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DISCUSSION PAPER

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

Do manufacturing plants respond to exogenous changes in electricity prices? Evidence from administrative micro-data

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Abstract

Climate policy often implies increasing energy prices. Due to incomplete regulation across the globe, concerns about their competitiveness and employment effects play an important role in the policy debate. Using micro-data on electricity network charges and the official census data for Germany, we study the impact of rising electricity costs on plant performance in German Manufacturing. Electricity network charges are determined through regulation in Germany and therefore exogenous to manufacturing plants, while making up a substantial share of final electricity prices. Our estimates imply a negative own-price elasticity of electricity of -0.4 to -0.6 in the short-run: A one cent increase in average network charges leads to a decrease in electricity procurement of roughly 3 %. There is suggestive evidence that this elasticity of response is decreasing over time, in line with non-linearly increasing marginal abatement costs. Generally, we do not find significant effects on revenues, investments or capital stocks.

Keywords: Network charges, Electricity Use, Firm Performance, Climate Policy, Manufacturing

JEL-Classification: D22, L60, Q41, Q48

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1 Introduction

The challenge posed by climate change is considerable. The world set an ambitious target in Paris at the 21st Conference of the Parties meeting in 2015. Since then, little has happened and global greenhouse gas emissions continue to rise. While a solution in terms of pricing the climate externality either through emissions trading or a tax on greenhouse gas emissions is available, failure to implement globally coordinated policies continues to hold back the policy response across the globe: If a country implements stricter regulation than its trading partners, it might suffer from a loss of competitiveness or jobs. Unilateral policies might also induce leakage effects, i.e. emissions might shift from regulated to unregulated economies, reducing the share of global emissions addressed by regulation. Such concerns have acted as deterrent for unilateral policy efforts in the past and continue to play a prominent role in the policy debate as regulatory stringency is likely to increase in the coming years.

The extent to which concerns regarding leakage and competitiveness losses are valid has been studied in several instances. Much of the previous literature in this context has focused on emissions trading as a prime example of climate policy price instruments (see e.g. Lehr *et al.* 2020 or Naegele and Zaklan 2019 or Martin *et al.* 2016 for an overview). The emphasis in these studies has been on the direct effects of implemented policy measures, and on the primary energy consumption of affected firms. However, many climate policy instruments ultimately result in price increases of secondary energy carriers like electricity (e.g. by the means of pass-through of emission allowances onto electricity prices, as in Hintermann 2016 or Fabra and Reguant 2014). Due to several empirical challenges, in particular the unavailability of electricity price data and the endogeneity of electricity prices, as of today, these indirect effects of climate policy measures on firm performance are much more poorly understood. Studies focussing on the effects of electricity prices typically rely on quasi-experimental designs such that effects are estimated on specific subsets of the data which puts limits on their external validity (Gerster and Lamp, 2020; Flues and Lutz, 2015; Martin *et al.*, 2014). In this paper, we contribute by studying the effects of an exogenous source of variation within electricity prices, specifically electricity network charges, on the electricity usage behaviour as well as several competitiveness indicators of German manufacturing plants.

Electricity network charges are fees that electricity consumers in Germany pay for the usage of the electricity grid. For industrial users, they make up approximately 15-30 % of total electricity prices. We can treat network charges as plausibly exogenous to manufacturing plants and hence recover causal effects for three reasons: First, network operators are centrally regulated by a Federal Agency. Second, for each manufacturing plant, the location completely determines the relevant network operator. Third, network charges are set and published prior to the consumption decision of manufacturing plants. Combining detailed plant-level data from the German Manufacturing Census with data on spatially and temporally varying electricity network charges from the ene't GmbH for more than 7,000 manufacturing plants between 2009 and 2017, we find that a rise in average network charges leads to a reduction in manufacturing plants' electricity usage. Specifically, a one cent increase in average network charges reduces electricity procurement by about 3 % on average in the short-run, translating into an own-price elasticity of electricity of -0.4 to -0.6. While the 3 % constitute an average effect, there is suggestive evidence for the elasticity of response to decrease over time from more than 4 % in 2009 to roughly 2 % in 2017. This finding is in line with non-linearly increasing marginal abatement costs, where plants, once the easy to implement adjustments are made, require larger changes in electricity prices to take the next abatement step. While we find significant responses of manufacturing plants to network charges with respect to electricity consumption, we generally cannot identify significant negative effects on revenues, employment, investments or capital stocks.

Our paper contributes to two strands of literature. First, we add to the already cited strand of research on the causal effects of climate policy price instruments on energy demand and firm performance. Our unique setting with both temporally and spatially varying network charges in combination with detailed plant-level panel data allows us to deepen the understanding of the effects of rising energy prices in several dimensions: Among others, we can analyse effect heterogeneities and discuss potential mechanisms as in Aldy and Pizer (2015), however using micro- instead of sector-level data. The data structure also allows us to investigate effect dynamics, both with respect to at which moment in time adjustment processes occur for a given shock, and with respect to whether the response to an identical shock changes over the years in size or direction. To the best of our knowledge, we are the first ones not to impose a constant response to price changes in estimating electricity price effects on micro-data. Lastly, we are able to contrast short- and long-run effects, exploiting annual variation in a classic panel study on the one hand and using a long-differences design on the other hand. Estimates of long-run effects of climate policies are still scarce, and we contribute by using a longer time frame to identify such effects than previous studies (e.g. Marin and Vona 2021).

Second, our paper also contributes to the literature on own-price elasticities of electricity in industrial production (see e.g. Abeberese 2017, Bardazzi *et al.* 2015 and Boyd and Lee 2016 for elasticities in the manufacturing sectors in India, Italy and the United States). We complement this literature by providing evidence on Germany retrieved from plant-level analyses instead of only exploiting variation at the state-level like previous studies.

Our findings suggest that climate policies have a significant impact also upon small industrial consumers which so far have not been the focus of academic study. The strong response of manufacturing plants' electricity usage to prices in the short-run, both at the beginning and at the end of our study period, corroborates that price-based policies are very effective in combatting climate change – even though there remain many unexplained factors besides prices governing manufacturing plants' electricity usage patterns.

The remainder of the paper is structured as follows: Section 2 describes the network structure and regulation of network charges in Germany. Section 3 provides a brief conceptual framework of electricity prices and marginal costs to abate electricity consumption. Section 4 introduces the data and discusses the research design. Section 5 reports our results. In Section 6 we conclude.

2 Background on electricity prices and networks

2.1 Electricity prices and price components in Germany

Total electricity prices in Germany comprise three different components: (1) the costs of generation and supply; (2) taxes, levies and surcharges; and (3) network charges. Figure 1 depicts the development of these price components over time for different consumption bands. As can be seen, the importance of taxes, levies and surcharges has substantially grown over time, today making up approximately 40 % of final electricity prices depending on the consumption band. This strong increase is mostly rooted in the development of the Renewable Energy Surcharge imposed at the national level. Network charges – while varying at the network level – account for up to 30 % of final electricity prices and also tend to increase over time. In contrast, the generation and supply component is gradually decreasing. This decline in wholesale prices is likely driven at least in parts by the expansion of renewable energies. Due to exemptions and lower charges for large electricity users, prices generally are the lower the higher the consumption. Variation in electricity prices among users stems from customers choosing different electricity providers,[1] 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 and concession fees at the regional level.

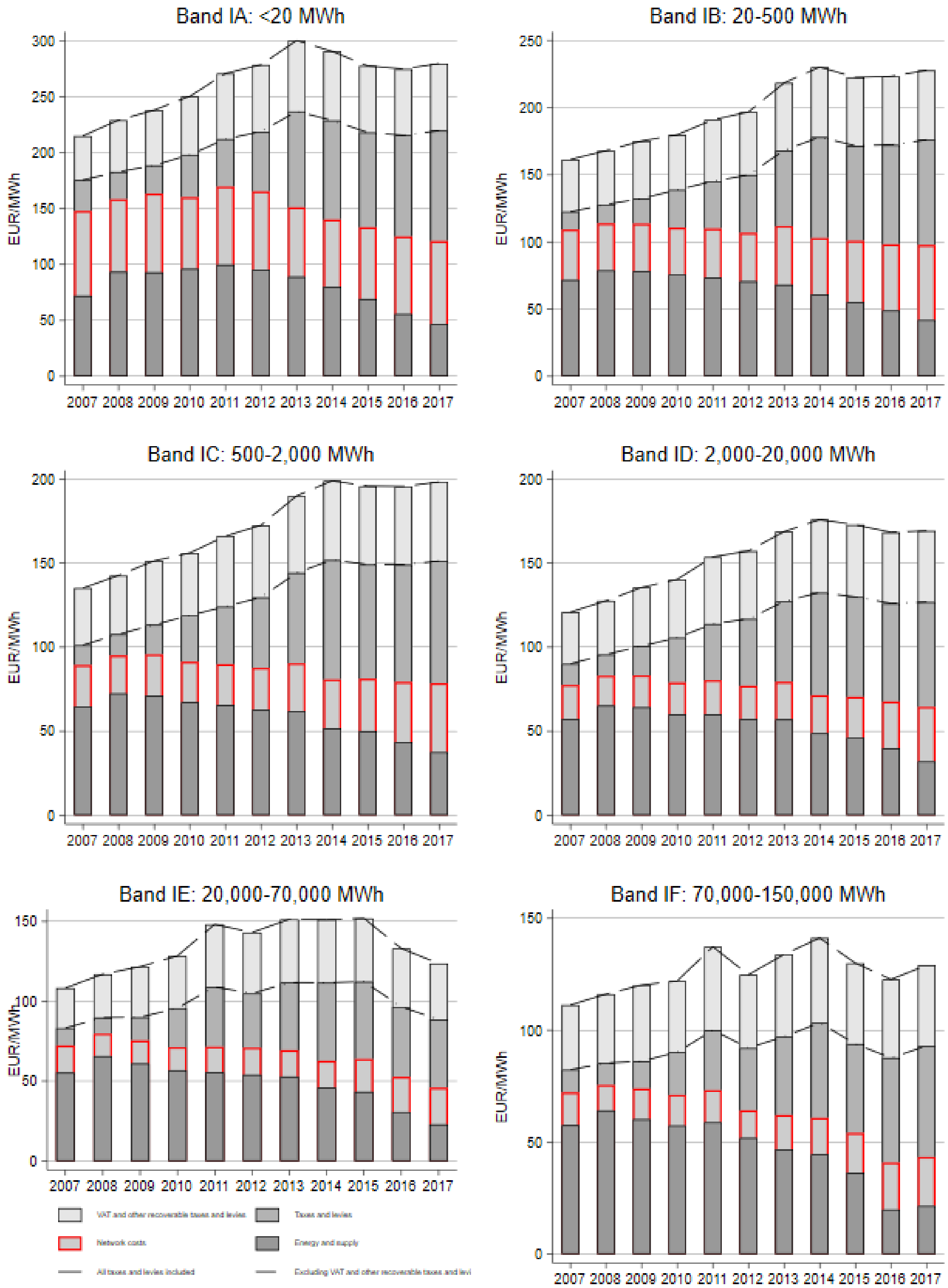
2.2 Electricity networks and the exogeneity of network charges

The German electricity market has undergone notable changes over time. Prior to 2005, it 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. In this context, the Federal Network Agency was established to regulate network charges so as to reduce monopoly profits and inefficiencies in network operation.

