RUHR ECONOMIC PAPERS

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Do Electricity Prices Matter? Plant-Level Evidence from German Manufacturing

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#672

Imprint

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

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Editors

Editorial Office

Ruhr Economic Papers #672

Responsible Editor: Manuel Frondel

ISSN 1864-4872 (online) – ISBN 978-3-86788-779-3

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Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

Das RWI wird vom Bund und vom Land Nordrhein-Westfalen gefördert.

http://dx.doi.org/10.4419/86788779
ISSN 1864-4872 (online)
ISBN 978-3-86788-779-3

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Do Electricity Prices Matter? Plant-Level Evidence from German Manufacturing

Abstract

In many countries, the transition process towards a low-carbon economy has been associated with increasing electricity prices. Microeconometric evaluations of the causal impact of electricity price changes on plant-level outcomes are rare, though. By exploiting local randomization induced by thresholds in exemption rules, we estimate the local average treatment effects of electricity levy exemptions using a fuzzy regression discontinuity (RD) design. The results indicate that exempted German manufacturing plants increase electricity use substantially and substitute it for fossil fuels, while we do not find evidence for short-run effects on gross output, exports and employment.

JEL Classification: D22, H23, L60, Q41, Q48

Keywords: Environmental taxation; electricity prices; manufacturing; regression discontinuity design

January 2017

1 Andreas Gerster, RWI and RGS Econ. *– I am grateful for invaluable comments and suggestions by Mark Andor, Sebastian Petrick, Colin Vance, and, in particular, Manuel Frondel, as well as by participants of the 30th Annual Congress of the European Economic Association in Mannheim, Germany, the 8th Annual Workshop on Empirical Methods in Energy Economics in Maryland, USA, the 6th Atlantic Workshop on Energy and Environmental Economics in A Toxa, Spain, the 8th RGS Doctoral Conference at University Duisburg-Essen, Germany, and the 14th European Conference of the International Association for Energy Economics in Rome, Italy.* *– All correspondence to: Andreas Gerster, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: gerster@rwi-essen.de*

1. Introduction

To accelerate the transition process towards a low-carbon economy, many countries have employed energy taxes and levies. In Germany, for example, subsidies for renewable electricity generation technologies are financed through the so-called EEG levy, a surcharge on electricity prices that has sharply increased from 0.19 cent per kilowatthour (kWh) in 2000 to 6.24 cent per kWh in 2014. Whether higher electricity prices foster the energy efficiency of plants or rather induce job losses and drops in domestic production levels is at the center of a vivid political debate (OECD 2001, OECD 2010).

Using an administrative data set that captures the universe of German manufacturing plants, this paper investigates the causal effects of EEG levy exemptions on the energy use and the competitiveness of the manufacturing industry. Our empirical strategy exploits the fact that plants are only eligible for exemptions when, two years earlier, their electricity use exceeded a threshold of 10 GWh. We analyze exemptions in 2010 and 2011 that were made possible by sufficiently large electricity uses in 2008 and 2009, when the financial crisis prevented plants from strategically selecting on either side of the eligibility threshold, and identify causal effects using a fuzzy regression discontinuity (RD) design.

Ex-post evaluations based on microdata that investigate the effects of environmental taxation on the manufacturing industry are scarce, despite their high policy relevance. As one of several rare examples, Martin et al. (2014) find that the introduction of carbon taxes on a variety of energy sources in Great Britain decreased firms' electricity use and their energy intensity of production. Investigating the effects of carbon pricing on German manufacturing, Petrick and Wagner (2014) conclude that the European Emissions Trading System was effective to curb CO_2 emissions, while leaving firms' gross output, employment or exports unaffected.

Our results demonstrate that exempted plants increase their electricity use substantially and substitute it for fossil fuels, such as natural gas and oil. Because the carbon emisison factor of electricity in Germany exceeds those of natural gas and oil, we find evidence of an increase in the overall carbon intensity of the plants' energy mix. Furthermore, we cannot detect any effect of reduced electricity prices on the competitiveness of plants in the manufacturing industry, as measured by gross output, the export share and employment.

The remainder of the paper is structured as follows. Section 2 describes the institutional background and the data set. Section 3 presents the empirical strategy, while Section 4 discusses the estimation results and robustness checks. Section 5 summarizes and concludes.

2. Institutional background and data

In 2000, the Renewable Energy Sources Act (Erneuerbare-Energien-Gesetz, EEG) established one of the world's most ambitious renewable energies support regime in Germany. It obliges transmission system operators to pay fixed feed-in tariffs to producers of "green electricity" and to pass on their additional cost to household and business customers by charging a per kWh levy on electricity.

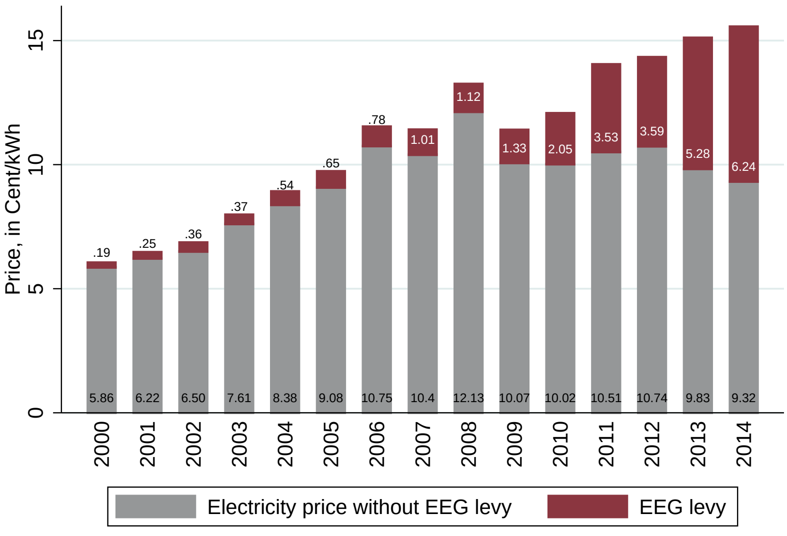
Figure 1 displays average industry electricity prices for plants with annual electricity uses between 160 megawatthours (MWh) and 200 gigawatthours (GWh), highlighting the contribution of the EEG levy. It demonstrates that the EEG levy has increased substantially from 0.19 cent per kWh initially to 6.24 cent per kWh in 2014, paralleling the development of renewable energies during that time span. In relative terms, the levy accounted for only about 3% of electricity prices in 2000, reaching more than 40% by 2014.

In response to rising concerns about adverse impacts of rising electricity prices on the competitiveness of the German industry, the EEG was modified in 2003 to allow for exemptions from the levy for energy-intensive plants of the manufacturing, mining and railway sector. The eligibility for an exemption is based on two cutoff rules: first, the electricity use of a plant has to exceed 10 GWh in the previous business year and, second, the ratio of electricity cost to gross value added at the firm level has to be larger than 15%.[1]

To apply for exemptions, electricity contracts and bills from the previous year, as well as a calculation of gross value added, have to be confirmed by a certified accountant and then be sent to the Federal Office for Economic Affairs and Export Control (Bundesamt für Wirtschaft und Ausfuhrkontrolle, BAFA). The BAFA decides upon exemptions for the following year and thus introduces a time lag of two years between the time period that determines a plant's eligibililty and an exemption. Exempted plants pay a drastically reduced EEG levy of 0.05 cent per kWh for all of the plant's electricity use exceeding 10% of the baseline use that determines eligibility. If electricity use is above 100 GWh and the ration of electricity cost to gross value added exceeds 20%, an exemption applies for the entire electricity use.

