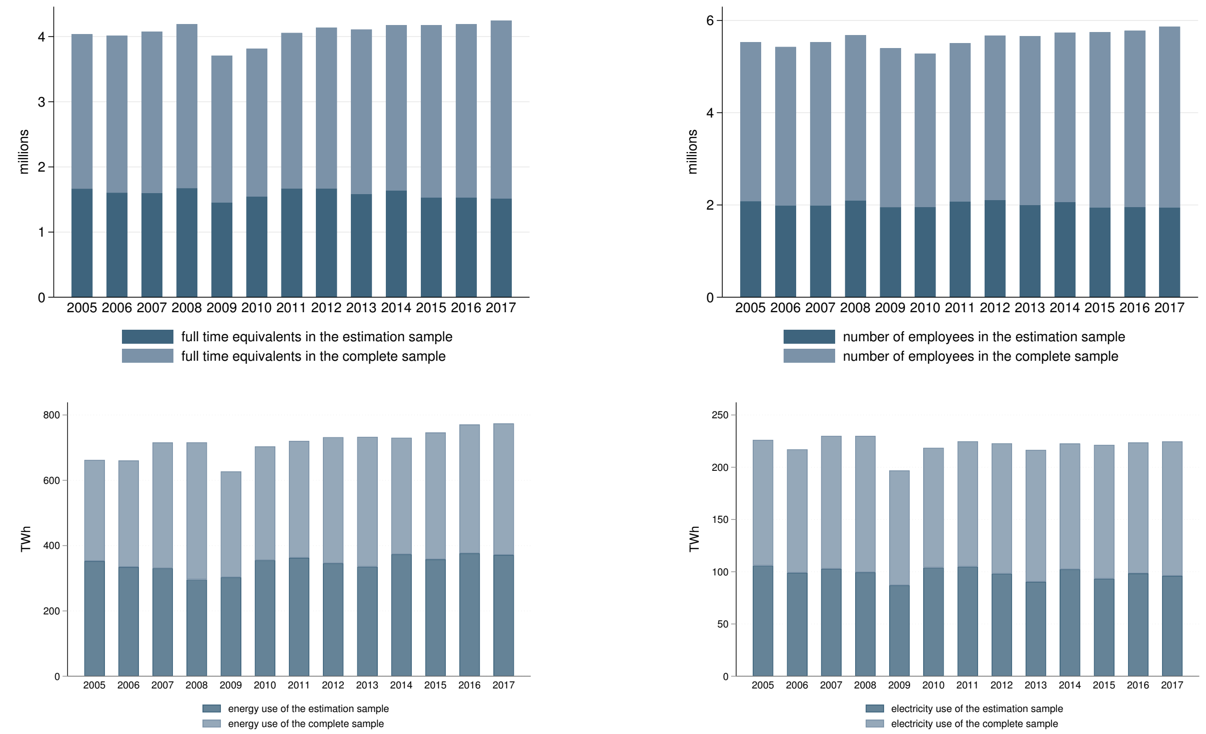

Figure 13: Coverage of key variables of the estimation sample as compared to the full Manufacturing Census

Source: Own calculations.

8.6 Calculating average network charges at the plant-level

Average network charges depend on the grid operator, the voltage level at which it is connected to the grid, its peak load, its operating hours and which customer group applies. Table 9 summarizes the different tariff structures.

Table 9: Structure of network charges

Customer group	Standard load profile (SLP)	Interval-metered (RLM)	Individual charges (§19)
Annual procurement	≤ 100 MWh	> 100 MWh	> 10 GWh, min. 7,000 hours of use *or* off-peak usage of the grid
Transmission level	Low voltage	Low, medium and high voltage	Low, medium and high voltage
Tariff structure	Two-part tariff	Three-part tariff	Eligible for reduced
"Arbeitspreis"	Price per unit (EUR/MWh)	Price per unit (EUR/MWh)	network charges
"Grund-/Leistungspreis"	Base price per year (EUR)	Peak load price (EUR/MW)	
		Tariff varies by hours of use: ≤ or > 2,500 hours/a	

Notes: Based on the Electricity Network Charge Regulation.