Network operations take place at different voltage levels. In Germany, there are four Transmission System operators (TSOs) operating the extra high voltage networks and transporting electricity around the country, and up to 900 Distribution System Operators (DSOs) running the low, medium and high voltage networks, connecting final customers to the electricity grid. Both transmission and distribution networks are natural monopolies and therefore subject to the regulation of the Federal Network Agency.

While in the initial years of regulation, network operators were allowed to recover their costs plus a regulated markup through network charges (the cost plus regulation), since 2009, they are subject to the incentive regulation. Due to the regulatory change, our analysis is limited to the years from 2009 onwards. Under the incentive regulation, the

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



Source: Eurostat time series nrg_pc_205 and nrg_pc_205_c.

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

Federal Network Agency benchmarks different network operators against each other. The result of this procedure in combination with the network operators' levels of unalterable (in the short-run) costs serves 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 translation of revenue caps into marginal and peak load price components is regulated and leaves little leeway for network operators.[2]

The incentive regulation leads to network charges varying over time, where prices that will apply in the next year are published in October; and over space due to different DSOs.[3] The spatial variation is depicted in 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 2017.[4] Higher network charges apply to many of the states belonging to the former Eastern Germany. However, there is substantial variation at a small spatial scale.

Figure 3 shows density plots of average network charges for the same hypothetical chemical plant over time. Clearly, there is substantial variation both over time and cross-sectionally. Network charges have increased and become more heterogeneous. In other voltage levels, the development is similar.

Drivers of variation in network charges across DSOs include grid-level variation in a variety of cost components, among them costs 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 likely increased both the level of system support services required and the costs for connecting new generation sources to the grid.

[2] The setting of revenue caps and individual network charges price components across different voltage levels is described in more detail in the Appendix.

[3] There are 8-900 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 DSOs across Germany and correspondingly there is less spatial variation in network charges at the high voltage level.

[4] The hypothetical chemical plant consumes 950 MWh of electricity per year with a peak load of 152 kW and shift work (operating hours in excess of 2,500 hours)

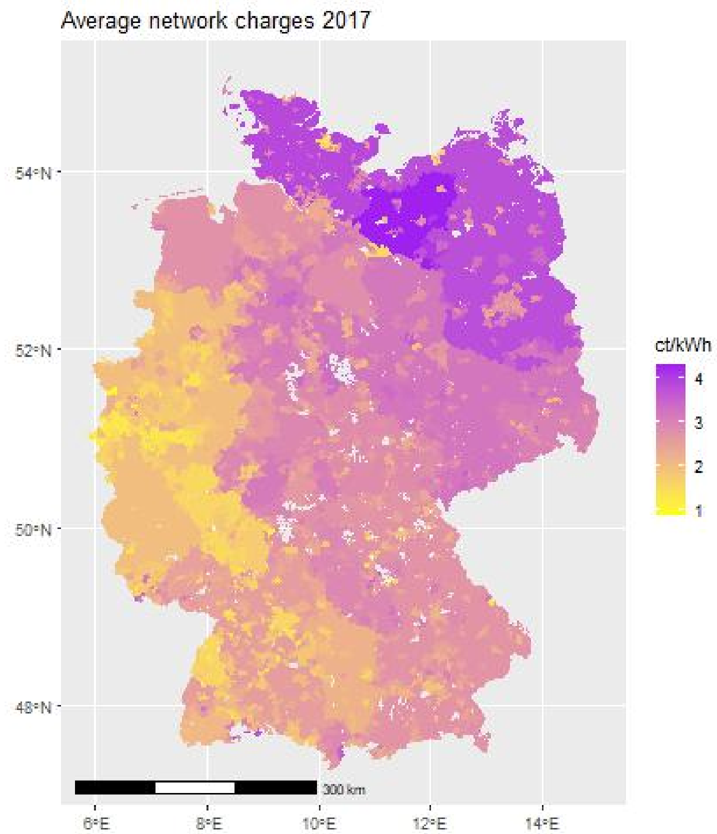


Figure 2: Average network charges of a hypothetical chemical plant in 2017

Source: Own calculations. The map shows average network charges 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 in 2017. The plant is connected to the medium voltage level.

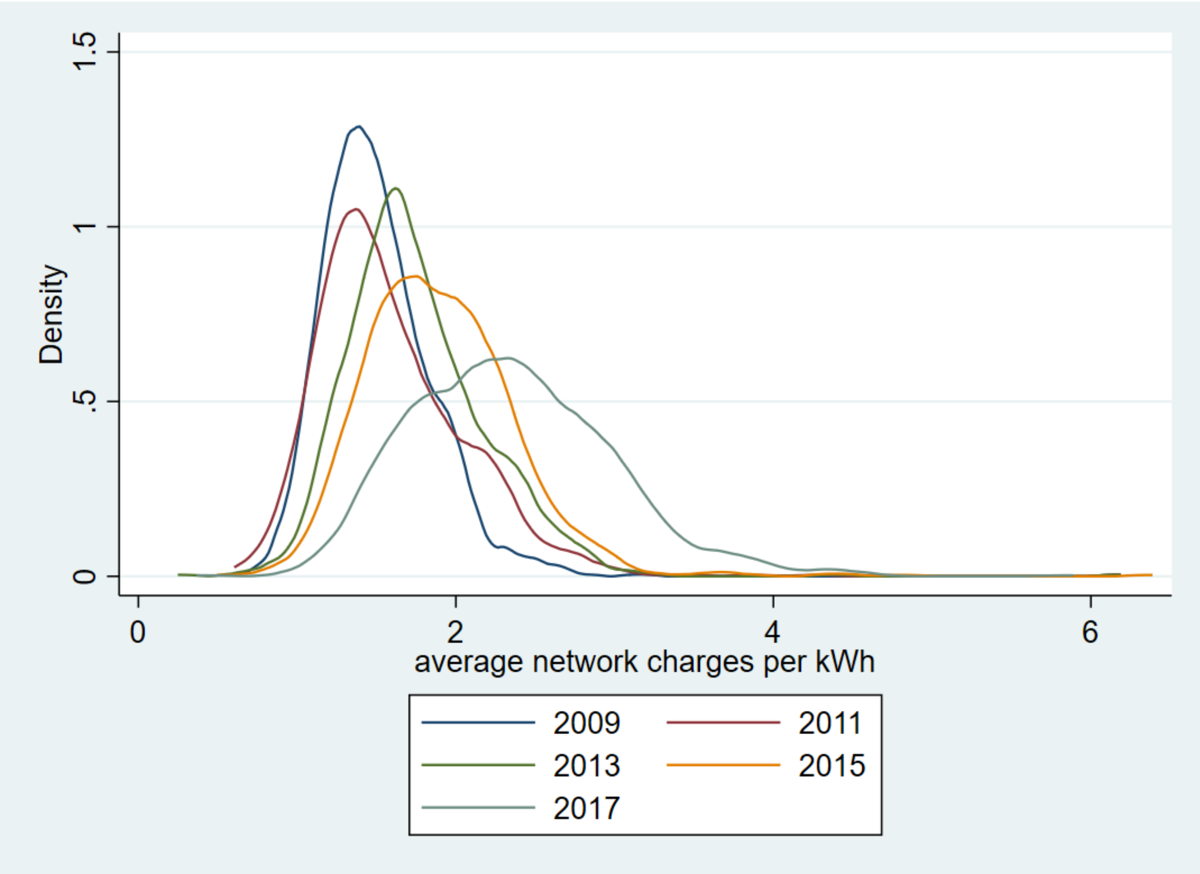


Figure 3: Density of average network charges of a hypothetical chemical plant over time

Source: Own calculations. The figure shows the distribution of average network charges in cents per kWh for a hypothetical chemical plant over time. The exemplary plant consumes 950 MWh per year with a peak load of 152 kW, conducts shift work (annual operating hours $> 2,500$), and is connected to the medium voltage level.

Against this background, we can treat network charges as exogenous to manufacturing plants. This claim warrants a more detailed discussion given its importance in the empirical analysis. The reasons for the exogeneity of network charges are threefold: First, for each electricity consumer in Germany, the location completely determines the relevant DSO. Hence, contrary to, e.g., electricity retail markets, consumers cannot pick and choose between different suppliers. Once they are located in a certain area, the network operator is fixed. While manufacturing plants in principle 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 should be minimal.[5]

Second, the local DSO is not free to set network charges due to the regulation through the Federal Network Agency. DSOs cannot strategically set network charges in a way as to attract and keep industry and production. Regulation both for a DSO's revenue cap and its translation into individual price components is very detailed and leaves little scope for strategic action.

These two facts do not rule out the possibility of reverse causality, i.e. network charges being affected by the demand behaviour of manufacturing plants, e.g., because a higher utilization of the grid leads to the revenue cap being split among more users, or because higher industrial activity impacts re-dispatch tasks. However, we are identifying effects based on within-plant variation in network charges. In our analyses, only the change in network charges needs to be exogenous. This is a much weaker requirement: Network charges depend, as discussed, on a variety of factors and the consumption behaviour of lots of (large) electricity users aside from manufacturing plants (like, e.g., warehouses, hospitals, movie theatres, and households). As a consequence, changes in demand behaviour have to be large in order to have a significant effect on the development of network charges. In general, 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 case. Additionally, the timing of network charge determination and demand responses implies that there is no scope for simultaneity. Network charges for a given

[5] Additionally, Janser *et al.* (2022) do not find any evidence that municipalities with decreasing network charges experience an increase in plant entries (or a decrease in plant exits) which also speaks against selection effects playing a major role.