[1] Furthermore, firms have to document that they operate a certified energy management system. This is not a strict requirement, however, as firms can resort to a simplified procedure that only requires them to judge possible energy savings for all energy consuming sites. In 2012, 84% of all firms took that option (BAFA, 2014).

Figure 1: Average Industry Electricity Prices in Germany



Notes: Average industry electricity prices (including taxes) in Germany for plants with an annual electricity use between 160 MWh and 200 GWh (BDEW, 2014).

We employ data from the AFiD (Amtliche Firmendaten in Deutschland) panel, which is an extensive administrative data set on firm- and plant-level outcomes collected by the statistical offices of the German federal states and only accessible under strict confidentiality rules. It covers the the entirety of German plants from the manufacturing and industry sector, excluding only plants with less than 20 employees. Because electricity from own-generation facilities is not subject to the levy, our analysis focusses solely on plants without own-generation facilities.

The data set contains a variety of plant-level characteristics, such as their gross output, exports, and the number of employees. It also comprises detailed information on a plant's energy use for various energy sources, most notably electricity, which allows to observe whether the first eligibility criterion is met. Based on the disaggregated information on energy uses, we calculate CO_2 emissions using the emission coefficients of the respective fuel types, as described in Petrick et al. (2011). Furthermore, we determine the CO_2 intensity of energy use and the CO_2 intensity of production by dividing total CO_2 emissions by a plant's total energy use and gross output, respectively.

In addition, information on the energy cost and the gross value added at the firm level can

Table 1: Summary Statistics (Pooled over 2010 and 2011)

	Exempted plants			Non-Exempted plants		
Variable	Mean	Std. Dev.	# of Obs.	Mean	Std. Dev.	# of Obs.
Plant-level information						
Gross output, in million €	119.32	203.32	790	28.79	351.11	75,463
Export share, in %	0.31	0.29	790	0.20	0.25	75,463
Number of employees	248.63	306.71	777	114.89	400.35	73,893
Electricity use, in GWh	105.39	194.25	789	2.57	15.58	75,229
Energy use (w/o electricity), in GWh	308.13	583.28	789	7.61	135.65	75,229
Electricity share in total energy, in %	0.55	0.31	789	0.52	0.26	75,229
Gas share in total energy, in %	0.24	0.27	789	0.28	0.29	75,229
Oil share in total energy, in %	0.03	0.11	789	0.15	0.25	75,229
Coal share in total energy, in %	0.06	0.17	789	0.01	0.06	75,229
Renewables share in total energy, in %	0.11	0.23	789	0.04	0.16	75,229
CO_2 emissions, in 1,000 t	103.29	188.52	789	2.58	44.61	75,266
CO_2 intensity of energy use, in g per kWh	398.27	133.38	789	414.26	134.17	75,229
CO_2 intensity of production, in g per EUR	1,436.83	2,123.62	784	140.45	1,550.91	73,152
Firm-level information						
Energy cost to gross value added ratio, in %	0.64	0.78	430	0.09	1.14	27,250

Source: Research Data Centres of the Federal Statistical Offices and the Statistical Offices of the Länder: AFiD Panel Manufacturing Plants, AFiD Module Energy Use, and Cost Structure Survey, 2008-2011 (henceforth: AFiD Panel, 2007-2011), own calculations.

be observed for a representative sample of firms. Unfortunately, a firm's electricity cost is unobserved, so that we do not know whether a firm's electricity cost to gross value added ratio exceeds 15%, as required by the second eligibility criterion.

Our second data source is a list of exempted plants that has been published by the BAFA since 2010. Using Bureau van Dijk identifiers, tax identification numbers and official municipality keys, we merge this information to the AFiD panel for the years 2010 or 2011. Starting with the entire BAFA list, we drop the plants that do not belong to the manufacturing sector. Of the remaining 715 plants, we are able to merge 662 plants, resulting in a matching rate of 93%. Using the years 2007-2011 from the AFiD panel, the combined data set allows to observe both plant-level outcomes and EEG levy exemptions for the years 2010 and 2011. Furthermore, we can track the eligibility for exemptions in those years, which is determined in the years 2008 and 2009, respectively.

As exemptions from the EEG levy are central to this paper, Table 1 reports the descriptive statistics separately for exempted and non-exempted plants, pooling the two outcome years 2010 and 2011. The table illustrates that exempted plants are substantially larger, both in terms of gross output and employees. Furthermore, they have higher electricity and energy uses of about 105 and 308 GWh, respectively, compared to less than 3 and 8 GWh for non-exempted plants, and emit substantially more CO_2.

Differences with regard to the fuel mix are less pronounced: the share of coal in the fuel mix is slightly larger for exempted plants, while the share of oil to total energy use is larger in the group of non-exempted plants. However, both the CO_2 intensity of production and the ratio of energy cost to gross-value added are substantially higher for exempted plants, which indicates largely different production processes for exempted and non-exempted plants.

3. Empirical strategy

Following the literature on the evaluation of causal effects, we describe the empirical strategy using the Rubin Causal Model framework (Rubin, 1974). Let $Y_i(1)$ and $Y_i(0)$ denote the potential outcomes for plant i, depending on whether it is subject to treatment. In our case, treated plants are those that pay the reduced EEG levy. We are interested in the causal treatment effect, given by the difference $Y_i(1) - Y_i(0)$, and in its population counterparts, such as the average treatment effect (ATE), $E\left(Y_i(1) - Y_i(0)\right)$, or the average treatment effect on the treated (ATT), $E\left(Y_i(1) - Y_i(0)|T_i = 1\right)$. The fundamental problem of causal inference (Holland, 1986) is that the difference between the two potential outcomes is unobservable, as only one of them materializes.

A treated, i.e. exempted, plant is denoted by the binary random variable T_i and the eligibility of treatment, represented by Z_i, depends on whether a so-called running variable R_i exceeds some threshold value c, $Z_i = 1(R_i \geq c)$, where $1(\cdot)$ denotes the indicator function. In our example, R_i is the baseline electricity use and c represents the cutoff value of 10 GWh. Following the local average treatment effect (LATE) framework of Imbens and Angrist (1994), we allow for heterogeneous treatment effects and introduce a potential treatment status variable $T_i(Z)$, $Z \in \{0, 1\}$, that gives the individual treatment status in the hypothetical situations of passing the cutoff. Depending on their potential treatment status, we can categorize plants into two groups: never-takers, i.e. plants that are never treated, irrespectively of passing the threshold and compliers that are only treated when passing the threshold.[2]

[2] Typically, the potential treatment status notation distinguishes four groups: never-takers by $T_i(0) = 0$ and $T_i(1) = 0$, always-takers by $T_i(0) = 1$ and $T_i(1) = 1$, compliers by $T_i(0) = 0$ and $T_i(1) = 1$ and defiers by $T_i(0) = 1$ and $T_i(1) = 0$. As exemptions can only be granted eligible firms, always-takers and defiers cannot exist in our setting.

3.1. Fuzzy RD

The central idea of a RD design is to take advantage of institutional rules that determine the eligibility for a treatment based on cutoff values. In general, RD designs can be either sharp, when passing the cutoff deterministically leads to treatment, or fuzzy, when the probability of treatment jumps by less than one at the cutoff (Imbens and Lemieux, 2008). The central identifying assumption is that individuals can only imprecisely control the corresponding running variable R_i, so that observations on either side of the cutoff are similar in both observable and unobservable characteristics. This situation of local randomization can then be exploited to estimate local average treatment effects for the subgroup of compliers close to the cutoff (Lee and Lemieux, 2010). As they closely mimic a randomized experiment, RD designs are considered as a method with a high degree of internal validity (Imbens and Lemieux, 2008). Furthermore, as shown by Hahn et al. (2001), there is a close analogy to instrumental variables estimation, where the dummy variable of passing the threshold, Z_i, takes the role of an instrument for treatment.