We classify plants as SLP customers connected to the low voltage level (column (1) of Table 9) if their electricity procurement is below 100 MWh throughout the study period.[57] All other plants are classified as RLM customers. We assume no manufacturing plant in our sample is exempt from paying full network charges (column (3) of Table 9). While this leads to some error, we believe it to be small. Each year, there are only around 4,000 to 5,000 exemptions at most across all sectors of the economy, less than half of which are in manufacturing. Most of these exemptions are granted based on atypical usage which does not systematically vary with procurement levels. Plants exempt due to their procurement levels are very likely to be exempt from the RES as well as the eligibility criteria overlap. Therefore the RES dummy controls for these plants to a large extent. In sum, we expect this omission to lead to classical measurement error biasing our estimates towards zero.

For all RLM customers (column (2) of Table 9), we use information on shift work to distinguish plants above or below the threshold in annual operating hours (2,500 hours). Note that 2,500 hours of use are achieved by plants operating 6 days a week and 8 hours

[57] There are a number of manufacturing plants that fluctuate around the threshold of 100 MWh. To prevent any bias resulting from a misclassification of these plants, we remove them from our sample.

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.

The voltage level at which manufacturing plants are connected to the grid and their annual peak loads are not observed. We therefore make additional assumptions to calculate average network charges at the plant-level which are described in detail in the following. Here we briefly summarize them for convenience. For assigning manufacturing plants to voltage levels, we approximate peak loads by average loads based on an assumption about the plant's operating hours. In personal conversation with several DSOs we gathered threshold values in peak loads for assignment to different voltage levels. The average loads are also used to approximate peak loads in the calculation of average network charges.

This assignment of manufacturing plants to different tariff groups and voltage levels involves some measurement error. Assuming classical measurement error, our estimates are subject to attenuation bias and should be considered a lower bound on an effect. The assumptions used are laid out in more detail below:

To calculate average network charges we must make assumptions about 1) the voltage level of the plant, 2) the peak load of the plant, and 3) the operating hours of the plant. These assumptions are interconnected. To assign plants to voltage levels we rely on threshold values for peak loads retrieved from communications with DSOs. These threshold values are grounded in 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: $\leq$ 100 kW: low voltage level; $>$ 100 and $\leq$ 300 kW: transformation level low to medium voltage; $>$ 300 kW and $\leq$ 4 MW: medium voltage level; $>$ 4 MW and $\leq$ 5 MW: transformation level medium to high voltage; $>$ 5 MW: high voltage level. This assignment is prone to some degree of error: The decision on which voltage level to connect a user to is subject to the individual situation of the DSO and the respective user, projections about future developments and the technical equipment of the DSO. However, using the aforementioned thresholds yields a reasonable approximation given our data. Our assignment procedure leads to patterns very similar to what we can observe in the applications for reduced network charges (column (3) of Table 9) which is the only data source we have on manufacturing users' voltage levels. More information is available from the authors upon request.

Unobserved peak loads are approximated by average loads. This is a reasonable assumption since high peak loads are associated with substantial costs so that there is a strong incentive to flatten load profiles. Average loads in turn are calculated by dividing annual electricity procurement by assumed operating hours where the assumption on operating hours differs 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 use an expected value of operating hours. This expected value is calculated using more detailed information on working modes available in the year 2001. In this year, the surveyed plants are asked whether they are conducting any of the following work modes: night work, Sunday work, and shift work. The distinction into these different work modes (instead of just one aggregate measure, as in later years) allows a more narrow determination of plants' and sectors' operating hours. We calculate expected operating hours for all plants with more than a single shift by the product of the share of plants that are conducting shift work, night work, Sunday work or any combination of these in 2001 and the implied annual operating hours of these different options. We calculate different expected values for sectors that in general exhibit higher operating hours (more than 7,000 in the median) and the remaining sectors. This yields expected operating hours of 7,064 and 6,419, respectively. 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 procurement over our complete observation period, and drop plants that are switching into/out of shift work for the calculation of the (hence time-invariant) average loads that are underlying the assignment to voltage levels. Annual peak loads necessary to calculate the annual peak load price component for RLM customers are approximated by the same procedure. However, for this purpose, we calculate time-varying peak loads based on annual electricity procurement.