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 which therefore cannot have immediate effects on network charges.

Network charges consist of a marginal and a fixed price component, where the latter depends on the peak load for those customers with registered load metering (RLM) but not for standard load profile (SLP) customers. Both price components depend on the local DSO and on the voltage level at which the user is connected. For RLM customers, tariffs differ depending on whether operating hours exceed 2,500 hours per year. Due to the way in which marginal and fixed price components are derived from the revenue caps, they are negatively correlated within a voltage level. For this reason, we base our analysis on average network charges faced by a plant. More discussion on how we calculate average network charges and on the network charge data can be found in the data section. SLP customers typically pay network charges to their electricity provider (who then transmits them to the respective DSO) as part of their electricity bill. RLM customers in contrast pay network charges directly to their DSO. The development of network charges therefore, at least for RLM customers, should be quite salient. The Appendix gives further information on the billing procedure.

This exogeneity of (changes in) network charges allows us to recover causal effects. In different reduced form regressions, we proxy unknown and endogenous electricity prices by the exogenously given electricity network charges faced by manufacturing plants. Under the reasonable assumption that industrial users respond in the same way to rising electricity prices in general and rising network charges, our findings extend to electricity prices.[6]

3 Conceptual Framework

At this point, it is worthwhile to take a step back and conceptually outline the expected consequences of electricity price increases and how this response may change over time.

When electricity prices increase, e.g., because network charges rise, standard economic theory predicts that, all else equal, manufacturing plants reduce their electricity

[6]While a natural approach to estimating the causal effects of electricity prices would consist in an IV regressor with network charges as instruments for plant-level electricity prices, the lack of data on plant-level electricity prices renders such an analysis impossible.

procurement. To do so, they have different options available. They may reduce their electricity use by improving energy efficiency. Another option is to substitute away from procurement through onsite electricity generation or by outsourcing the production of electricity intensive intermediates. Electricity use can also be reduced by decreasing production output or by switching towards producing less electricity intensive goods. Each of these options comes with (opportunity) costs. Ranking the adjustment options by their marginal cost creates the plant's marginal abatement cost curve. Textbook economics then shows that in a static framework it is optimal for plants to reduce electricity procurement up to the point where marginal abatement cost equal the current electricity price.

What about effect dynamics over a longer time period, such as our sample ranging from 2009 to 2017? Will the response to rising electricity prices be constant over time? This is not a priori clear and depends on the slope of the marginal abatement cost curve (MACC), as depicted in Figure 4. It also depends on expectations about how prices (and abatement costs) will change over time.

The left side of the figure depicts the textbook case of a firm with a linear MACC (see e.g. Phaneuf and Requate 2017). In that scenario, depicted in the solid line, a one cent electricity price increase will always lead to the same amount of electricity procurement being abated. Identical price increases from p_0 to p_1 and then p_2 lead to abatements ΔE_1 and ΔE_2 of the same magnitude. The response is constant over time as long as the MACC does not shift.

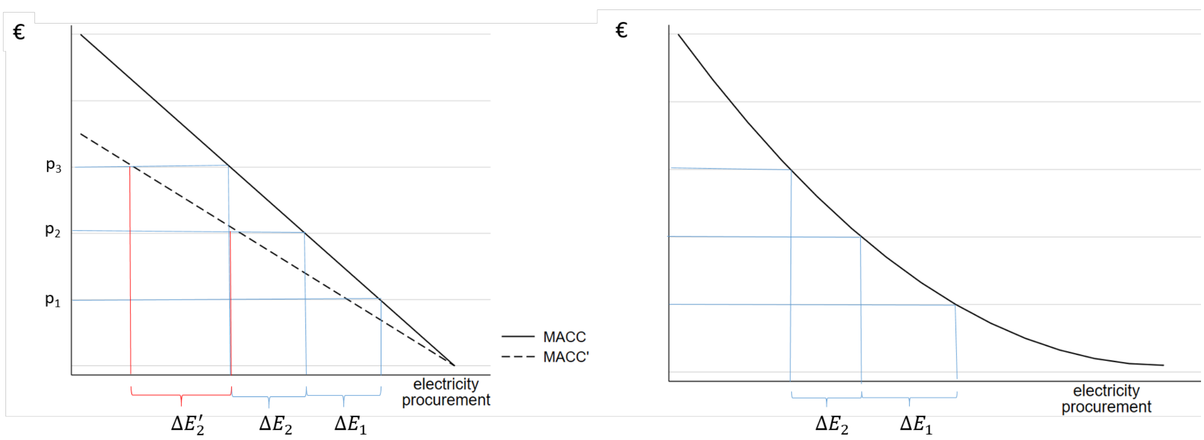


Figure 4: Different marginal abatement cost curves

Suppose now that the firm benefits from technical progress, and has new, more electricity efficient machinery available. This will pivot the MACC downwards as shown in the line $MACC'$. Intuitively, as the new machinery is more electricity efficient, forgone output to abate one additional kWh of electricity is lower than before. If the firm switches from $MACC$ to $MACC'$, in this case, the response to a similar increase in electricity prices could grow over time (see $\Delta E_2'$).

Contrast that case with the convex MACC depicted in the right panel of the figure. Consider again a price increase first from p_0 to p_1 and then to p_2. Because the slope of the MACC is increasing, the second (equivalent) price increase will raise abatement by less than the price change from p_0 to p_1. Intuitively, since the costs for reducing electricity consumption by one additional kWh become increasingly high, manufacturing plants will require a larger change in electricity prices for the same amount of abatement.

Note that the MACCs depicted in Figure 4 constitute simplifications in several regards. First, they present examples for single firms. MACCs might differ across firms, and importantly across sectors: Specifically, manufacturing sectors for which electricity is an important production input (i.e. with a high electricity intensity) might in general have steeper MACCs as it might be harder to substitute away from electricity. Second, in reality, MACCs are likely to be step-wise instead of smooth functions. As such, marginal abatement costs might be constant until a point of discontinuity is reached.

Aside from the MACC, in a dynamic context, expectations of future price developments play a major role, in particular if investments are irreversible. This is formally shown by Viscusi (1983) in the context of uncertain future environmental regulation. In his example, a firm in each of two periods,chooses (irreversible) investment in abatement (quality) and production quantities. In this setting a firm may overinvest in abatement due to stricter expected regulation (in our case higher prices) in the future than what in fact is realized. In consequence, the firm produces more than originally planned in the second period. Responses to increasing electricity costs therefore depend also on the development of (expected) electricity prices over time.[7]

[7] We mention this channel here because plants in Germany have experienced several changes in electricity pricing due to regulation. In particular, over the study period, the exemption options for the renewable energy surcharge were amended resulting in a substantial increase in exempt plants which is studied in Gerster and Lamp (2020). In addition, the EU ETS prices were much lower than most people

Summarizing, there are good reasons to believe that the response to rising electricity prices is not constant over time. IWhether the responsiveness increases or decreases depends on the MACC and how it evolves over time, as well as how expectations about electricity prices compare to realized electricity prices. We test empirically whether in German manufacturing, abatement elasticities get larger, smaller or remain constant in the period from 2009 to 2017. We also examine which abatement options German manufacturing plants use in response to increasing network charges, by looking at effects of electricity network charges on output-related measures (revenues and employment), on investments, and on onsite electricity generation. The sectoral differences in MACCs are taken into account by analysing heterogeneities across subsectors of manufacturing.

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 1, implicitly assuming a constant elasticity of response to rising network charges. Due to the use of plant fixed effects μ_i, identification is achieved by using the within-plant variation in network charges over time.

$$y_{it} = \beta \times avgnc_{ijt} + \pi_{st} + \mu_i + RES_{it} + \tau \times CT_{ijt} + \epsilon_{ijst} \tag{1}$$

y_{it} denotes the log outcome variable of plant i in year t. 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.[8][9] Potential

had expected at below 15 Euro per tonne of CO2 for much of the study period. In consequence, for some plants prices may not have increased as much as anticipated in the beginning of the period.

[8]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 11 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.

[9]Average network charges are calculated by adding up the product of peak load price and peak load (for RLM customers; for SLP customers, this expression simplifies to the fixed price component itself)

confounders are controlled for by using different fixed effects and control variables: First, μ_i controls 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. Among others, these trends capture sector-specific demand shocks, or the development of electricity wholesale prices and national levies and surcharges. Moreover, we control for plants being exempt from paying the full Renewable Energy Surcharge (RES_{it}). This surcharge is an important component of electricity prices in Germany which accounts for up to 30 % of electricity prices, as discussed in Section 2. Becoming exempt therefore leads to a substantial drop in electricity prices which we do not want to confound our estimates. Finally, as network charges differ on a spatial scale similar to the level at which commercial tax rates vary – which have been found to have an effect on plant behaviour (Fuest *et al.*, 2018) – we also control for the commercial tax rate at the plant location, CT_{ijt}.

A few clarifications might be in order here. Note that we use average network charges as an explanatory variable. Hence, plant behaviour is explained by a weighted average of changes in the fixed and marginal price component. We abstain from using the price components themselves 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 the Appendix. The strong correlation makes it difficult to back out separate effects of marginal and peak load prices. Second, the weight on marginal and fixed price components in the plant's total network charges differs substantially across manufacturing plants. For users with high peak loads, the fixed price component constitutes the lion's share of total network charges, while it is the other way round for smaller customers. Due to this heterogeneity even among plants for which the same tariff structure applies, estimating average effects of each of the different price components does not properly take into account their relative importance. This is naturally achieved by looking at average prices instead.[10]

with the product of marginal price and electricity procurement, and then dividing this total of network charges by electricity procurement. Average network charges are measured in cents per kWh of electricity procured.

[10]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.

Identification is achieved by using the year to year variation in network charges. Regression results can hence be interpreted as 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.