In formal terms, the identifying assumptions of the fuzzy RD approach read as follows (Imbens and Lemieux, 2008). First, the probability of treatment has to jump at the cutoff c:

$$\lim_{\epsilon \downarrow 0} P(T_i = 1 | R_i = c + \epsilon) \neq \lim_{\epsilon \uparrow 0} P(T_i = 1 | R_i = c + \epsilon).$$

In our case, treatment probabilities jump by less than one at the threshold of 10 GWh, as EEG levy exemptions are only granted if an application procedure is completed and another elilgibility criterion is met, which qualifies the design as fuzzy RD.

Second, the conditional expectations of the potential outcomes, $E(Y_i(j)|R_i = r)$ for $j \in \{0, 1\}$, are assumed to be continuous in r at the cutoff. This assumption formalizes the notion that only imprecise control over the running variable is allowed for this method to be valid. If precise manipulation were possible, plants that would benefit most by treatment would select above the threshold, leading to discontinuous conditional expectations of potential outcomes at the cutoff.

Third, passing the threshold is assumed to affects every plant in the same direction, so that no plant would be more likely to receive treatment if it lost eligibility. This statement is similar to the monotonicity requirement in instrumental variables settings that there are no defiers (Imbens and Angrist, 1994).

When these identifying assumptions are satisfied, the average treatment effect for compliers at the cutoff is identified by the following expression (Imbens and Lemieux, 2008):

$$\text{ATT} = \frac{\lim_{\epsilon \downarrow 0} E(Y_i|R_i = c+\epsilon) - \lim_{\epsilon \uparrow 0} E(Y_i|R_i = c+\epsilon)}{\lim_{\epsilon \downarrow 0} E(T_i|R_i = c+\epsilon) - \lim_{\epsilon \uparrow 0} E(T_i|R_i = c+\epsilon)}, \tag{1}$$

which represents the jump in the outcome variable at the threshold, divided by the jump in the treatment probabilities. As the group of treated plants merely consists of compliers in our case, this treatment effect corresponds to the ATT at the cutoff (Battistin and Rettore, 2008).

The treatment effect can be estimated by replacing the conditional expectations from (1) by sample counterparts, using either parametric or nonparametric techniques. As proposed by Hahn et al. (2001), we estimate conditional expectations of the outcome variable by local linear regressions, which have been shown to have bias-reducing properties (Porter, 2003). This method fits linear regressions separately for each side of the threshold, using only observations within a certain bandwidth h and weighting them according to a kernel function. The local linear estimator for the conditional expectation of the outcome variable slightly above the threshold, $\lim_{\epsilon \downarrow 0} E(Y_i|R_i = c+\epsilon)$, for example, is given by $\hat{a}$ from the following expression:

$$(\hat{a}, \hat{b}, \hat{d}) = \underset{a,b}{\operatorname{argmin}} \sum_i (Y_i - a - b(R_i - c))^2 K\left(\frac{R_i - c}{h}\right) 1(R_i > c),$$

where $K(\cdot)$ denotes the Kernel function, Y_i and R_i represent the outcome and the running variable, respectively, c the cutoff value. To decrease sampling variability, extensions of RD designs allow to include explanatory variables that are predetermined relative to the running variable R_i (Lee and Lemieux 2010, Calonico et al. 2016). Lags of the outcome variable are particularly suited for this purpose as they are strongly correlated with the outcome variable.

In our main specification, we employ a triangular kernel and include the lagged outcome variable determined one year prior to the running variable into the regression. Following Calonico et al. (2014) and Calonico et al. (2016), we determine bandwidths using a fully data-driven selection procedure that minimizes the mean squared error (MSE) of the estimator. As conventional nonparametric local polynomial estimators tend to over-reject the null hypothesis, we conduct inference based on robust bias-adjusted confidence intervals that have better coverage rates in finite samples (Calonico et al., 2014).

3.2. Selection

One might be concerned about the validity of the fuzzy RD design, because firms may have an incentive to increase their electricity use above the threshold in order to benefit from the exemptions two years later. Such selection could violate the core identifying assumption of the RD design that requires conditional expectations of potential outcomes to be continuous at the threshold.

A central advantage of the fuzzy RD design is that the continuity assumption has testable implications. First, if plants have only imprecise or no control over the running variable, its density has to be continuous at the threshold. In contrast, selection would generally lead to a discontinuity, with more plants using slightly more electricity as required by the threshold. For the years 2008 and 2009, Figure 2 plots the number of plants in 0.5 MWh bins of electricity use and demonstrates that there is no evidence for such selection. This finding is also confirmed more formally by the results from a density test, as proposed by McCrary (2008). Table 2 shows that the null hypothesis of a continuously distributed running variable cannot be rejected for the years 2008 and 2009 that determine eligibility.

Second, local randomization implies that all variables measured prior to the running variable are balanced around the cutoff, similar to randomized experiments where observables have to be balanced across the treatment and control group. As a consequence of balancedness, fuzzy RD regressions on such predetermined baseline variables should not indicate any treatment effect at the cutoff. Table 5 in the Appendix presents the estimates from such fuzzy RD regressions and illustrates that we cannot detect any discontinuity at the cutoff for variables determined prior to the exemptions, which is consistent with local randomization.

Accordingly, we find no evidence that plants increased their electricity uses in 2008 and 2009 to become eligible for exemptions. The absence of strategic manipulations of the electricity use in both years may reflect the severe financial crisis that had an unparalleled impact on German manufacturing. For example, in 2009, gross value added in the manufacturing sector plummeted by 20.7% and many manufacturing firms resorted to short-term working arrangements for many of their employees. Under these circumstances of great economic uncertainty, plants seem to have avoided the upfront costs of manipulation, such as electricity cost or wear and tear, given that is was very difficult to hit a fixed electricity use target.

That the financial crisis prevented plants from manipulating electricity uses is further supported by 2010 data. Emplying McCrary's test for that year, we can reject with 95% confidence

Figure 2: Number of Plants in 0.5 GMh Bins of Electricity Use in 2008 and 2009

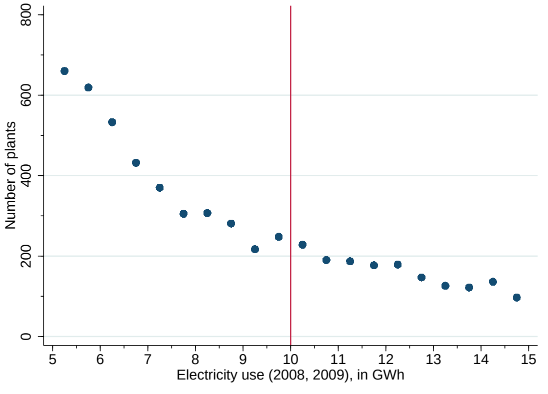


Table 2: McCrary's Test of Continuity

Year	2008	2009
Test statistic	0.07	0.13
	(0.10)	(0.11)
# of obs.	39,502	37,867

Notes for Figure 2: Absolute frequency of plants within 0.5 MWh bins of electricity use in the years 2008 and 2009. Source: AFiD Panel, 2007-2011, own calculations. *Notes for Table 2:* Test statistics from McCrary's test of continuity (McCrary, 2008) for electricity use at the 10 GWh threshold. The bandwidths used for the estimation are 4.04 and 3.93 GW for 2008 and 2009, respectively. As the heavy right skew in the electricity use distribution challenges convergence, plants with an electricity use of more than 50 GWh are excluded. Standard errors in parentheses. Source: AFiD Panel, 2007-2011, own calculations.

