Electricity Taxation, Firm Production and Competitiveness: Evidence from German Manufacturing *

Andreas Gerster†   Stefan Lamp ‡

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Abstract

Electricity taxes have strongly gained in importance over the past years. Intended as a corrective carbon tax or as an instrument to finance renewable energy sources (RES), electricity taxes can represent an important cost factor for the industry with potential negative implications for firm competitiveness. Based on comprehensive data from the German Manufacturing Census, this paper investigates the causal impact of an exemption from the RES levy, accounting for roughly 30% of the average industry electricity price, on plant-level electricity consumption, fuel input choices, and competitiveness indicators. Employing a matching difference-in-differences estimator, we find that plants increase electricity consumption by about 5-7.5% in response to the exemption. We show that exempt plants substitute electricity for gas and reduce own electricity generation capacities. By contrast, we do not find evidence that the exemption had an impact on competitiveness indicators. Investigating response heterogeneity, we find that electricity-intensive plants adjust energy inputs more strongly in response to an exemption. Export-oriented firms respond less, which contrasts the policy objective to foster the competitiveness of exporters in international markets.
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†University of Mannheim, L7 3-5, 68161 Mannheim, Germany; phone: +49 201 8149-521, e-mail: gerster@uni-mannheim.de.

‡Toulouse School of Economics, University of Toulouse Capitole, Manufacture des Tabacs, 21 Alleé de Brienne, 31015 Toulouse Cedex 6, France; phone: +33 561-12-2965, e-mail: stefan.lamp@tse-fr.eu.

1 Introduction

The global threat of climate change has put actions to reduce carbon emissions on the government agenda of most counties.[1] A key element in reducing carbon emissions in electricity markets are energy taxes. They promise to improve energy efficiency by internalizing the external cost of energy generation from fossil fuels, while simultaneously raising public funds that can be used to spur the development of renewable energy sources (RES). In Germany, for example, feed-in tariffs (FiTs) for producers of “green electricity” have been financed through a levy on electricity prices, the so-called renewable energy levy (EEG levy). Paralleling the massive deployment of renewable energy sources over the past decade, the EEG levy has risen from 0.19 Euro-cent per kilowatt hour (kWh) in 2000 to 6.24 Euro-cent per kWh in 2014. Similar FiT schemes have found wide adoption in a number of jurisdictions around the world including California, Japan, and Australia.

The prospect of increasing energy prices has led to a heated policy debate about potential negative impacts on firm competitiveness, especially in the energy-intensive industry. As a consequence, governments have implemented exemptions from paying energy taxes for heavy electricity users. The decision to exempt firms from paying the levy is mostly based on the assumption that firms might lose international competitiveness. Yet, firms might be able to substitute energy inputs or passing on the cost to their consumers (Ganapati et al. 2016). Despite its high policy relevance, evidence on firm’s response to energy taxation and the size of potential adverse impacts on firms’ competitiveness is scarce.

This paper exploits a policy change in Germany that considerably extended the eligibility criteria for firms to be exempt from the EEG levy, to study the impact of a large drop in electricity prices on fuel inputs, fuel substitution, and competitiveness indicators in the manufacturing industry. We also explore whether the policy has produced unintended consequences, for example, by inducing more carbon emissions through higher electricity consumption. Furthermore, we test for heterogeneous treatment effects by energy-intensity and export share, which allows us to assess whether the policy has reached its stated goal of supporting exporters in international markets.

[1] The United Nations Framework Convention on Climate Change, COP21 (Paris agreement) has been ratified by 184 out of 197 parties to the convention (December 2018).

We conduct our analysis in Germany, where increasing RES shares have made the EEG levy the most important component of electricity cost, accounting for roughly 30% of the industry electricity price in 2014. The 2012 policy reform that we study lowered the threshold for plants to apply for the exemption from 10 Gigawatt hours (GWh) annual electricity consumption to 1 GWh and considerably extended the number of exempt plants in the manufacturing sector from 683 to 1,667.[2] To estimate the causal impact of the EEG levy exemption on plant-level outcomes, we use rich administrative data (Amtliche Firmendaten in Deutschland, AfiD) covering the universe of manufacturing plants with more than 20 employees. We focus our analysis on the short-run impact of the EEG levy exemption in the first year a plant benefitted from the exemption.