We follow Burke and Emerick (2016) in obtaining long-run effects by estimating the same regression in long differences, as shown in equation 2.

$$\Delta y_i = \beta \times \Delta avgnc_{ij} + \pi_s + \Delta RES_i + \tau \times \Delta CT_{ij} + \epsilon_{ijs} \tag{2}$$

In this approach, we explain the change in the log dependent variable over a longer time period, Δy_i, by the change in average network charges, $\Delta avgnc_{ij}$ over the same time period. By using first differences, we still control for plant-invariant factors that might affect outcome variables. The coefficient of interest, β, is estimated from a combination of short- and long-run variation. To recover true long-run effects, we take two steps: 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 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.

In both equations 1 and 2, the coefficient of interest, β, is assumed to be constant over time. If this is not the case, as suggested by the considerations in Section 3, β represents an average of different elasticities. To obtain estimates of whether and in which direction elasticities of response towards rising network charges have changed over our estimation period, we additionally estimate equation 3:

We empirically test the importance of the fixed price component by additionally running regressions in which we include marginal network prices instead of average network charges. Results are reported in Table 12 in the Appendix. As in Ito (2014), we find that responses to marginal prices are weaker than to average prices.

$$\begin{aligned}
\Delta y_{ij} &= \beta_{t1}\, NC_{ijt1} - \beta_{t0}\, NC_{ijt0} + ... \\
&= \beta_{t1}\, NC_{ijt1} - \beta_{t0}\, NC_{ijt0} + \beta_{t1}\, NC_{ijt0} - \beta_{t1}\, NC_{ijt0} + ... \\
&= \beta_{t1}\, (NC_{ijt1} - NC_{ijt0}) + (\beta_{t0} - \beta_{t1})\, NC_{ijt0} + ... \\
&= \beta_{t1}\, \Delta NC_{ij} + \Delta\beta\, NC_{ijt0} + ...
\end{aligned} \tag{3}$$

As in equation 2, we take long differences, but allow β to change across start and end period. Adding and subtracting the product of end period elasticity and start period network charges and rearranging yields that the change in the log 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 as well as baseline period network charges, we can get estimates both for β_{t1} and for $\Delta\beta$ and thereby learn about direction and size of a potential change in manufacturing plants' response to rising electricity prices.

Note that in all three regressions, standard errors are clustered at the county-level to account for spatial correlation of observations.[11]

4.2 Data

To estimate these regressions, we combine several data sources. For information about plant-level economic indicators as well as electricity usage behaviour, we refer to the German Manufacturing Census. This confidential administrative data set contains different modules and, for several of these, covers all German manufacturing plants with more than 20 employees. Other modules are only available for stratified subsets of manufacturing plants. Participation in the respective surveys is mandatory. Responses are back-checked by the Federal Statistical Offices of the Bund and the Länder, so that data overall are reliable. Still, we drop some observations with implausible reporting. Details can be found in the Appendix. We have data available for the period from 2003 to 2017 – however, our

[11] In principle, it would be most appropriate to cluster standard errors at the level of grid areas. As these frequently change over time, e.g. due to mergers or acquisitions of DSOs, we refer to the more stable counties as an approximation of grid areas. These are also more similar in size and thus more likely to capture shared regional shocks than the grid areas, which can vary from a neighborhood in a city to an area spanning almost an entire federal state.

analysis is limited to the time period from 2009 onwards due to the regulatory change in network charges from cost-plus to incentive regulation.

The Manufacturing Census contains information on manufacturing plants' locations (i.e., counties and postal codes) as well as their sector affiliation. We also use information on their electricity consumption and procurement, both measured in kWh per year. Furthermore, the Census covers manufacturing plants' revenues, hours worked, total investments and investments into energy efficiency. These variables are available for the full sample of plants with more than 20 employees. Additionally, as a proxy for annual operating hours, we make use of information on whether manufacturing plants are conducting shift work. This variable is only available every four years for a stratified sample of manufacturing plants and hence defines our estimation sample.[12] Specifically, our estimation sample consists of all German manufacturing plants that report about shift work at least once in 2006, 2010, or 2014. For the remaining years, we use linear extrapolation.[13] Lastly, for a subsample and the same select years, we exploit firm-level data on electricity expenditures from an additional Census module to check whether developments in average network charges are reflected in firms' electricity expenditures. This is indeed the case.

We combine the German Manufacturing Census with data on electricity network charges purchased from the ene't GmbH. This data provider compiles the information that DSOs are legally required to publish annually. We use data from 2009 onwards. 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 via spatial identifiers, namely county and postal codes. In certain years, some county-postal code areas are divided between multiple DSOs. Since we do not know a manufacturing plant's exact location within a county-postal code and hence can-

[12]Strata are given by federal states, sectors and employee size classes. Plants with more employees are more likely to be sampled, and plants with more than 1,000 employees are always in the sample.

[13]To keep the burden for manufacturing plants as small as possible, participation in the survey is rotated. The deliberate rotation leads to the samples of two years overlapping only to a small degree. Since all plants with more than 1,000 employees have to participate in the survey, this rotation particularly affects plants with fewer employees. Owing to the small overlap, we cannot confine ourselves to manufacturing plants for which we observe shift work multiple times. The extrapolation might induce some measurement error. However, from plants observed multiple times in the survey, it seems that the decision (not) to conduct shift work is quite stable so that the error should be small.

not identify the exact DSO to which it is connected, we drop those observations from our estimation sample. The ambiguities frequently occur in cities so that our final estimation sample somewhat underrepresents manufacturing plants in urban areas.[14]

As discussed in Section 4.1, we use information on commercial tax rates and exemptions from the Renewable Energy Surcharge as controls and therefore merge commercial tax rates from the Federal Statistical Office and RES exemption information from the Federal Office of Economics and Export Control.[15]

While the dependent variables for our analysis – electricity procurement and consumption, revenues, hours worked, investments and capital stocks – are directly contained in the manufacturing Census,[16] the construction of our explanatory variable warrants further discussion.

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 1 again summarizes the different tariff structures.

Table 1: Structure of network charges

Customer group	Standard load profile (SLP)	Interval-metered (RLM)	Individual charges (§19)
Annual procurement	$\leq$ 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:	
		$\leq$ 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 1) if their electricity procurement is below 100 MWh throughout the study

[14]Figure 9 in the Appendix 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 due to the ambiguous network assignment in certain areas.

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

[16]Capital stock information are not included in the Census surveys, but is computed by the Perpetual Inventory Method following Lutz (2016).

period.[17] 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 1). 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 criteria overlap to a large extent. Therefore the RES dummy controls for these plants to some extent. In sum, we expect this to lead to classical measurement error biasing our estimates towards zero.

For all RLM customers (column (2) of Table 1), we use information on shift work to distinguish plants above or below the 2,500 threshold in annual operating hours. Note that 2,500 hours of use are achieved by plants operating 6 days a week and 8 hours a day all year round (52 weeks), so that manufacturing plants with regular double shifts (16 hour work days) will exceed 2,500 annual operating hours, whereas plants with a single shift and a 40 hours 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 Appendix. 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 a possible effect.

[17]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.

4.3 Sample statistics

Due to areas in which the DSO cannot be determined unambiguously and due to the fact that our estimation sample is constrained to manufacturing plants on which we have information about their shift work at least once, the estimation sample is substantially smaller than the full sample of manufacturing plants represented in the Census data. Table 2 and Figure 5 contrast our estimation sample and the full sample from the German Manufacturing Census with respect to sector composition, full time equivalents and electricity consumption.

Table 2: 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	11.56	11.55
11	Beverages	1.24	2.39	2.51
12	Tobacco products	0.06	0.14	x
13	Textiles	1.64	3.71	3.71
14	Wearing apparel	0.56	1.41	1.44
15	Leather and related products	0.29	0.68	0.66
16	Wood and products of wood and cork, except furniture	2.56	2.99	2.94
17	Pulp, paper and paper products	2.09	4.06	4.18
18	Printing and reproduction of recorded media	2.96	3.90	3.81
19	Coke and refined petroleum products	0.15	0.46	x
20	Chemical products	3.55	5.30	5.23
21	Basic pharmaceutical products and pharmaceutical preparations	0.8	1.75	1.64
22	Rubber and plastic products	7.38	6.13	6.29
23	Other non-metallic mineral products	6.51	5.74	5.85
24	Metal production and processing	2.43	4.36	4.45
25	Fabricated metal products	17.76	8.32	8.22
26	Computer, electronic and optical products	4.33	5.41	5.39
27	Electrical equipment	4.96	5.32	5.37
28	Machine manufacturing	13.99	8.87	9.15
29	Motor vehicles	3.01	4.69	4.74
30	Other transport equipment	0.73	1.74	1.67
31	Furniture	2.33	3.03	2.99
32	Other manufacturing	3.77	4.14	4.09
33	Repair and installation of machinery and equipment	4.7	3.88	3.53
	Total number of plants	44,853	9,061	8,330

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

Overall, our estimation sample is similar to the complete Manufacturing Census with respect to sector composition, even though some subsectors show larger deviations. Despite the fact that the estimation sample contains less than 20 % of manufacturing plants from the Manufacturing Census, it covers 30-50 % of the Census' full-time equivalents, employees, energy consumption and electricity consumption, indicating that large plants are overrepresented in the estimation sample. Still, as can be seen in Figure 6, our study captures a lot of small manufacturing plants that have not been part of previous analyses.[18]

Table 3 contains summary statistics on calculated average network charges, electricity consumption and electricity procurement for the estimation sample. 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 too 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 that range between 4.99-5.85 and 1.43-2.06 cents per kWh in the time period from 2009 to 2017, respectively.

Table 3: Summary statistics of key variables in 2016 (top panel) and 2010 (bottom panel)

	energy use (MW)	**electricity use (MW)**	**employees**	**average network charges (Ct/kWh)**
2016				
p10	317	140	31	1.55
p50	2,742	1,375	109	2.60
mean	50,000	13,600	295	3.11
p90	42,200	19,100	559	5.37
N	8,875	8,875	9,009	
2010				
p10	291	135	29	1.06
p50	2,438	1,245	96	2.05
mean	43,100	12,500	257	2.36
p90	38,400	17,500	502	4.31
N	9,791	9,791	9,922	

[18]Figure 10 in the Appendix displays the according histogram for the full sample for comparison.