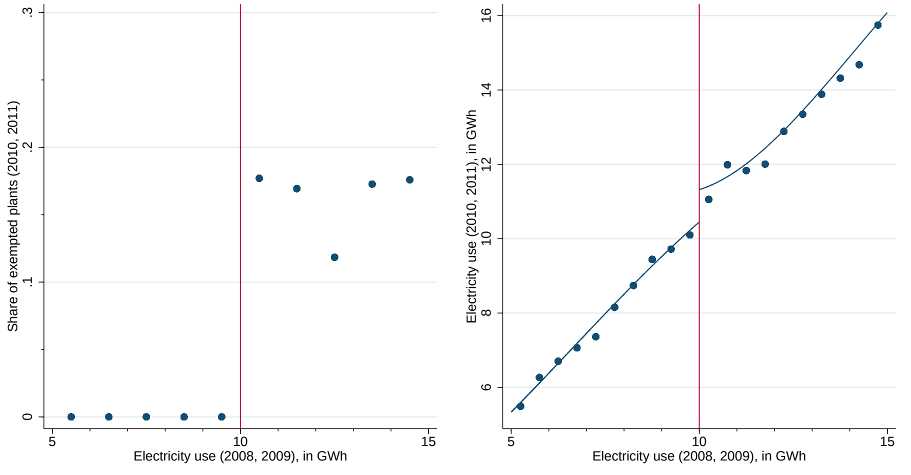
that electricity uses are continuously distributed at the cutoff (test statistic: 0.36, standard error: 0.11, reported only in the text). This finding suggests that plants manipulated their electricity use to surpass the eligibililty threshold as soon as the financial crisis became less severe in Germany.

4. Results

We start by a graphical investigation of the effect of EEG levy exemptions. As illustrated by the left part of Figure 3, the percentage of exempted plants increases from 0 to some 18% when the electricity use in the baseline period crosses the eligibility threshold of 10 GWh. The remaining non-exempted plants with electricity uses above the threshold may either not pass the second eligbility criterion or not have applied for an exemption.

The right part of Figure 3 plots the electricity use in the outcome years (2010 - 2011) against the electricity use in the baseline years (2008 - 2009) that determined eligibility, superimposing fitted lines from third order polynomials. It indicates that plants slightly exceeding the eligibililty threshold in the baseline period use more electricity two years later. As the economic

Figure 3: Mean Exemption Shares in 2010 and 2011 (Left Panel) and Mean Electricity Use in 2010 and 2011 (Right Panel)



Notes: Mean EEG exemption shares (2010 and 2011) correspond to averages within 1 MWh bins of electricity use two years before (2008 and 2009). For reasons of confidentiality, the bin width had to be increased to 1 MWh. Mean electricity uses in the years 2010 and 2011 correspond to averages within 0.5 MWh bins of electricity use two years before (2008 and 2009). The lines represent fitted values from third order polynomials, estimated separately for both sides of the threshold. Source: AFiD Panel, 2007-2011, own calculations.

crisis in the baseline years prevented selection of plants above the threshold, this difference reflects the higher exemption probabilities for plants that exceed it and thus gives a first indication of a positive exemption effect on electricity use. For the sake of completedness, we present the full set of graphs for all outcome variables in Figure 5 in the Appendix.[3]

Next, we turn to the estimation of treatment effects for all outcome variables. To improve the precision of the fuzzy RD estimates, our preferred specification excludes firms with an energy cost to gross value added ratio below 15 %. These plants certainly do not meet the second eligibility criterion and thus cannot hep to identify the treatment effect of interest. Furthermore, we drop as outliers the 1% of observations with the highest or lowest relative changes in electricity use between the baseline years (2008 and 2009) and the outcome years (2010 and 2011).[4] In the main text, we present bias-robust standard errors and confidence intervals (Calonico et al.,

[3] Corresponding to our main specification that employs lagged values as explanatory variables, these graphs isolate the unexplained variation in an outcome variable by plotting the residuals from a regression on its lagged values ($t-3$).

[4] In Table 6 of the Appendix, we show that including firms with an energy cost to gross value added ratio below 15 % leaves point estimates largely unchanged, but reduces their precision. Furthermore, the robustness checks in Section 4.1 illustrate that different outlier deletions leave point estimates virtually unaffected.

Table 3: **Fuzzy RD Estimates of the ATT (at the Cutoff)**

	ATT	Robust Std. Err.	Robust 90% Conf. Intervals	# of Obs.
Direct effect				
Electricity use, in GWh	3.94**	2.01	[0.78, 7.40]	36,834
Competitiveness effects				
Gross output, in million €	3.64	24.81	[-34.49, 47.12]	38,026
Export share, in %	-0.08	0.07	[-0.21, 0.03]	38,026
Number of employees	17.40	41.59	[-59.13, 77.68]	36,599
Effects on fuel mix				
Other energy use, in GWh	-14.70	14.26	[-39.81; 7.11]	36,846
Electricity share in total energy, in %	0.21*	0.14	[0.02, 0.48]	36,834
Gas share in total energy, in %	-0.13	0.12	[-0.35, 0.05]	36,834
Oil share in total energy, in %	-0.07*	0.04	[-0.16, -0.01]	36,834
Coal share in total energy, in %	0.02	0.05	[-0.05, 0.10]	36,834
Effects on carbon emissions				
CO_2 emissions, in 1.000 tons	-1.06	3.85	[-7.98, 4.67]	36,855
CO_2 intensity of energy use, in g per kWh	120.81*	81.86	[9.11, 278.41]	36,843
CO_2 intensity of production, in g per EUR	76.70	331.60	[-450.04, 640.83]	35,951

Notes: Standard errors are clustered at the firm level. **,* denote statistical significance at the 5%, 10% level, respectively. The MSE-optimal bandwidth selector (Calonico et al., 2016) yields the following bandwidths: 2.62, 3.45, 3.96, 3.23, 2.87, 3.20, 3.80, 4.16, 3.35, 1.22, 1.77, 2.06 GWh (in order of appearance in the table). Source: AFiD Panel, 2007-2011, own calculations.

2014). Table 7 in the Appendix shows that inferences based on conventional confidence intervals remain unchanged. As fuzzy RD designs are very data-intensive and use only observations within a certain bandwidth around the cutoff, we report 90% confidence intervals throughout.

Our fuzzy RD estimates in Table 3 show that the EEG levy exemptions increased electricity use on average by some 4 GWh for exempted plants that have barely met the eligibility threshold of 10 GWh during the baseline period. While there is some uncertainty on the exact size of the treatment effect, as illustrated by the large 90% confidence intervals from the fourth column of 3 that range from 0.78 to 7.40 GWh, we can reject the null hypothesis of no effect. The estimates on gross output, the export share and employment do not indicate competitiveness effects at any conventional significance level. As our estimates capture short-term effects that arise when a plant is exempted from the levy in a certain year, they may not necessarily generalize to the effects in the long run, though.

One potential explanation for higher electricity uses, but unchanged gross output and employment, is that plants respond to an exemption by substituting energy fuels. Indeed, Table 3 shows that exempted plants increase the electricity share in total energy use on average by 21 percentage points, an effect that is statistically significant at the 10% level. This increase comes at the expense of fossil fuels, such as oil and natural gas, whose shares are on average reduced by 7 or 13 percentage points, respectively. The finding of a fuel switch from fossil fuels to electricity is further supported by the negative point estimate on the total energy use from all sources other than electricity, such as oil, coal, gas, and renewables, which is not statistically significant at any conventional level, however.