8.7 Distribution of manufacturing plants with respect to their electricity consumption

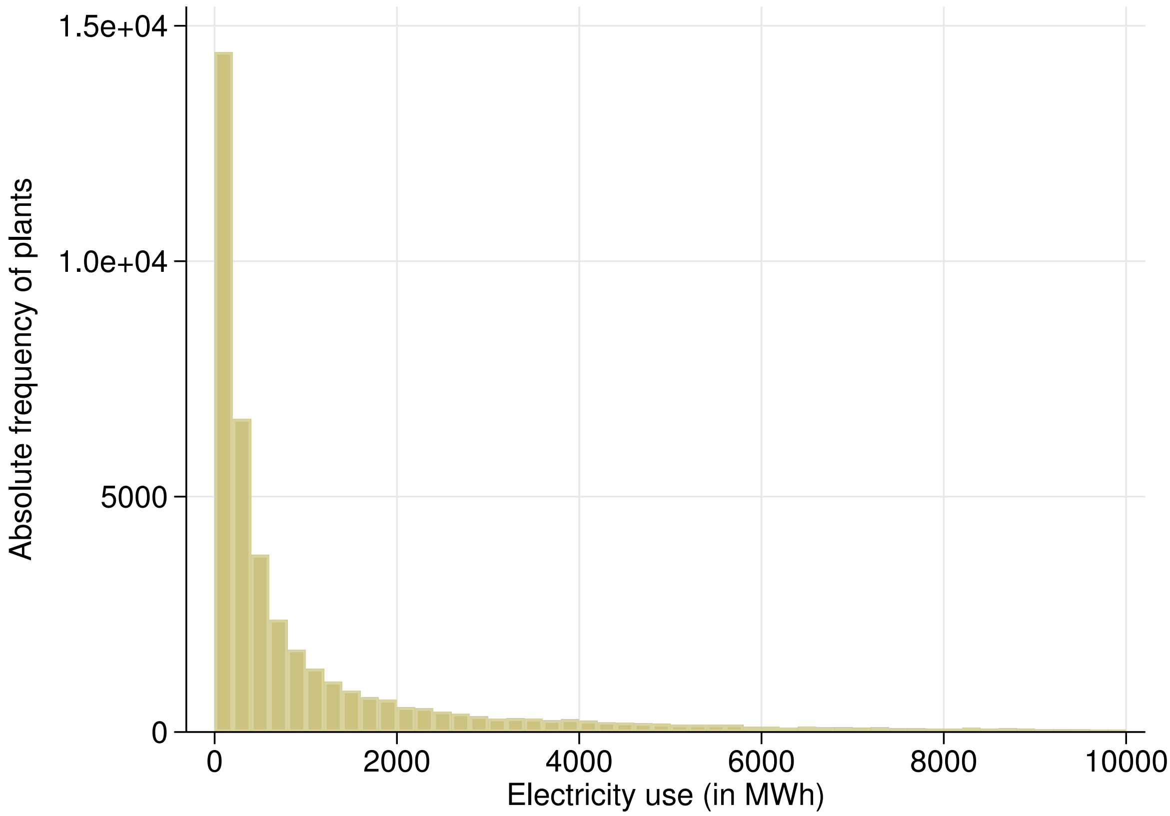

Figure 14: Distribution of manufacturing plants in the full sample with respect to their electricity consumption in 2017

Source: DOI 10.21242/43531.2017.00.03.1.1.0.