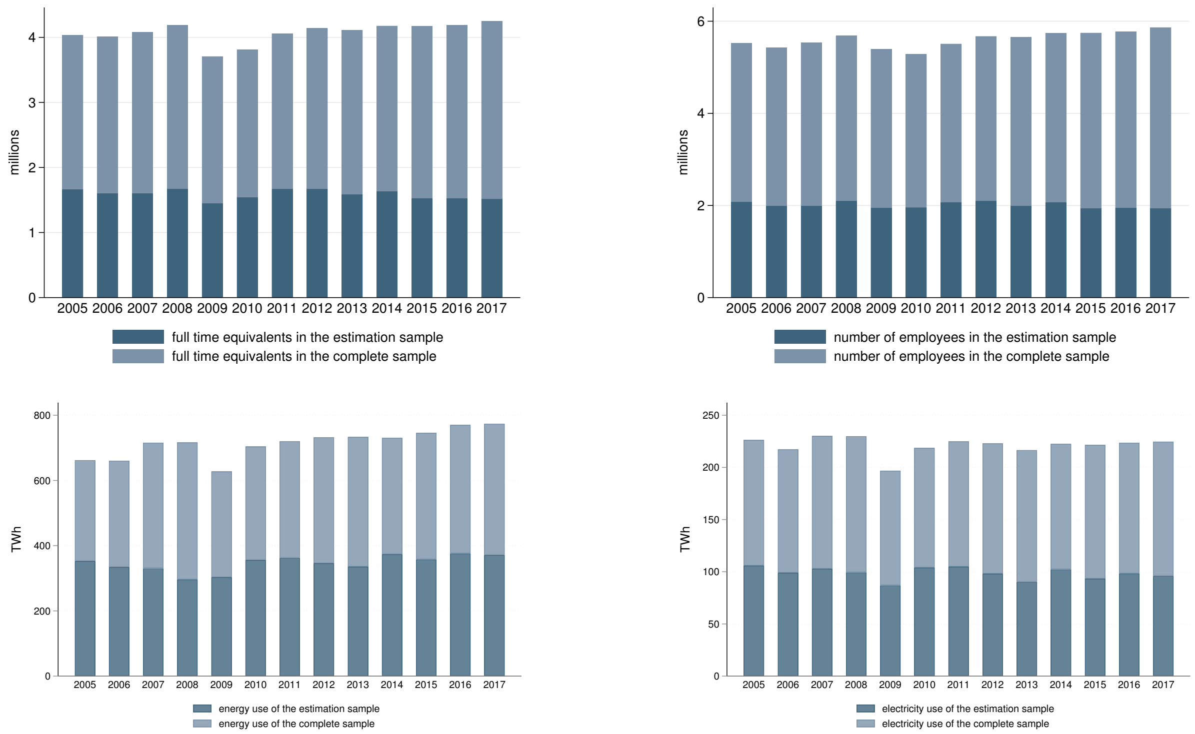


Figure 5: Coverage of key variables of the estimation sample as compared to the full Manufacturing Census

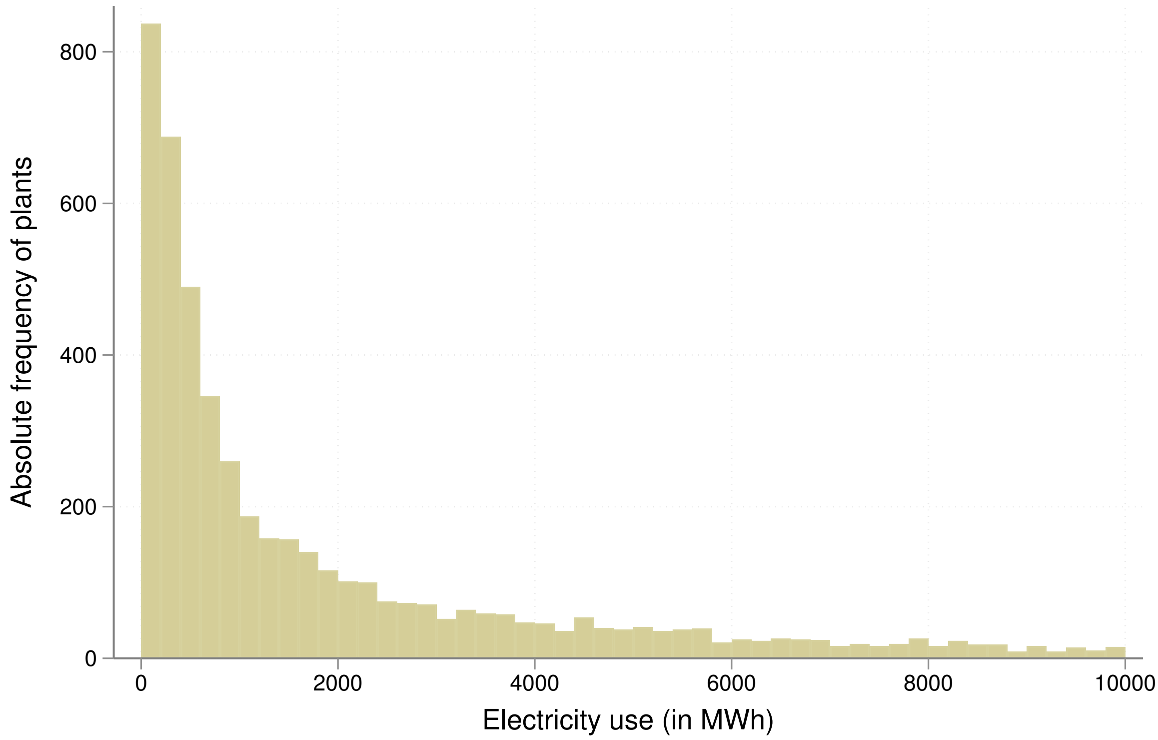


Figure 6: Distribution of manufacturing plants in the estimation sample with respect to their electricity consumption in 2017

In the Appendix, 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 9 and 11). Calculated network charges account for 10-18 % of total electricity expenditures for single-plant firms between 25th and 75th percentile of the distribution in our sample. This fares well with the statistics from Eurostat displayed in Figure 1. Running within-firm regressions of electricity expenditures on total network charges (controlling for year fixed effects and RES exemptions), we find evidence that increases in network charges are associated with statistically significantly rising electricity expenditures.

Table 4 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 4: Number of manufacturing plants assigned to different tariff groups and voltage levels in 2016

Voltage level	**Tariff group**	**Number**
Low	SLP	740
Low	RLM 1	487
Low	RLM 2	1,137
Low to medium	RLM 1	963
Low to medium	RLM 2	1,430
Medium	RLM 1	753
Medium	RLM 2	2,862
Medium to high	RLM 1	16
Medium to high	RLM 2	128
High	RLM 1	57
High	RLM 2	480

Source: 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).

5 Results

5.1 The effects of network charges

Table 5 summarizes the results on the effects of average network charges on electricity usage and different competitiveness indicators, obtained by estimating equations 1 to 3. Panel A contains short-run effects from the panel regression, panel B shows results from the long-differences design, while panel C decomposes long-differences effects into a change in network charges and a change in the elasticity of response. The different columns show results on various dependent variables.

Table 5: The effects of average network charges on German manufacturing plants

	Electricity procurement	**Hours worked**	**Revenues**	**Investments**	**Capital stocks**
	(1)	(2)	(3)	(4)	(5)
	Panel A: panel regression				
Average network charges	-0.033***	0.011**	0.004	-0.004	-0.001
	(0.011)	(0.005)	(0.005)	(0.021)	(0.007)
N	57,382	42,899	56,360	52,084	56,863
number plants	7,626	5,975	7,523	7,404	7,597
R^2	0.084	0.150	0.180	0.055	0.091
	Panel B: long-differences				
Delta network charges	-0.012	0.023***	0.012	0.005	-0.005
	(0.011)	(0.009)	(0.008)	(0.032)	(0.010)
N	5,682	4,239	5,576	5,174	5,600
number plants	5,682	4,239	5,576	5,174	5,600
R^2	0.062	0.092	0.096	0.054	0.080
	Panel C: long-differences extended				
Delta network charges (β_{t1})	-0.022*	0.017*	0.012	0.033	0.002
	(0.011)	(0.009)	(0.008)	(0.034)	(0.011)
Lagged network charges ($\Delta\beta$)	0.023***	0.009	0.002	-0.059**	-0.015**
	(0.006)	(0.006)	(0.005)	(0.023)	(0.006)
Implied β_{t0}	-0.045***	0.008	0.010	0.092*	0.017
	(0.014)	(0.013)	(0.011)	(0.047)	(0.014)
N	5,682	4,239	5,576	5,174	5,600
number plants	5,682	4,239	5,576	5,174	5,600
R^2	0.065	0.093	0.096	0.056	0.080

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. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

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 in the short-run. A one cent increase in average network charges on average reduces manufacturing plants' electricity procurement by 3.3 percent in the short-run.[19] 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 %.[20] Assuming that manufacturing plants respond in the same way to electricity price 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 (2020) 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.[21]

Panel B in contrast depicts the effects estimated from the long-differences design as specified in equation 2. In long-differences, we identify negative, but insignificant effects of average network charges on electricity procurement. One potential explanation for the smaller effects compared to the short-run estimates could lie in a decrease in manufacturing plants' responsiveness to electricity price changes. As discussed in Burke and Emerick (2016), panel estimates will be larger than long-differences estimates if a decline in responsiveness occurs towards the end of the panel.

[19]Note that this effect actually constitutes an average of the effects of a given price shock over multiple periods. Figure 11 in the Appendix 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.

[20]Table 10 in the Appendix 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.

[21]Note that reassuringly, the RES exemption studied by Gerster and Lamp (2020), 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 (2020).

The results in Panel C on the decomposition into changing network charges and changing elasticity of response are in line with the elasticity of response decreasing over time, and provide an additional explanation for the insignificant long-differences effects in Panel B. The elasticity of response towards rising network charges 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. The fact that base period network charges and the change in network charges are positively correlated (i.e., absolute increases in network charges tend to be stronger for plants with already high network charges in 2010/2011, with a correlation coefficient of roughly 0.3) means that omitting base period network charges in the pure long-differences design will result in estimates being biased towards zero.