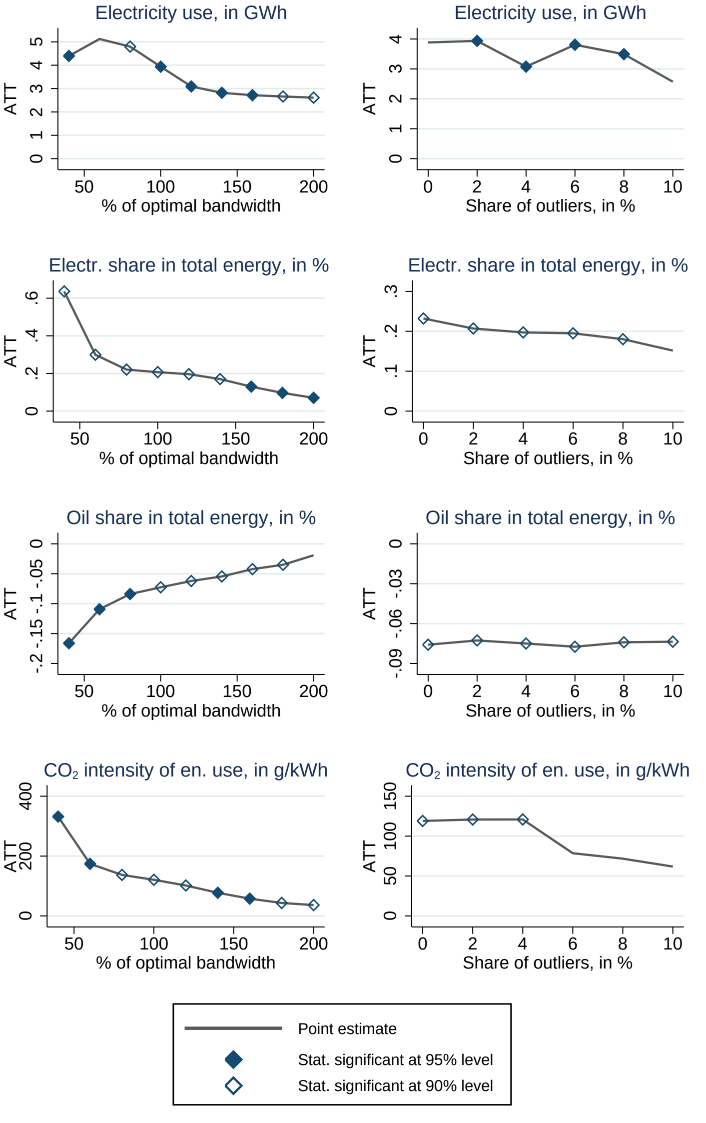
The results from the second last row of Table 3 show that exempted plants increase the CO_2 intensity of their energy mix by a statistically significant 121 g per kWh. This finding reflects the fact that the emission factor of electricity in Germany is higher than that of most fossil fuels and reaches around 550 g $C0_2$ per kWh, compared to only around 270 g per kWh for oil and some 200 g per kWh for natural gas. In contrast, we cannot detect an effect of the exemptions on total emissions or the CO_2 intensity of production.

4.1. Robustness checks

In this section, we investigate whether our finding are robust to the treatment of outliers, to functinal form assumptions and to changes in bandwidth. First, we focus on the bandwidth choice, which is characterized by a compromise between precision and bias (Lee and Lemieux, 2010). Larger bandwidths increase the number of observations that are used for the estimation, but can increase bias due to a worse fit of a linear approximation to the conditional mean of the outcome variable. To ensure that the results are not due to a specific bandwidth choice, the left panel of Figure 4 depicts the ATT estimates for a variety of bandwidths ranging from 40 to 200% of the MSE-optimal bandwidth choice used in our main specification, highlighting statistically significant ATTs by diamonds. For electricity use, the shares of electricity and oil in total energy use and the carbon intensity of energy use, the figure illustrates that the estimates are robust to specific bandwidth choices and remain statistically significant throughout, except when bandwidths are very small or large.

Next, we investigate whether our results are robust to different ways of excluding outliers. The right panel of Figure 4 displays the ATT estimates for a variety of excluded percentiles, ranging from no outlier removal to excluding the 10% of the sample with the largest relative changes in electricity use between the period that determines elgibility and the outcome period two years later. It demonstrates that the size of the estimates remains virtually unchanged and that statistical significance is only lost for the ATT estimate on electricity use in the extreme case of no outlier removal or for the ATT estimate on carbon intensity when at least 6% of the

Figure 4: Treatment Effects (ATT) under Different Bandwidths (Left Panel) and Alternative Outlier Definitions (Right Panel)



Notes: Optimal bandwidths correspond to the bandwidths from the footnote of Table 3. The shares of outliers gives the percentage of observations that have been removed as outliers. For instance, a 2% share of outliers correspond to a deletion of the top and bottom 1% with regard to relative electricity use changes between t and $t-2$. Figure 6 and 7 in the Appendix presents the figures for all outcome variables, including robust and conventional 90% confidence intervals. Source: AFiD Panel, 2007-2011, own calculations.

Table 4: Fuzzy RD Regression Results, Robustness Checks

	Second order polynomials			Firms with one plant		
	ATT	Robust Std. Err.	# of Obs.	ATT	Robust Std. Err.	# of Obs.
Direct Effect						
Electricity use, in GWh	6.54	4.65	36,834	5.01*	2.85	30,353
Effects on the fuel mix						
Electricity share in total energy	0.34*	0.38	36,834	-0.03	0.09	30,353
Oil share in total energy	-0.12*	0.08	36,834	-0.04	0.04	30,353
CO_2 intensity of energy use	215.11*	236.64	36,843	66.16	92.50	30,353

Notes: Standard errors are clustered at the firm level. **,* denote statistical significance at the 5%, 10% level, respectively. The MSE-optimal bandwidth selector (Calonico et al., 2016) yields the following bandwidths: 2.62, 1.53, 4.16, 1.77 GWh (left panel, in order of appearance) and 2.65, 1.33, 3.49, 2.27 GWh (right panel, in order of appearance). The comprehensive results for all outcome variables are presented in Table 8 and 9 in the Appendix. Source: AFiD Panel, 2007-2011, own calculations.

observations are excluded.

Another concern might be that the fit from local linear regressions is poor due to some curvature in the conditional mean function that could better be captured by flexible polynomial expressions. We investigate this issue by estimating local quadratic regressions, using the bandwidth of the preferred specification to facilitate comparability. The first panel of Table 4 shows that the ATT point estimates are very similar to the estimates from our main specification. Only their precision deteriorates, which is not surprising as additional parameters need to be estimated and degrees of freedom are lost.

A last concern might be a violation of the stable unit treatment value assumption that rules out indirect treatment effects on non-exempted plant. In particular, production might be shifted within a firm towards exempted plants in an attempt to benefit from reduced marginal electricity prices. However, such intra-firm decision-making is unlikely to explain the treatment effect that we find. Excluding all firms with multiple plants from the analysis gives ATT estimates on electricity use that remain comparable in size and statistically significant at the 10% level (second panel of Table 4). For the other treatment effects, statistical significance is lost, which may simply reflect the smaller sample used for the estimation. Their sign and magnitude remain comparable, though, except for the ATT on the electricity share in total energy.

Our empirical strategy exploits the fact that plants are only eligible for exemptions when, two years earlier, their electricity use exceeded a threshold of 10 GWh.

5. Summary and conclusions

Using a fuzzy Regression Discontinuity (RD) approach and a data set capturing the universe of German manufacturing plants, we estimate the causal impact of electricity prices on various plant outcomes, such as electricity use, gross output, exports and employment. We take advantage of a unique institutional setting that creates substantial variation in electricity prices by allowing for exemptions from a levy that accounted for 17% and 25% of average industry electricity prices in 2010 and 2011, respectively.