8.8 Electricity costs and electricity prices in the estimation sample

Table 10: The effects of network charges on electricity prices

	Average electricity price	Average electricity prices
Marginal network charges	0.691	
	(0.450)	
Average network charges		0.887**
		(0.451)
RES exemption	-4.108***	-4.072***
	(0.739)	(0.739)
N	4,460	4,460
number plants	3,408	3,408

*Notes: The table depicts results from a regression of single-plant firms' average electricity prices (annual electricity expenditures divided by electricity consumption) on their network charges. Column (1) uses marginal network charges as explanatory variable, column (2) average network charges. The regression is run with firm fixed effects and year fixed effects. It includes observations from 2010 and 2014. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.*

Table 11: Average electricity costs for single-plant firms in 2014 (column (1)) and 2010 (column (2))

Average electricity cost (Ct/kWh)	**2014**	**2010**
	(1)	**(2)**
p10	10.15	9.02
p50	16.91	12.69
mean	20.54	15.10
p90	24.41	19.54
N	2,116	2,461

Source: Own calculations.

Table 12: 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**	**2010**
	(1)	**(2)**
p10	7.6	7.5
p25	9.9	10.1
p50	12.9	13.6
p75	18.3	18.4
p90	24.5	25.0
N	3,021	3,324

Source: Own calculations.

8.9 Tariff groups and voltage levels in the estimation sample

Table 13 shows the result to our assignment procedure of manufacturing plants to voltage levels and tariff groups. It shows that our estimation sample is dominated by plants connected to the low to medium voltage levels. Generally, there are more manufacturing plants exceeding 2,500 annual operating hours, especially at higher voltage levels. Assignments at the sector level are available from the authors upon request. While there is substantial heterogeneity across sectors, energy intensive industries like chemicals or coke and petroleum tend to be connected to higher voltage levels, whereas less energy intensive industries like repair and installation of machineries are often connected to the low voltage level.

Table 13: 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

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).

9 Appendix C: Additional results

Distributed lag model

Figure 15 shows event-study results from estimating the following distributed lag model:

$$
\begin{aligned}
y_{it} = \beta_t \times avgnc_{ijt} + \beta_{t-1} \times avgnc_{ijt-1} + \beta_{t-2} \times avgnc_{ijt-2} + \beta_{t-3} \times avgnc_{ijt-3} \\
+\pi_{st} + \mu_i + RES_{it} + \tau \times CT_{ijt} + \epsilon_{ijst}
\end{aligned}
\tag{13}
$$

The displayed numbers are obtained by summing up current and lagged effects, as described in Schmidheiny and Siegloch (2023). As can be seen, the effects of a shock in network charges on electricity consumption tend to phase out over time and lose their statistical significance after two years. In the context of price shocks occurring on an annual basis, it makes sense that manufacturing plants are responding to the current (and one-year lagged) price changes and not to price shocks way back.