Point estimates suggest that a one cent increase in average network charges lead to a decrease in electricity procurement of approximately 4.5 % on average in 2010/2011, but only of 2.3 % in 2016/2017. The implied own-price elasticity hence is decreasing from -0.7 – -0.9 to -0.3 – -0.5. Relating back to the conceptual framework presented in Section 3, this result would be in line with marginal abatement costs increasing more than linearly, so that manufacturing plants are requiring larger increases in electricity prices to take the next abatement step than they did in earlier years. Note however that while the coefficient on base year network charges is statistically significant, the implied elasticities at base and end period are not statistically different from each other so that this evidence should be taken as suggestive.[22]

The three different specifications show that rising network charges – and in extension rising electricity prices – lead manufacturing plants to reduce their electricity procurement substantially. In contrast, we find no significant effect of network charges on revenues in any of the specifications. This finding in itself doesn't rule out a potential adverse effect of electricity prices on output: Manufacturing plants could reduce output and at the same time increase prices such that revenues remain unaffected. Hintermann *et al.* (2020) indeed find evidence for German manufacturing plants passing on energy costs to their customers (even though pass-through is incomplete). However, we also generally do

[22]Running the panel regression from equation 1 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 13 in the Appendix.

not find significant negative effects of network charges on hours worked as a measure of employment.[23] On the contrary, effects tend to be significantly positive. Together, those results suggest that electricity price increases in the order of magnitude of past changes in network charges do not lead to negative competitiveness effects. There is no strong evidence that manufacturing plants reduce electricity use in response to rising prices by reducing output.

The evidence with regard to investments and capital stock is mixed. In the short run we find no statistically or economically significant effects of network charges (panel A, columns (4) and (5)). However, the extended long-run estimates (panel C) suggest a sizeable positive impact on investments in the beginning of the period, though this coefficient is only significant at the 10 %-level. For the capital stock there is also some evidence that responsiveness (β) has declined, but the coefficients from the early and late period (though positive) are not statistically significant at conventional levels.

5.2 Discussion of potential channels

The fact that rising electricity prices lead to a response with respect to electricity procurement, but not competitiveness indicators is broadly in line with previous research. Gerster and Lamp (2020) too find significant effects of the RES exemption on electricity usage in German manufacturing, but generally not on competitiveness indicators. Lehr *et al.* (2020) find no negative effects of the EU ETS on the competitiveness of German manufacturing firms. Still, the question remains how the reduction in electricity procurement we find is achieved, if there are neither indications for a decrease in output nor for an increase in investments. In this section, we analyse three potential channels by which electricity procurement might be reduced, specifically the redirection of investments towards electricity efficiency, the substitution of electricity procurement by onsite generation, and within-firm leakage effects.

While we find insignificant effects of network charges on the total sum invested by manufacturing plants, rising electricity prices could induce manufacturing plants to redirect their investments towards more electricity efficiency. Table 6 shows the sum invested by

[23] We look at hours worked instead of the number of employees since this variable exhibits more variation. Labour laws in Germany render it difficult to lay off employees in the short-run while it is potentially easier to reduce working hours.

our estimation sample into machinery in general and energy efficiency specifically. Investments in energy efficiency include, e.g., the installation of heat pumps, heat exchangers for heat recovery, CHP, efficient grids, thermal insulation or new, more environmentally friendly heating technologies. Note that most of these relate rather to heat generation and use, but could also have important implications for electricity use (through e.g. CHP or grids). At the plant-level, investments into energy efficiency are extremely lumpy and do not lend themselves for an analysis in a regression framework which is why we resort to the indicative summary statistics shown in Table 6.

Table 6: Sum of investments by the estimation sample into machinery and energy efficiency

Year	Sum Investments (Machinery)	Sum Investments (Energy Efficiency)	Mean Investments (Machinery)	Mean Investments (Energy Efficiency)	Number of observations (Total)	Number of observations (Energy Efficiency)
2009	17.8	0.162	2,462	363	7,229	446
2010	19.9	0.140	2,795	270	7,124	518
2011	24.0	0.241	3,407	394	7,051	612
2012	24.0	0.272	3,526	434	6,817	626
2013	21.8	0.227	3,280	317	6,654	717
2014	22.9	0.243	3,569	310	6,404	783
2015	20.8	0.297	3,377	349	6,155	851
2016	22.7	0.294	3,823	358	5,939	821
2017	23.0	0.234	3,974	284	5,776	825

Notes: Only for plants in the estimation sample. Values in billion (except for mean investments which are in thousands) EUR at deflated 2015 EURs.

The sum invested by our sample into energy efficiency has increased quite substantially over time – despite the fact that the estimation sample is getting smaller. In contrast, average sums invested into energy efficiency – conditional on conducting such investments – do not exhibit such a clear trend. The increase in investments results from an extensive margin effect: There is a growing number of manufacturing plants investing into energy efficiency. If such types of investments are induced by rising electricity prices, this could be an explanation for the reductions in electricity usage we observe. Note however that the table also shows a general increase in investments into machinery in our estimation sample. Average investments into machinery are also growing. To the extent that new capital stock is more efficient than old capital stock, this may also be a channel through which plants reduce electricity use by replacing old capital stock sooner when network charges increase.

A further explanation for the reduction in electricity procurement in response to rising network charges may lie in onsite generation. von Graevenitz and Rottner (2020) document an increase of 50 % in the amount of electricity generated onsite from 2005 to 2014 in German industry. Rising network charges could play a role in that development since electricity generated onsite is largely exempt from network charges. We test empirically whether manufacturing plants that are generating their own electricity at some point (roughly 1,300 in our sample) respond differently to rising network charges than other industrial users. Results from a panel regression including an interaction of network charges with an indicator for onsite-generating plants are reported in Table 7. Indeed, we find manufacturing plants with own electricity generation responding to rising electricity prices more strongly with respect to their electricity procurement. At the same time, they reduce electricity consumption (i.e., procurement plus self-generated electricity) by less as compared to other industrial consumers. This suggests that indeed, rising electricity prices induce manufacturing plants to replace electricity bought from the grid with electricity generated onsite.

Table 7: Effect heterogeneities: Self-generators and multi-plant firms

	Electricity procurement		**Electricity consumption**	
	(1)	(2)	(3)	(4)
Average network charges	-0.019*	-0.065***	-0.036***	-0.071***
	(0.012)	(0.020)	(0.011)	(0.020)
Network charges*self-generator	-0.076***		0.022**	
	(0.013)		(0.010)	
Network charges*single-plant firm		0.041**		0.048***
		(0.017)		(0.017)
Implied aggregate effect	-0.095***	-0.025**	-0.014	-0.023**
	(0.014)	(0.010)	(0.011)	(0.009)
N	57,074	57,074	57,074	57,074
number plants	7,396	7,396	7,396	7,396
R^2	0.006	0.004	0.003	0.004

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. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

Table 7 also shows effect heterogeneities across single- and multi-plant firms. Multi-plant firms that have production sites in different grid areas of Germany are able to shift production and electricity procurement across plants. This adjustment possibility to rising electricity prices is not available to single-plant firms. In fact, we find that single-plant firms respond less strongly to rising network charges as compared to multi-plant firms which could indicate production shifting within firm. Note however that the stronger response of multi-plant firms is purely descriptive in nature and not to be interpreted in a causal way. The differing effects are not necessarily grounded in within-firm shifts and could also result from structural differences between single- and multi-plant firms.

These three channels – investments into electricity efficiency, onsite electricity generation, and within-firm leakage – are three potential explanations for the reductions in electricity procurement caused by rising network charges. There is some suggestive evidence for each of them. The list of potential channels however goes on: Manufacturing plants, e.g., could also be induced by rising electricity prices to switch the products they produce. Abeberese (2017) finds evidence for electricity prices inducing product switching in Indian manufacturing. As for Germany, in a statistical decomposition Rottner and von Graevenitz (2021) present descriptive evidence that manufacturing is shifting towards a less emission intensive production composition from 2011 onwards. Since, due to conversion and transportation losses, electricity is a very emission intensive energy carrier, this could be equivalent to a switch to less electricity intensive goods and also explain the patterns we observe. Another explanation could lie in manufacturing plants outsourcing the production of electricity intensive intermediate inputs. Lastly, the abatement options mentioned in Löschel *et al.* (2017), and in particular management practices like target setting or regular efficiency improvement assessments could play a role. The extent to which such practices are induced by rising network charges is beyond the scope of this paper.

5.3 Effect heterogeneities

Manufacturing is very heterogeneous. Subsectors differ strongly in their production processes, the associated energy and electricity intensities, and arguably in consequence also in their MACCs. These differences are also reflected in the responsiveness towards rising network charges, as shown in Table 8.

The Table shows results from running equation 1 separately for different 2-digit sectors.[24]

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

Table 8: Sector-level results of the main specification

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.

Results on electricity procurement appear to be mostly driven by the other non-metallic mineral products and the electrical equipment industries. Point estimates in most subsectors are negative however, and the insignificant effects could also stem from low power due to smaller samples.

Interestingly, however, the sectors for which we can identify significant negative effects on electricity procurement are not the ones for which we find significant effects on revenues or hours worked.[25] While results for the manufacturing sector as a whole might hide important heterogeneity, the sector-level results do not indicate reductions in electricity procurement in response to rising network charges coming at the expense of a reduction in output. On the contrary, network charges tend to have significant positive effects on labour input (in the textiles, printing and engineering industries). We also find a positive effect of network charges on revenues in the chemical industry which might hint at the occurrence of cost pass-through. Only in the pulp & paper and in the metal product sectors, do we find evidence of significant negative effects of network charges on revenues (without identifying effects on electricity procurement or consumption, though). Overall, the results underline the importance of taking into account the heterogeneity of different industrial users in assessing the effects of electricity prices.

5.4 Robustness

We test the robustness of our estimates in several ways. First, we run regressions in less demanding specifications by reducing the set of fixed effects included. Specifically, we use broader break-downs for the sector time trends on the three- or two-digit level. Results are virtually unchanged.

Conversely, we check for robustness by adding additional fixed effects: Controlling for tariff group- and voltage level-specific time trend does not substantially alter results.

Adding federal state time trends into the regression increases the estimated effects slightly (both the panel and the long-differences ones), but does not affect their significance.

Next, we change the sample underlying the regressions by dropping all plants which at some point are located in areas with an ambiguous network assignment (instead of just

[25]Results on dependent variables other than electricity procurement at the sector-level are available from the authors upon request.

dropping them in the specific years where assignment is unclear). This neither affects panel- nor long-differences results.