Our empirical strategy exploits the fact that plants are only eligible for exemptions if their electricity use exceeded a threshold of 10 GWh in a baseline year, here, 2008 and 2009. During these years, which coincide with the financial crisis that hit the German manufacturing industry in an unprecedented way, we do not find evidence that plants selected above the threshold to become eligible for an exemption. This finding indicates that the central identifying assumption of an RD design is met, requiring that plants did not strategically manipulate their electricity use.

The fuzzy RD estimates do not indicate that the exemptions had an impact on gross output, exports and employment. In contrast, our estimates show that exempted plants with baseline electricity uses of around 10 GWh significantly increased their electricity use by some 4 GWh in response to being exempted two years later. Furthermore, the reductions in electricity prices induce plants to substitute electricity for other energy sources, most notably fossil fuels, such as oil. As a consequence from such a fuel switch to electricity – a yet rather carbon-intensive fuel in Germany – we find evidence for an increase in the carbon-intensity of the energy use of plants.

Several checks show that our findings are robust to the choice of bandwidths, the treatment of outliers and to the estimation of second-order local polynomials regressions. Furthermore, there is no evidence that production shifts within multi-plant firms towards exempted plants strongly influence our results.

Based on our findings, the effectiveness of electricity levy exemptions to improve the competitiveness of manufacturing plants appears questionable. In contrast, the induced fuel switch to electricity may even suggest potentially adverse environmental impacts of that policy. From a more general perspective, though, the responsiveness of plants to energy prices found in this analysis underlines the potentials of environmental taxation. Taxes that increase – rather than decrease – prices for carbon-intensive energy sources could be an effective policy instrument to decrease the carbon intensity of the energy mix in the manufacturing industry.

Although we cannot detect effects on employment, exports and gross output, an important caveat is the short-term perspective of the analysis. Investigating long-term effects must be left open to future research when time horizons are sufficiently long to capture important structural adjustments, such as changes to the capital stock. Furthermore, our results may not necessarily generalize to heavily energy-intensive plants with electricity consumption levels far above the threshold of 10 GWh, so that additional analyses on such plants may prove valuable.

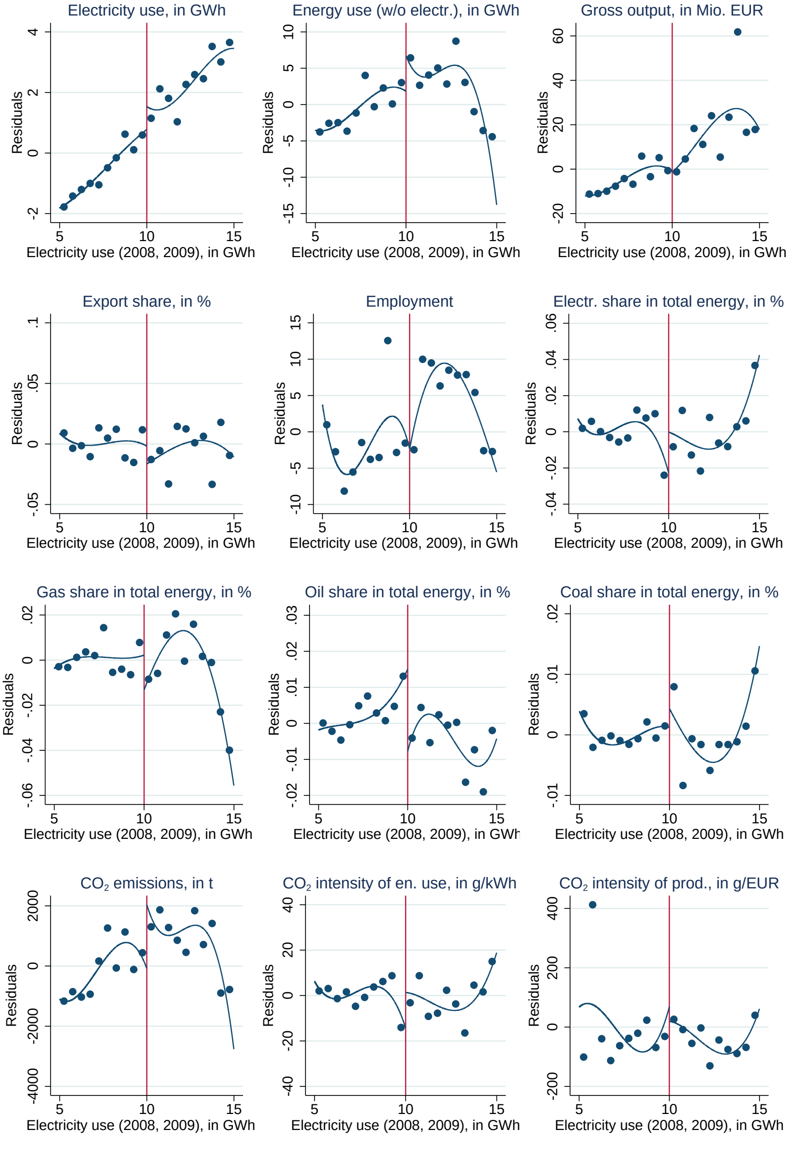
A. Appendix

Table 5: Fuzzy RD Estimates of the ATT, on Predetermined Covariates (t – 3)

	ATT	Robust Std. Err.	Robust 90% Conf. Intervals	# of Obs.
Direct effect				
Electricity use, in GWh	0.01	3.37	[-5.53, 5.55]	66,507
Competitiveness effects				
Gross output, in million €	54.08	116.76	[-137.97, 246.13]	67,357
Export share, in %	-0.29	0.29	[-0.76, 0.19]	67,357
Number of employees	-9.81	308.72	[-517.61, 498.00]	66,382
Effects on fuel mix				
Energy use (w/o electricity), in GWh	52.60	36.62	[-7.64, 112.84]	66,519
Electricity share in total energy, in %	-0.39	0.34	[-0.95, 0.16]	66,507
Gas share in total energy, in %	0.16	0.31	[-0.35, 0.67]	66,507
Oil share in total energy, in %	0.07	0.16	[-0.20, 0.35]	66,507
Coal share in total energy, in %	0.16	0.11	[-0.03, 0.34]	66,507
Effects on carbon emissions				
CO_2 emissions, in 1.000 tons	15.79	12.68	[-3.11, 38.60]	66,519
CO_2 intensity of energy use, in g per kWh	-252.71	224.68	[-698.50, 40.64]	66,507
CO_2 intensity of production, in g per EUR	598.24	1539.16	[-2,129.99, 2,933.41]	64,646