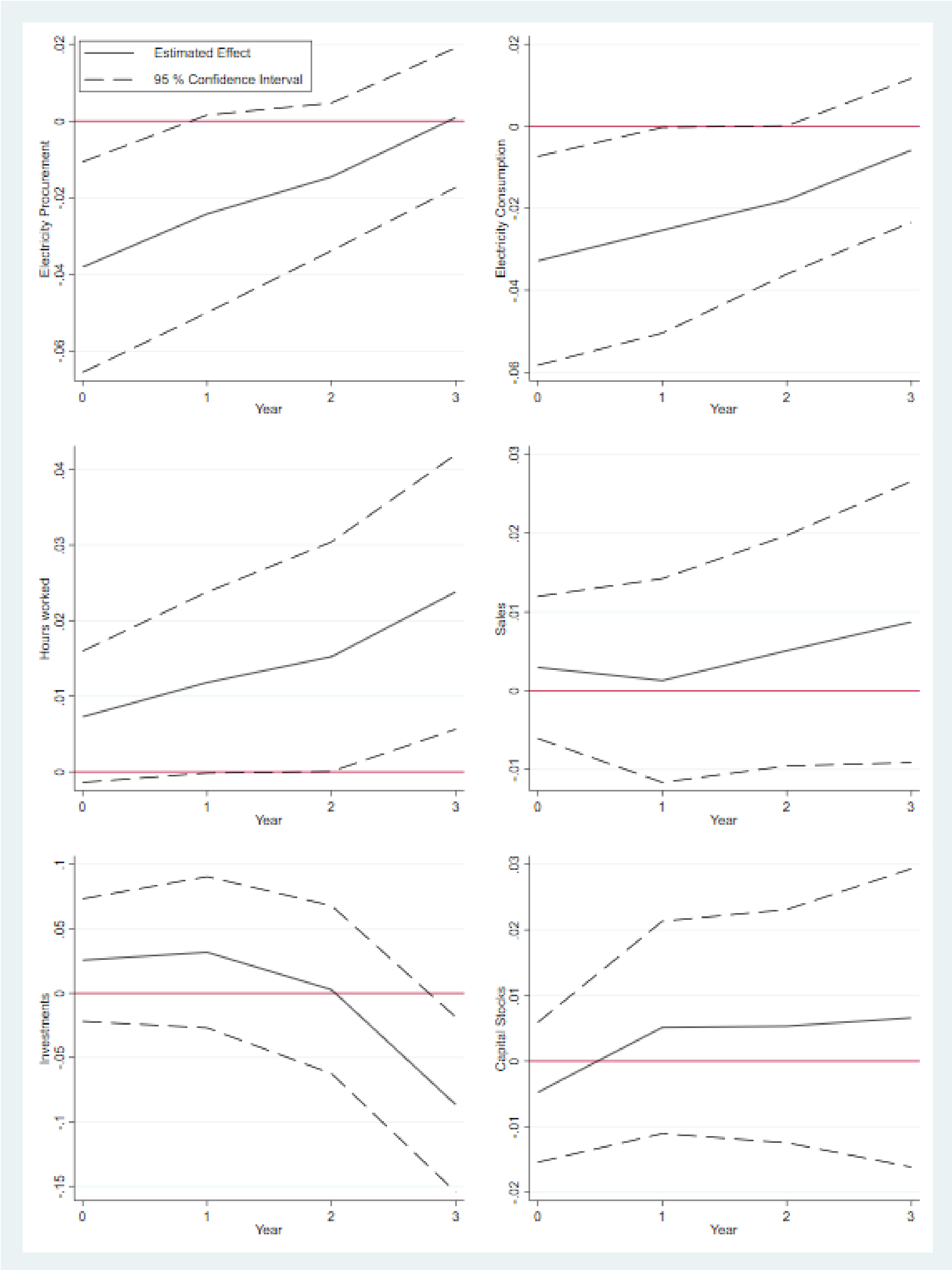

Figure 15: Distributed lag model

Source: Own calculations.

Marginal prices

Table 14 shows effects using marginal instead of average network charges as regressors.

Table 14: Short-run effects of marginal network charges on electricity procurement and consumption

	Electricity procurement		**Electricity consumption**	
	(1)	(2)	(3)	(4)
Marginal network charges	-0.006	-0.007	-0.011**	-0.010*
	(0.006)	(0.006)	(0.006)	(0.005)
RES	0.057***	0.046*	0.008	-0.001
	(0.020)	(0.024)	(0.013)	(0.016)
Commercial taxes	-0.000	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
N	57,382	43,980	57,382	43,980
number plants	7,626	6,036	7,626	6,036

*Notes: The regressions include observations from 2009–2017. The dependent variable is the logarithm of electricity procurement (columns (1) and (2)) or electricity use (columns (3) and (4)) per plant. All regressions are run with plant and 4-digit sector-by-time fixed effects. Standard errors are clustered at the county-level and displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Columns (1) and (3) contain results using the full estimation sample; in columns (2) and (4), regressions are run only using single-plant firms. Source: Own calculations.*

Effects for different two-digit sectors

Table 15 shows results from running equation (10) separately for different 2-digit sectors.[58]

[58] Only sectors with at least 150 distinct plants are shown.