Conversely, we try expanding our sample to include all manufacturing plants that are always located in ambiguous network areas. For these plants, we calculate an average of the network tariffs charged by the DSOs in that area. While this induces some additional measurement error, it alleviates concerns about the sample composition in case the ambiguous network areas (among them, many cities) differ structurally from the areas we include in our main specification. With this sample we cover 80 % of electricity used in manufacturing and 60 % of the full-time equivalents. These analyses lead to the same conclusions.

Moreover, to ensure our panel results do not confound intensive with extensive margin effects (e.g., because network charges lead to plants completely closing down), we run regressions on a sample of manufacturing plants that appears in the data both in 2009 and 2017. The results barely change.

Lastly, we alter our sample by including all manufacturing plants with an electricity procurement always below 100 MW. For these SLP plants, there is no differentiation in network tariffs according to their operating hours. Therefore, we can use the whole universe of small manufacturing plants, instead of the stratified sample for which information on shift work is available. While the effects differ quantitatively and tend to be larger, they qualitatively remain identical. The exact estimation results are reported in Tables 14, 15 and 16 in the Appendix.

6 Conclusion and Discussion

Climate policies like the European Union Emission Trading Scheme 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 changes in exogenous variation in electricity prices using a unique combination of administrative micro-level data and information on electricity network charges. Causal effects are obtained through the use of panel-estimation as well as long-differences designs.

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. Evidence is suggestive that manufacturing's responsiveness towards rising electricity prices declines over the period from 2009 to 2017. This is in line with marginal abatement costs increasing more than linearly such that larger price increases are necessary to induce the same absolute abatement response, but it is also in line with firms responding to overinvestments in abatement as realized electricity price increases were lower than anticipated.

While manufacturing plants respond to the price signal induced by network charges with respect to their electricity consumption, we generally find no significant negative responses on revenues and employment as competitiveness indicators. Evidence of positive effects investments and capital stocks is weak. In this regard, our paper mirrors the findings from Gerster and Lamp (2020) and Lehr *et al.* (2020) on the direct effects of the RES and the EU ETS. Hence, also among the smaller, less electricity intensive industrial users which are not directly subject to different climate policy (exemptions), we find no adverse effects on competitiveness.

It is however noteworthy that the results display a large degree of heterogeneity: Different subsectors of manufacturing respond differently to changing network charges. While we cannot identify negative employment effects in any subsector, there is some evidence of revenues decreasing in the paper and metal products industries in response to rising network charges – while the effect goes in the opposite direction in the case of the chemicals sector, potentially due to cost pass-through. Policies aiming at protecting industries exposed to high electricity costs like the indirect cost compensation under the EU ETS, under which the chemicals industry receives large compensation shares in Germany, therefore should be especially targeted to limit the costs of climate policies.

We also find evidence that rising electricity prices in Germany have contributed to increase onsite generation in manufacturing. The consequence of this trend on carbon emissions is not clear and depends on the fuels used for self-generation, the size of transmission losses avoided, and the coverage of industrial electricity generation under the EU ETS. We leave analysis of these aspects for future work.

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7 Appendix

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 7). 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 8.

The G-function needs to satisfy the following properties:

- It has a kink at 2,500 hours of use of the grid.

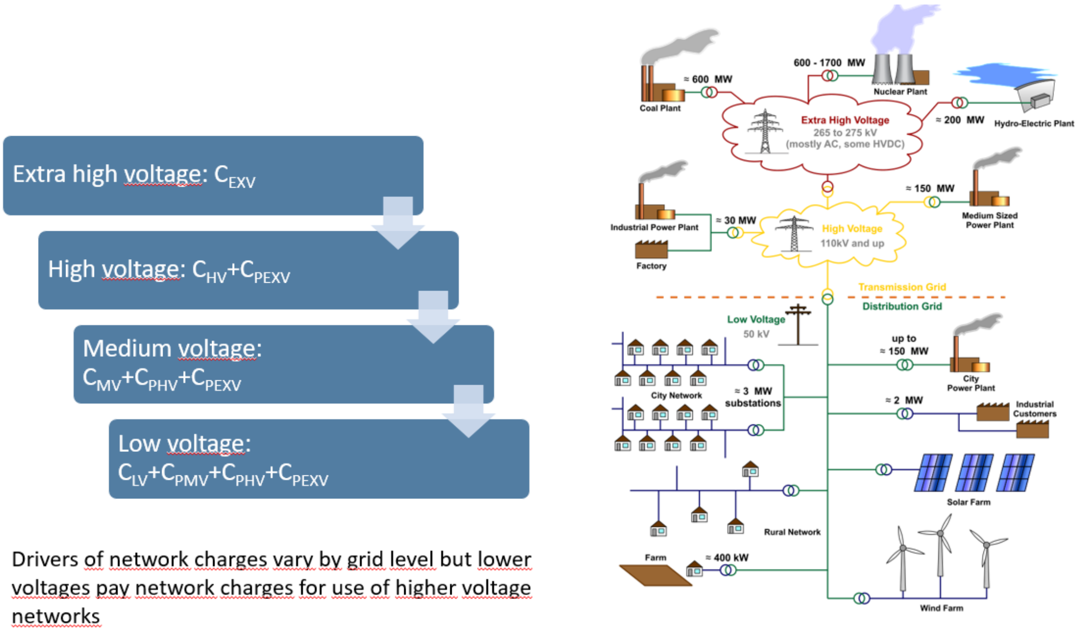


Figure 7: The structure of network charges

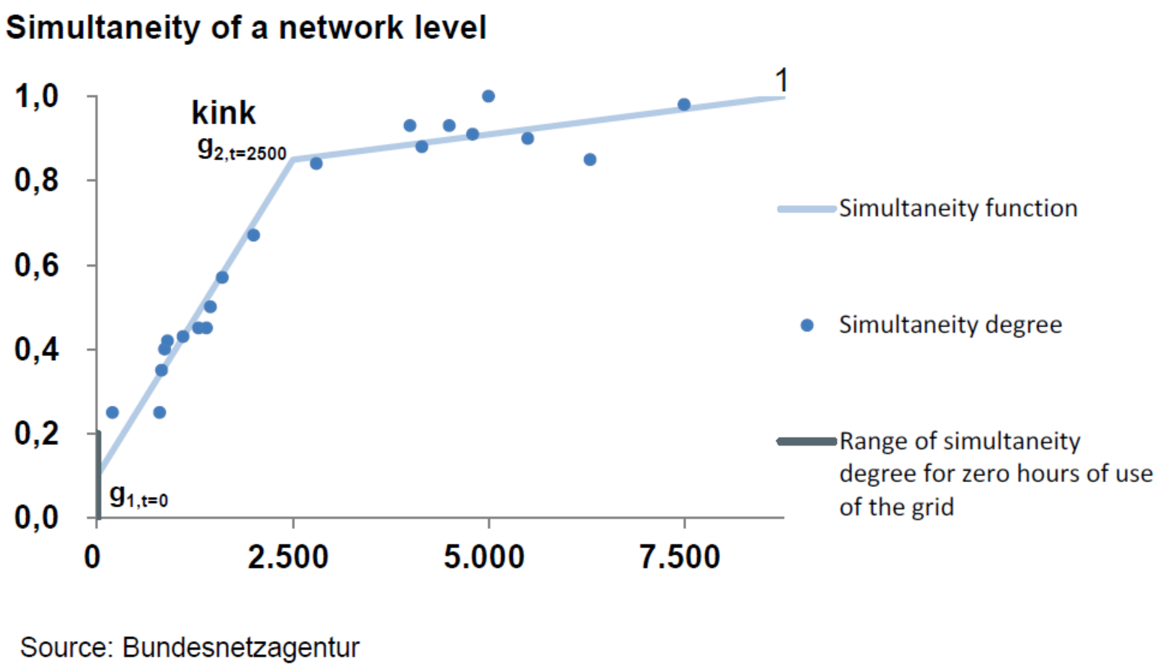


Figure 8: The simultaneity function

- 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.

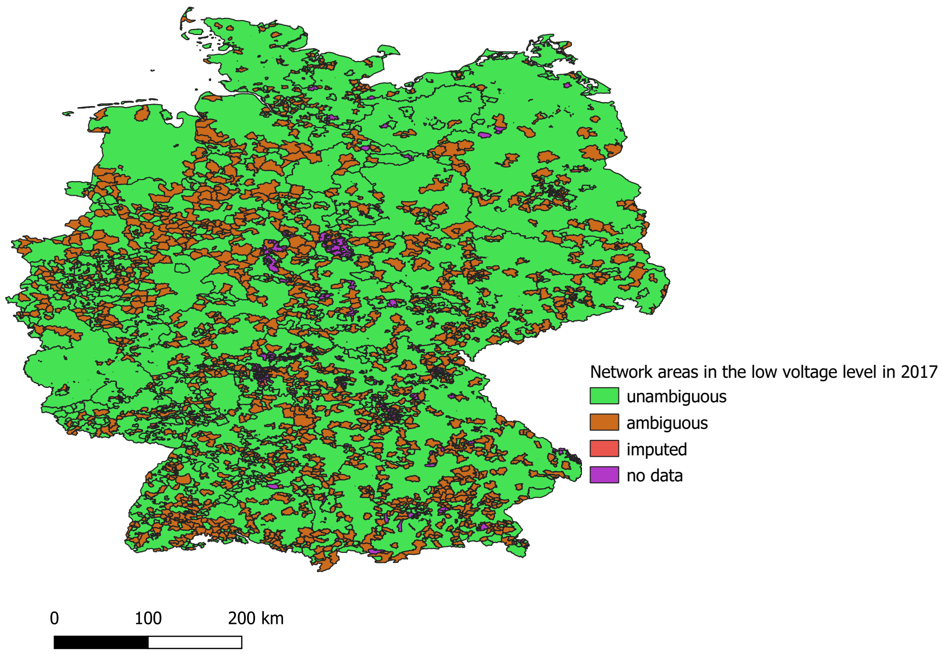
Second, the fact that many manufacturing plants pay network charges directly to their DSO (RLM customers by default, SLP customers if they opt in) suggests that network charges are indeed sufficiently salient to induce manufacturing plants to adjust. Contrary to e.g. households for whom network charges 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.

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). 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.