Our empirical analysis focuses on plants that became newly exempt from paying the full levy after the 2012 policy reform and compares their outcomes with similar plants that continue to pay the full levy. As treatment status – in our case the EEG levy exemption – is correlated with plant characteristics, such as its electricity intensity, we employ a matching difference-in-differences (DiD) approach to construct valid counterfactuals and to estimate causal treatment effects. This estimator has gained increasing attention in the literature on the ex-post evaluation of emission markets (see for instance Calel and Dechezlepretre 2016, Petrick and Wagner 2014, Fowlie et al. 2012). Combining matching with the standard DiD estimator allows us to exploit both the longitudinal structure of our dataset and the rich information on plant characteristics to recover the average treatment effect on the treated (ATT) under weaker identifying assumptions that allow for differences in characteristics between treated and control observations as long as they share a common trend.

One challenge for the identification of causal effects is that plants need to apply for exemptions, which might result in selection into treatment based on time-invariant plant characteristics, such as its productivity and managerial skills. By taking first differences, our empirical approach allows us to account for such factors. Nevertheless, selection into treatment could be problematic when it is related to unobserved time-varying factors, such as firms' growth expectations. As a robustness check, we exploit the policy change as a *natural experiment* and estimate intention-

[2]Source: BMU (2014). To be eligible for the exemption, plants need to verify that their annual electricity consumption exceeds 1 GWh and that they classify as energy-intensive, i.e. the ratio of the total payment for electricity to gross value added at the firm level needs to be at least 14%.

to-treat (ITT) effects of passing the lower eligibility threshold after the 2012 reform, regardless of individual exemption status. This estimator implicitly assumes that all newly eligible plants were treated and thus provides us with a lower bound for the ATT that is robust to selection.

Our main results show that EEG levy exemptions have a positive and significant impact on electricity consumption. In particular, plants that are exempt from the EEG levy in 2013 consume 5-7.5% more electricity compared to plants in the control group, which translates into a short-run own-price elasticity of electricity of -0.22 to -0.33. Furthermore, we find that treated plants adjust their energy input mix in the year of the exemption. They respond to the drop in electricity prices by substituting electricity for gas and by reducing their own electricity generation, which uncovers an important mechanism how plants respond to energy taxation. Fuel switches also imply unintended consequences for climate policy. When we calculate carbon emissions based on the average carbon content of all energy inputs, we find that plants' fuel substitution implies an increase in carbon emissions by 3.1-5.8%. This finding is mainly driven by the large share of coal and lignite in the German electricity-mix.[3] Regarding competitiveness indicators like sales and export share, we do not find any evidence that the levy exemption increases plant competitiveness in the short-run. Rather, we find a small, but negative impact on employment, which is in line with the reduction in own-electricity production in the treatment group. We perform additional robustness checks to our main results concerning the matching strategy, selection into treatment, the timing of the policy announcement, and intra-firm spillovers, which confirm our main findings. Finally, testing for heterogeneous effects, we do not find evidence that the exemption has particularly benefitted the export-oriented industry, which was the main focus of the policy. Rather, we find that plants with a high electricity-to-sales ratio were most responsive to the exemption. These findings suggest that the policy design was not effective and lead to rent-transfer to the energy-intensive industry. A back-of-the-envelope calculation shows that the EEG levy reform in 2012 led to a redistribution of about 190 million Euros from the group of electricity consumers to the group of newly exempt manufacturing plants, which illustrates that such exemptions have important distributional implications (see also Reguant 2018).

[3]Due to the increased share of RES production in the German electricity market, these technologies are often the marginal (price setting) plants. By using the average emission factors, our estimates provide a conservative estimates of the CO_2 impact.

Our study relates to two main strands of literature. First and foremost, it contributes to a growing body of literature that evaluates the impact of environmental regulation on industry outcomes (Abrell et al. 2011, Greenstone 2002, Greenstone et al. 2012, Hanna 2010, Martin et al. 2014a,b, 2016, Petrick and Wagner 2014, Colmer et al. 2018 or Dechezleprêtre and Sato 2017 for a review). Much of this literature focuses on the impact of carbon markets or carbon taxes on the industry. For instance, Martin et al. (2014b) analyze the impact of the European Emission Trading Scheme (EU ETS) on the competitiveness of the French manufacturing industry. While they do not find adverse competitiveness impacts, they find clear evidence for fuel substitution at the plant level. Similarly, Martin et al. (2014a) analyze the impact of the climate change levy on firms in the UK manufacturing sector and find that electricity use patterns and energy intensity are affected significantly by the tax, in contrast to competitiveness indicators. Other recent work in the US has found negative impact of energy prices on employment (Deschenes 2011, Kahn and Mansur 2013). Our results complement these earlier studies. In particular, the focus on the impact of the EEG levy exemption enables us to study the effects of a large *reduction in electricity prices* on energy input choices and plant-level outcomes. We are thus able to contrast previous results in terms of symmetric responses. Additionally, we contribute to the public policy debate on RES financing by highlighting that exemptions were poorly targeted.