Table 15: Sector-level results of the main specification on electricity procurement

Sector		**Average network charges**	**Standard errors**	**Number observations**
10	Food products	-0.029	(0.020)	6,541
11	Beverages	0.001	(0.027)	1,391
13	Textiles	0.021	(0.026)	2,042
16	Wood and wood products	-0.077	(0.068)	1,919
17	Pulp, paper and paper products	0.023	(0.026)	2,503
18	Printing and reproduction	0.006	(0.026)	2,368
20	Chemical products	-0.019	(0.030)	2,909
22	Rubber and plastic products	0.004	(0.019)	3,545
23	Other non-metallic mineral products	-0.050***	(0.019)	3,343
24	Metal production and processing	0.049	(0.046)	2,506
25	Fabricated metal products	-0.024	(0.019)	4,626
26	Computer, electronic and optical products	-0.094**	(0.041)	3,064
27	Electrical equipment	-0.026	(0.021)	3,106
28	Machine manufacturing	0.023	(0.021)	4,838
29	Motor vehicles	-0.046	(0.029)	2,782
31	Furniture	-0.006	(0.028)	1,914
32	Other manufacturing	-0.122	(0.084)	2,336
33	Repair and installation	-0.069	(0.048)	1,915

*Notes: The regressions include observations from 2009–2017. The dependent variable is the logarithm of electricity procurement per plant. Regressions are run separately for different sectors that contain at least 150 distinct manufacturing plants. All regressions are run with plant and 4-digit sector-by-time fixed effects. Standard errors are clustered at the county-level and displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.*

Effects in different regulatory periods

Table 16 shows results of the Panel regression with an interaction effect between network charges and a dummy indicating the regulatory period applying (2009-2013 or 2014-2018).

Table 16: Short-run effects of average network charges in the period 2009–2013 versus 2014–2017

	Electricity procurement	**Electricity consumption**
	(1)	(2)
Average network charges	-0.046***	-0.040***
	(0.013)	(0.012)
Average network charges ∗ 2nd regulatory period	0.012***	0.007*
	(0.004)	(0.004)
RES	0.058***	0.009
	(0.021)	(0.013)
Commercial taxes	-0.000	-0.000
	(0.000)	(0.000)
N	57,074	57,074
number plants	7,396	7,396

*Notes: The regressions include observations from 2009–2017. The dependent variable is the logarithm of electricity procurement (column (1)) or electricity use (column (2)) per plant. The regressions are run with plant and 4-digit sector-by-time fixed effects. The second regulatory period constitutes an indicator for the years from 2014 onwards. Standard errors are clustered at the county-level and displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.*

Competitiveness shocks along the distribution

Table 17: The effect of network charges on competitiveness along the distribution

	Hours worked	**Sales**	**Capital stocks**	**Investments**
	(1)	(2)	(3)	(4)
Location parameter	0.013***	0.008	-0.000	0.001
	(0.005)	(0.005)	(0.006)	(0.021)
Scale parameter	-0.002	0.000	0.000	0.003
	(0.002)	(0.002)	(0.002)	(0.010)
Q25	0.016***	0.009	0.001	-0.003
	(0.005)	(0.006)	(0.007)	(0.025)
Q50	0.013***	0.008	-0.000	0.001
	(0.005)	(0.005)	(0.006)	(0.016)
Q75	0.009*	0.008	-0.001	0.006
	(0.005)	(0.006)	(0.006)	(0.017)
N	43,280	56,683	57,227	52,432
number plants	5,937	7,424	7,505	7,329

*Notes: The regressions include observations from 2009–2017. Dependent variables are log-transformed. All regressions are run within-plant and with 4-digit sector time trends. Standard errors are clustered at the county-level and displayed in parentheses. The split-sample jackknife bias correction by Machado and Silva (2019) is applied to all estimates. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.*

Separating intensive margin effects of onsite generators

Table 18: The effects of average network charges on German manufacturing plants – onsite generators