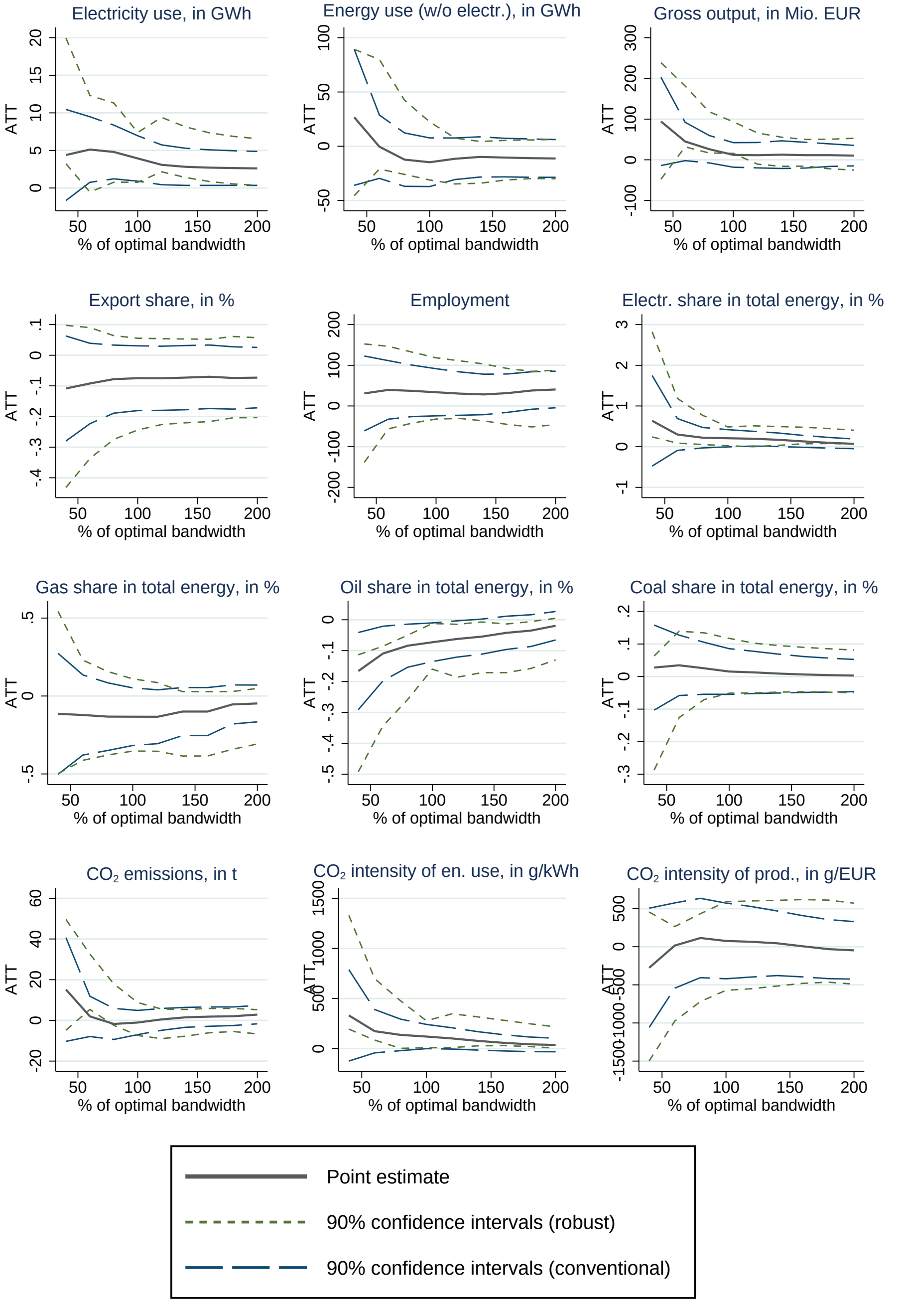
Notes: Standard errors are clustered at the firm level. Common (for both sides of the cutoff) MSE-optimal bandwidth selectors (Calonico et al., 2014) yield the following bandwidths: 1.69, 4.15, 2.83, 2.64, 2.47, 2.49, 3.08, 2.69, 1.42, 1.83, 2.33, 2.32 GWh (in order of appearance in the table). Source: AFiD Panel, 2007-2011, own calculations.

Figure 5: Mean Outcome Variables (Residuals from Regressions on Lagged Values in $t-3$) in 2010 and 2011



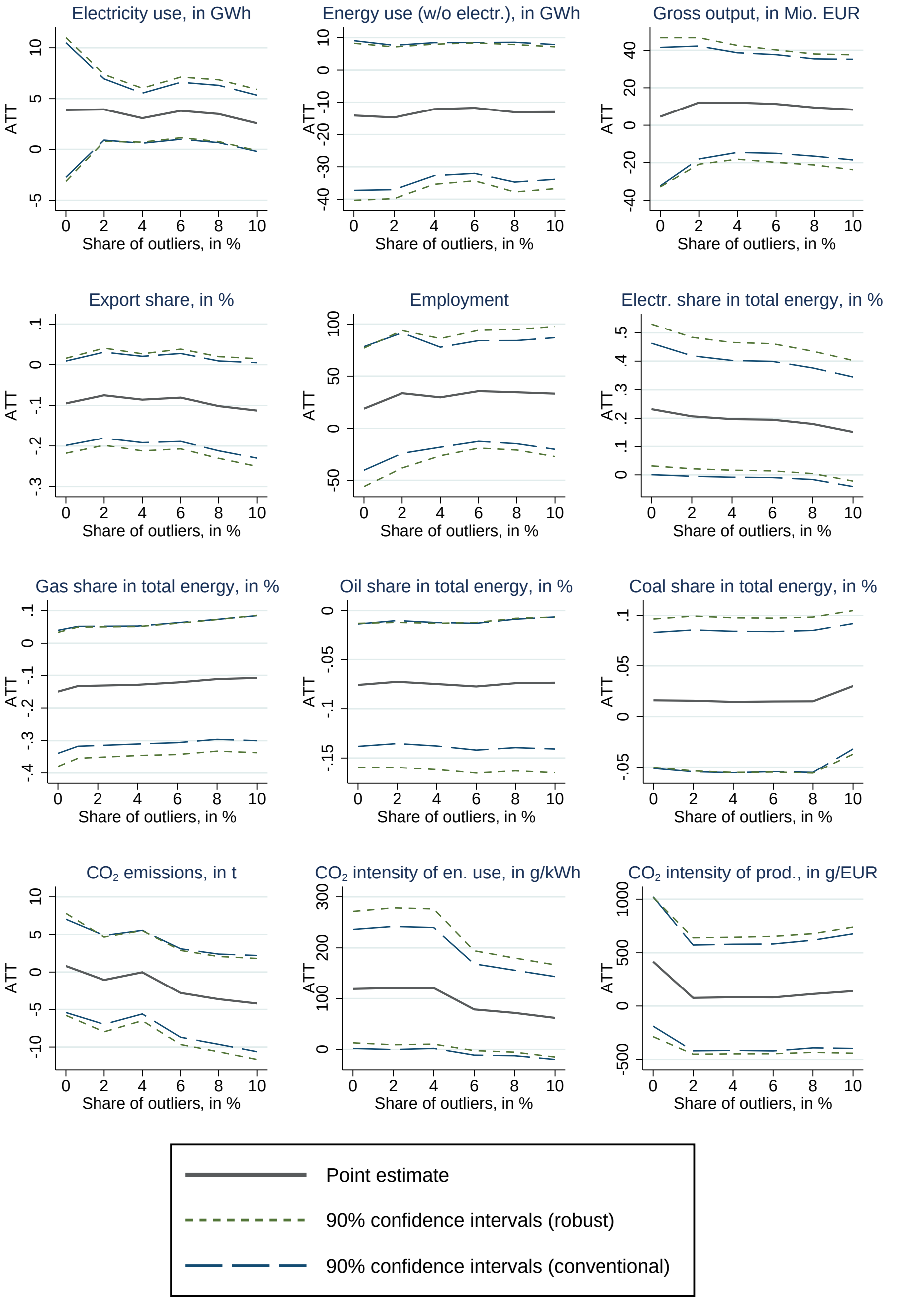
Notes: The figures plot residuals from a regression of the respective outcome variable in t (2010 and 2011) on the lagged outcome variable from $t-3$ (2007 and 2008). Mean residuals are calculated in 0.5 MWh bins of electricity use in period $t-2$ that determines eligibility (2008 and 2009). The lines represent fitted values from third order polynomials, estimated separately for both sides of the threshold. Source: AFiD Panel, 2007-2011, own calculations.

Figure 6: Fuzzy RD Estimates of the ATT for Varying Bandwidths



Notes: Robust confidence intervals are calculated as proposed by Calonico et al. (2014). Optimal bandwidths for the fuzzy RD analyses of all outcome variables are presented in the footnote of Table 3. Source: AFiD Panel, 2007-2011, own calculations.