Unique and ambiguous network areas



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

Figure 9: Unique assignment of low voltage level network areas to municipalities in 2017

Distribution of manufacturing plants with respect to their electricity consumption

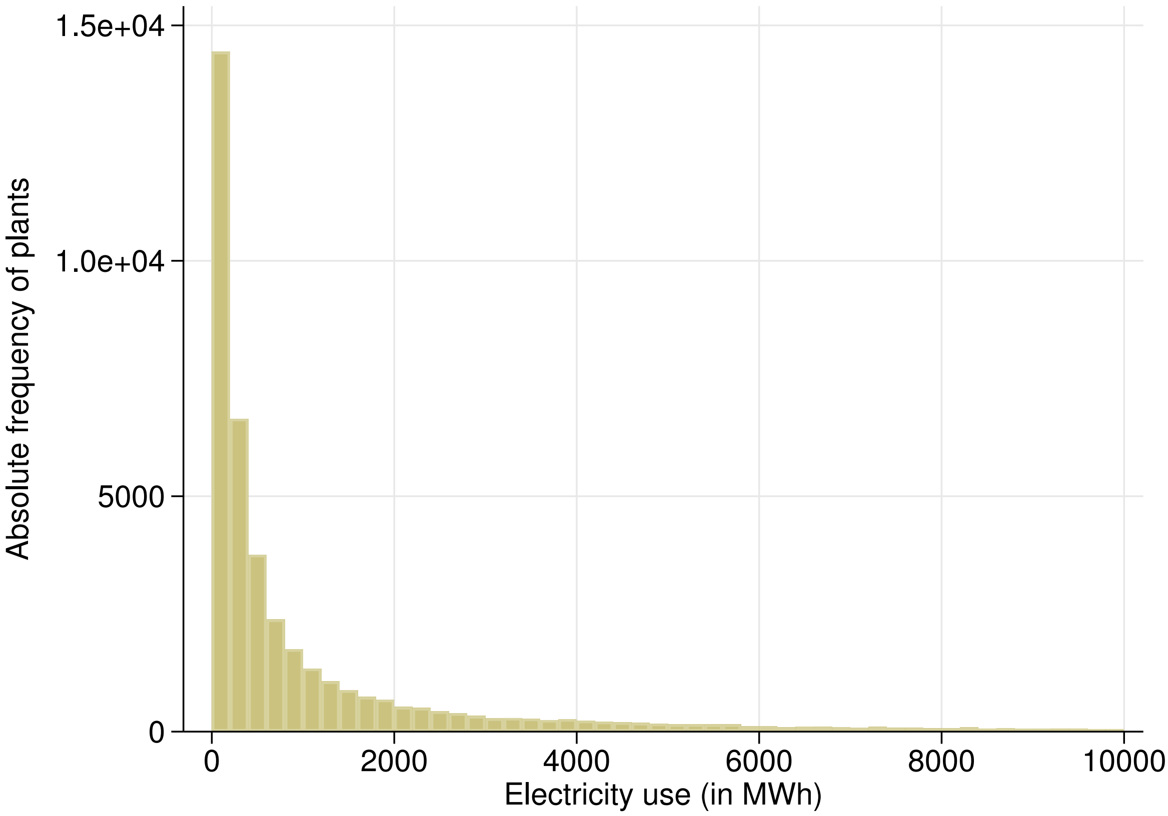


Figure 10: Distribution of manufacturing plants in the full sample with respect to their electricity consumption in 2017

Calculating average network charges

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 1) 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 fixed price component for RLM customers are approximated by the same procedure. However, for this purpose, we calculate time-varying peak loads, i.e. based on annual electricity procurement.

Electricity costs and electricity expenditures in the estimation sample

Table 9: The effects of network charges on electricity expenditures

Electricity expenditures	**Total network charges**	**BesAR**	**year=2014**
	0.507***	-729,094***	103,608*
	(0.090)	(242,463)	(61,775)
N	5,481		
number plants	4,176		
R^2	0.032		

Notes: The table depicts results from a regression of single-plant firms' electricity expenditures on their 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.

Table 10: 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	10.59	9.27
p50	16.94	12.71
mean	20.32	26.84
p90	24.39	19.66
N	3,033	3,339

Table 11: 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

Distributed lag model

Figure 11 shows event-study results from estimating the following distributed lag model:

$$\begin{aligned} y_{it} = \beta_t \times avgnc_{ijt} + \beta_{t-1} \times avgnc_{ijt-1} + \beta_{t-2} \times avgnc_{ijt-2} + \beta_{t-3} \times avgnc_{ijt-3} \\ + \pi_{st} + \mu_i + RES_{it} + \tau \times CT_{ijt} + \epsilon_{ijst} \end{aligned} \tag{4}$$

The displayed numbers are obtained by summing up current and lagged effects, as described in Schmidheiny and Siegloch (2020). 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.

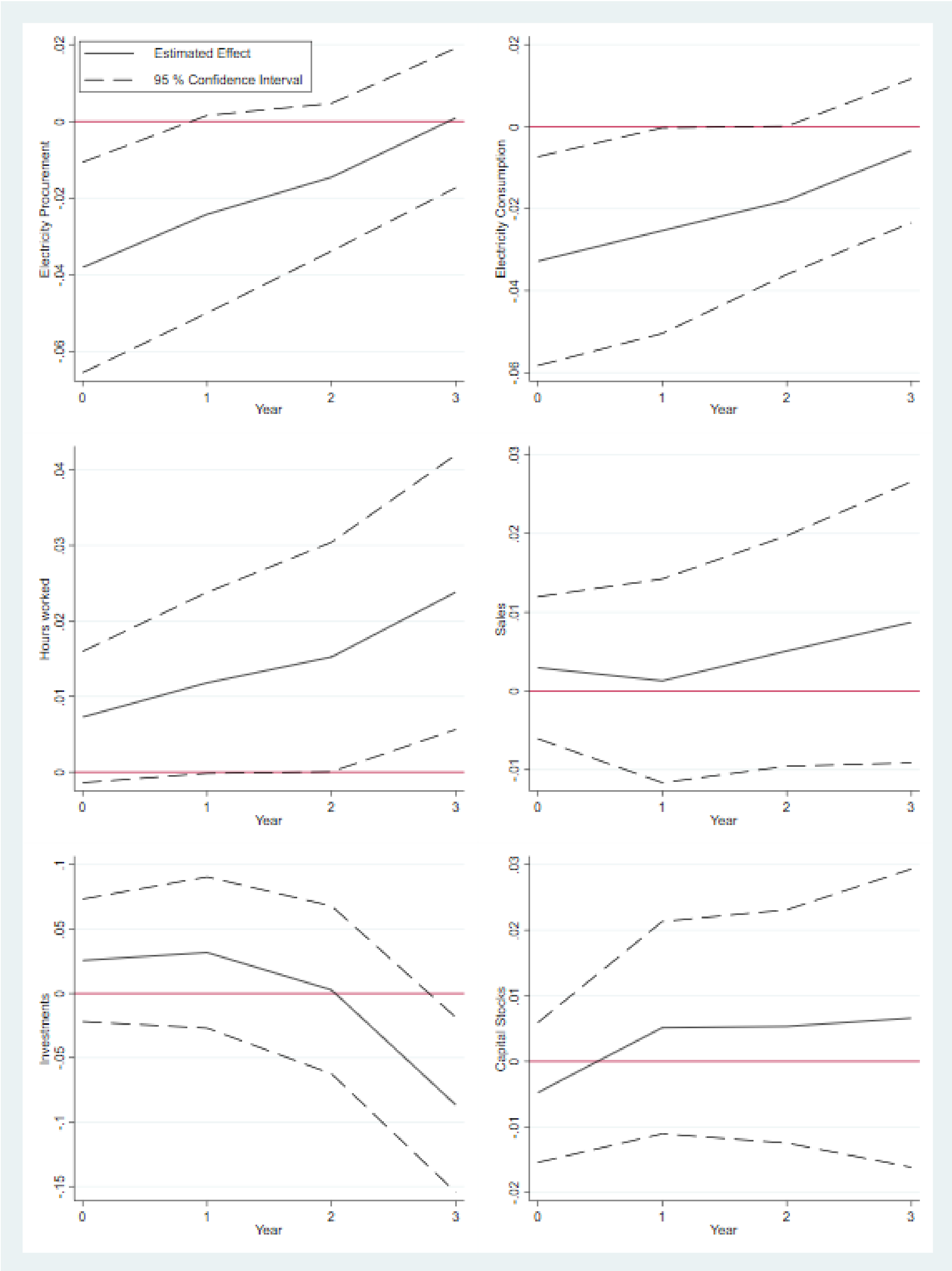


Figure 11: Distributed lag model

Marginal prices

Table 12: 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
R^2	0.083	0.103	0.090	0.111

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.

Effects in different regulatory periods

Table 13: 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
R^2	0.003	0.003

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.

Robustness checks

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

Electricity procurement								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Average network charges	-0.027**	-0.031***	-0.041***	-0.036***	-0.036***	-0.033***	-0.032***	-0.063***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)	(0.010)	(0.012)	(0.012)
RES	0.033**	0.049**	0.077***	0.053***	0.047**	0.047***	0.051**	0.053***
	(0.017)	(0.019)	(0.021)	(0.020)	(0.021)	(0.017)	(0.022)	(0.020)
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)
N	57,382	57,382	57,382	57,074	49,696	72,428	52,376	75,170
number plants	7,626	7,626	7,626	7,396	6,009	9,531	6,510	10,347
R^2	0.026	0.047	0.089	0.002	0.092	0.073	0.094	0.071

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.

Table 15: Long-run effects of average network charges on electricity procurement and consumption

Electricity procurement								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Delta Average network charges	-0.005	-0.011	-0.024*	-0.013	-0.010	-0.019	-0.017	-0.027***
	(0.011)	(0.011)	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)
Delta RES	0.023	0.041	0.095***	0.049	0.047	0.045	0.043	0.049
	(0.029)	(0.031)	(0.033)	(0.031)	(0.032)	(0.033)	(0.027)	(0.031)
Delta 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)
N	5,682	5,678	5,670	5,682	5,690	5,161	7,206	7,217
number plants	5,682	5,678	5,670	5,682	5,690	5,161	7,206	7,217
R^2	0.011	0.050	0.071	0.070	0.062	0.065	0.050	0.049

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 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.

Table 16: 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
R^2	0.016	0.034	0.071	0.070	0.063	0.068	0.051	0.051

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 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.

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