	Electricity procurement	**Electricity consumption**	**Fuel consumption**	**Indirect emissions**	**Direct emissions**	**Total emissions**
	(1)	(2)	(3)	(4)	(5)	(6)
Average network charges	-0.034***	-0.038***	-0.023**	-0.033***	-0.022**	-0.019***
	(0.012)	(0.012)	(0.010)	(0.012)	(0.009)	(0.007)
Network charges	-0.018	0.013	0.052*	-0.016	0.033	0.004
* Onsite generator	(0.015)	(0.013)	(0.027)	(0.015)	(0.029)	(0.014)
Effect onsite generators	-0.051***	-0.025*	0.028	-0.049***	0.011	-0.014
	(0.017)	(0.014)	(0.027)	(0.017)	(0.029)	(0.014)
N	47,123	47,123	47,123	47,123	47,123	47,123
number plants	5,811	5,811	5,811	5,811	5,811	5,811

*Notes: The regressions include observations from 2009–2017. Dependent variables are log-transformed. The variable Onsite generator is a dummy variable taking the value one if the plant generated electricity onsite both in 2009/2010 and in 2016/2017. All regressions are run within-plant and with 4-digit sector time trends. Standard errors are clustered at the county-level and displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Source: Own calculations.*

Competitiveness shocks split across types of electricity generators

In Figure 16, the effects of average network charges on plant-competitiveness are distinguished according to self-generation status, taking into account the energy carrier used for self-generation (fossil fuels versus renewables).

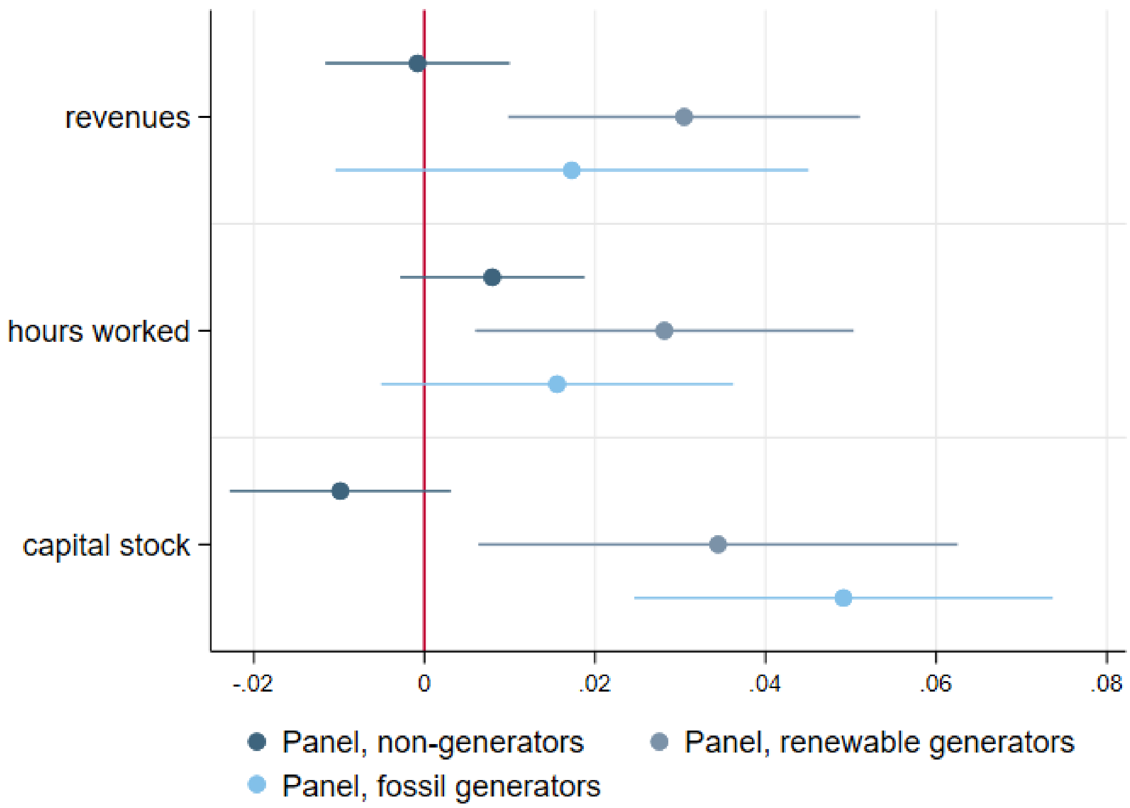

Figure 16: Estimated coefficients and confidence intervals for competitiveness indicators

Source: Own calculations.