Figure 7: Fuzzy RD Estimates of the ATT for Varying Outlier Definitions



Notes: Robust confidence intervals are calculated as proposed by Calonico et al. (2014). Source: AFiD Panel, 2007-2011, own calculations.

Table 6: Fuzzy RD Estimates of the ATT, no Selection Based on the Energy Cost to Gross Value Added Ratio at the Firm Level

	ATT	Robust Std. Err.	Robust 90% Conf. Intervals	# of Obs.
Direct effect				
Electricity use, in GWh	2.40	2.75	[-2.21, 6.84]	63,787
Competitiveness effects				
Gross output, in million €	-28.84	66.58	[-145.83, 73.20]	64,258
Export share, in %	0.04	0.12	[-0.15, 0.25]	64,258
Number of employees	77.64	116.33	[-126.37, 256.32]	63,069
Effects on fuel mix				
Energy use (w/o electricity), in GWh	21.90	35.61	[-34.87, 82.26]	63,796
Electricity share in total energy, in %	0.14	0.16	[-0.08, 0.46]	63,787
Gas share in total energy, in %	-0.15	0.14	[-0.40, 0.05]	63,787
Oil share in total energy, in %	-0.10	0.07	[-0.22, 0.01]	63,787
Coal share in total energy, in %	0.02	0.05	[-0.07, 0.10]	63,787
Effects on carbon emissions				
CO_2 emissions, in 1.000 tons	1.73	4.86	[-6.26, 9.72]	63,805
CO_2 intensity of energy use, in g per kWh	-29.51	81.01	[-162.76, 103.74]	63,796
CO_2 intensity of production, in g per EUR	33.69	324.85	[-500.65, 568.02]	61,837

Notes: Standard errors are clustered at the firm level. The MSE-optimal bandwidth selector (Calonico et al., 2016) yields the following bandwidths: 2.60, 2.87, 3.54, 2.31, 2.64, 2.43, 2.56, 3.64, 1.69, 1.38, 2.65, 1.73 GWh (in order of appearance in the table). Source: AFiD Panel, 2007-2011, own calculations.

Table 7: Fuzzy RD Estimates of the ATT, Conventional Inference

	ATT	Conventional Std. Err.	Conventional 90% Conf. Intervals	# of Obs.
Direct effect				
Electricity use, in GWh	3.94**	1.84	[0.91, 6.96]	36,834
Competitiveness effects				
Gross output, in million €	3.64	23.03	[-34.24, 41.52]	38,026
Export share, in %	-0.08	0.06	[-0.19, 0.02]	38,026
Number of employees	17.40	37.07	[-43.58, 78.39]	36,599
Effects on fuel mix				
Other energy use, in GWh	-14.70	13.57	[-37.03, 7.63]	36,846
Electricity share in total energy, in %	0.21	0.13	[-0.00, 0.42]	36,834
Gas share in total energy, in %	-0.13	0.11	[-0.32, 0.05]	36,834
Oil share in total energy, in %	-0.07*	0.04	[-0.14, -0.01]	36,834
Coal share in total energy, in %	0.02	0.04	[-0.05, 0.09]	36,834
Effects on carbon emissions				
CO_2 emissions, in 1.000 tons	-1.06	3.60	[-6.98, 4.87]	36,855
CO_2 intensity of energy use, in g per kWh	120.81	73.59	[-0.23, 241.85]	36,843
CO_2 intensity of production, in g per EUR	76.70	301.48	[-419.19, 572.59]	35,951

Notes: Standard errors are clustered at the firm level. **,* denote statistical significance at the 5%, 10% level, respectively. The MSE-optimal bandwidth selector (Calonico et al., 2016) yields the following bandwidths: 2.62, 3.45, 3.96, 3.23, 2.87, 3.20, 3.80, 4.16, 3.35, 1.22, 1.77, 2.06 GWh (in order of appearance in the table). Source: AFiD Panel, 2007-2011, own calculations.

Table 8: Fuzzy RD Estimates of the ATT, Linear Quadratic Regressions

	ATT	Robust Std. Err.	Robust 90% Conf. Intervals	# of Obs.
Direct effect				
Electricity use, in GWh	6.54	4.65	[-0.67, 14.64]	36,834
Competitiveness effects				
Gross output, in million €	63.15*	53.82	[6.49, 183.54]	37,410
Export share, in %	-0.09	0.12	[-0.32, 0.09]	37,410
Number of employees	43.89	66.94	[-60.42, 159.81]	36,052
Effects on fuel mix				
Energy use (w/o electricity), in GWh	6.92	42.14	[-15.73,122.90]	36,843
Electricity share in total energy, in %	0.34*	0.38	[0.04, 1.30]	36,834
Gas share in total energy, in %	-0.12	0.22	[-0.46, 0.27]	36,834
Oil share in total energy, in %	-0.12***	0.08	[-0.34, -0.08]	36,834
Coal share in total energy, in %	0.04	0.08	[-0.12, 0.16]	36,834
Effects on carbon emissions				
CO_2 emissions, in 1.000 tons	2.25**	11.62	[9.70, 47.94]	36,852
CO_2 intensity of energy use, in g per kWh	215.11*	236.64	[16.79, 795.27]	36,843
CO_2 intensity of production, in g per EUR	0.04	427.47	[-1,003.14, 403.12]	35,949

Notes: Standard errors are clustered at the firm level. ***,**,* denote statistical significance at the 1%, 5%, 10% level, respectively. The MSE-optimal bandwidth selector (Calonico et al., 2016) yields the following bandwidths: 2.62, 1.65, 4.26, 3.13, 1.04, 1.53, 1.69, 4.16, 1.96, 1.22, 1.77, 2.06 GWh (in order of appearance in the table). Source: AFiD Panel, 2007-2011, own calculations.

Table 9: Fuzzy RD Estimates of the ATT, Excluding Firms With More Than 1 Plant

	ATT	Robust Std. Err.	Robust 90% Conf. Intervals	# of Obs.
Direct effect				
Electricity use, in GWh	5.01*	2.85	[0.64, 10.03]	30,353
Competitiveness effects				
Gross output, in million €	25.53	27.04	[-18.85, 70.11]	31,161
Export share, in %	-0.08	0.11	[-0.13, 0.24]	31,161
Number of employees	33.45	47.65	[-36.13, 120.62]	30,893
Effects on fuel mix				
Energy use (w/o electricity), in GWh	-1.14	7.64	[-13.76, 11.37]	30,360
Electricity share in total energy, in %	-0.03	0.09	[-0.17, 0.13]	30,353
Gas share in total energy, in %	-0.05	0.09	[-0.21, 0.09]	30,353
Oil share in total energy, in %	-0.04	0.04	[-0.12, 0.03]	30,353
Effects on carbon emissions				
CO_2 emissions, in 1.000 tons	4.11	3.06	[-0.64, 9.43]	30,360
CO_2 intensity of energy use, in g per kWh	66.16	92.50	[-70.97, 233.33]	30,353
CO_2 intensity of production, in g per EUR	-62.17	263.83	[-488.84, 379.08]	30,043

Notes: Standard errors are clustered at the firm level. **,* denote statistical significance at the 5%, 10% level, respectively. The MSE-optimal bandwidth selector (Calonico et al., 2016) yields the following bandwidths: 2.65, 1.50, 5.29, 4.79, 1.33, 3.02, 3.49, 2.79, 1.96, 2.27, 1.77 GWh (in order of appearance in the table). Treatment effects on the coal share in total energy cannot be estimated due to missing variation around the cutoff when excluding firms with multiple plants. Source: AFiD Panel, 2007-2011, own calculations.

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