Robustness checks

Table 19 depict the results for estimating equation (10) for a variety of differing specifications (results shown in figure 5 in main text).

Table 19: Short-run effects of average network charges on electricity procurement and consumption

Electricity procurement	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Average network charges	-0.027**	-0.031***	-0.041***	-0.036***	-0.036***	-0.033***	-0.032***	-0.063***	-0.028**
	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)	(0.010)	(0.012)	(0.012)	(0.012)
RES	0.033**	0.049**	0.077***	0.053***	0.047**	0.047***	0.051**	0.053***	0.057***
	(0.017)	(0.019)	(0.021)	(0.020)	(0.021)	(0.017)	(0.022)	(0.020)	(0.021)
Commercial taxes	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	57,382	57,382	57,382	57,074	49,696	72,428	52,376	75,170	52,040
number plants	7,626	7,626	7,626	7,396	6,009	9,531	6,510	10,347	6,700

*Notes: The regressions include observations from 2009–2017. The dependent variable is the logarithm of electricity procurement per plant. All regressions are run with plant, and sector-by-time (column (1) on the 2-digit level, column (2) on the 3-digit level, all other on the 4-digit level) fixed effects. Standard errors are clustered at the county-level and displayed in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively. Column (3) additionally includes tariff group-by-year and voltage-by-year fixed effects. Column (4) adds federal state-by-year fixed effects. In column (5), all plants are dropped from the sample that at some point are located in an ambiguous network area. Column (6) adds all plants to the sample that are always located in ambiguous network areas. In column (7), the sample is restricted to those plants that were in operation both in 2009 and 2017. Column (8) extends the sample to additionally cover all plants with an electricity procurement always below 100 MW. In column (9), only plants are included that were already present in the Census data in 2005. Source: Own calculations.*

Table 20 depict the results for estimating equation (11) for a variety of differing specifications.

Table 20: Decomposing: Changing network charges and changing elasticities

Electricity procurement								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Delta network charges (β_{t1})	-0.019*	-0.021*	-0.024*	-0.021*	-0.021	-0.029**	-0.025**	-0.029***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.014)	(0.012)	(0.012)	(0.010)
Lagged network charges ($\Delta\beta$)	0.023***	0.021***	0.014	0.017**	0.021***	0.020***	0.017***	0.015***
	(0.006)	(0.006)	(0.013)	(0.007)	(0.006)	(0.007)	(0.005)	(0.005)
Implied β_{t0}	-0.045***	-0.042***	-0.038**	-0.038**	-0.042***	-0.046***	-0.042***	-0.044***
	(0.014)	(0.014)	(0.018)	(0.016)	(0.016)	(0.015)	(0.014)	(0.012)
N	5,682	5,678	5,670	5,670	5,674	5,161	7,206	7,217
number plants	5,682	5,678	5,670	5,670	5,674	5,161	7,206	7,217

Notes: The regressions include observations from 2010–2017. The dependent variable is the change in the logarithm of electricity procurement per plant. All regressions are run with plant, and sector (column (1) on the 2-digit level, column (2) on the 3-digit level, all other on the 4-digit level) fixed effects. Standard errors are clustered at the county-level and displayed in parentheses. *, ** *and* *** *indicate significance at 10%, 5% and 1%, respectively. Column (3) additionally includes tariff group and voltage fixed effects. Column (4) adds federal state fixed effects. In column (5), averages for start and end period are taken over three years instead of two (i.e. difference between 2010-2012 and 2015-2017). In column (6), all plants are dropped from the sample that at some point are located in an ambiguous network area. Column (7) adds all plants to the sample that are always located in ambiguous network areas. Column (8) extends the sample to additionally cover all plants with an electricity procurement always below 100 MW. Source: Own calculations.*

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