Second, this paper relates to recent work that analyzes electricity taxation and plant level outcomes in the manufacturing sector (Dussaux et al. 2018, Flues and Lutz 2015, Gerster 2017, Marin and Vona 2017). Compared to most of these studies, our setting allows us to rely on a large exogenous variation in the electricity price for identification. To the best of our knowledge, Gerster (2017) is the only paper that analyses EEG levy exemptions in Germany. Compared to his work, which investigates how plants respond to short-run variation in eligibility status induced by the financial crisis, our study focuses on the impact of a reduction in eligibility thresholds that induces a long-run (permanent) reduction in energy prices for exempted manufacturing plants. We document the potential for fuel substitution and adjustments of the capital stock that may explain why long-run elasticities found in the literature typically exceed short-run elasticities. Furthermore, our identification strategy allows us to test for heterogeneity in treatment effects and possible mechanisms, such as own electricity production, both of which might have important implications for policy design.

The remainder of this paper is structured as follows. The next section explains in detail the institutional background of the EEG levy design. Section 3 introduces the datasets and data linking procedure, while Section 4 develops on the empirical strategy. Section 5 presents the main results, robustness, and elaborates on heterogeneous effects. Finally, Section 6 puts our results in further context and Section 7 concludes.

2 Institutional Setting

Germany is a worldwide leader for RES deployment such as wind and solar.[4] This success is often associated with the introduction of the renewable energy act (*Erneuerbare Energien Gesetz, EEG*) in 2000, which established feed-in tariffs (FiTs) for private investors. FiT pay a fixed price per kWh of electricity produced by renewable resources and are financed through a levy on electricity prices. Due to increasing RES deployment, the surcharge has increased from 0.19 cent per kWh in 2000 to 6.24 cent per kWh in 2014. Figure 1 displays the average industry electricity price for plants with an annual electricity consumption between 0.2 GWh and 200 GWh in 2013, highlighting the contribution of the EEG levy to the electricity prices in the industry. The EEG levy exemption is the single largest cost component of electricity, accounting for about 30% of the industry electricity price.[5] The figure highlights the overall importance of surcharges and levies on electricity prices in the industry: plants that are non-exempt face one of the highest electricity prices in Europe, while plants that qualify for the exemptions (fully-exempt) have one of the lowest electricity prices in Europe.[6]

The introduction of the EEG has led to a heated policy debate about the loss of international competitiveness of the German manufacturing industry due to increasing electricity prices. As a result, the policy-maker allowed energy-intensive plants in the manufacturing, mining, and railway sector to be exempt from 2003 onwards. The exemptions initially focused on large industrial plants exceeding 10 GWh annual electricity consumption that qualify as 'energy intensive', i.e.

[4]Despite its small size, in 2014 Germany was the global leader in installed solar PV capacity and third largest country in terms of installed wind capacity (REN 21, Global Status Report 2015.)

[5]Electricity prices based on survey data (Source: German federal network agency). As we focus on small and medium-sized manufacturing plants consuming between 1 and 10 GWh of electricity, the EEG levy is likely to represent an even larger share of total electricity prices.

[6]Source: Eurostat.

that have a ratio of electricity cost to gross value added at the firm level of at least 15%. Plants apply on an annual basis for the exemption based on certified accounts. Exempt plants paid a 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.

As the EEG levy continued to increase continuously in the late 2000s (see Appendix Figure A.1), the political pressure increased to extend the eligibility criteria and to include smaller energy-intensive manufacturing plants. The eligibility rules have been revised in an 2012 amendment to the original EEG, decreasing the eligibility cutoffs to 1 GWh of electricity in the previous business year and to a share of electricity cost to gross value added at the firm level of at least 14%. The updated eligibility criteria were first employed in 2013. For a plant to be exempt in 2013, it must apply in 2012, based on the electricity consumption in 2011.[7] As a result of this reform, the number of exempt plants in the manufacturing sector grew considerably from 683 in 2012 to 1,663 in 2013. Furthermore, to avoid incentives for plants to strategic manipulate their electricity consumption and to place right of the threshold, the payment schedule has been revised as part of the 2012 reform. All plants pay the full EEG levy for the first GWh of electricity and, if exempt, they pay 10% of the levy for any consumption between 1 and 10 GWh, and 1% for consumption above 10 GWh. Figure 2 depicts the EEG payment schedule for exempt and non-exempt plants. As the EEG levy corresponds to the largest individual component of industrial electricity prices, plants have strong incentives to apply if eligible.[8]

This paper exploits the 2012 amendment to the EEG to investigate the causal effects of the EEG levy exemptions in 2013. As the revision of the eligibility rules passed the legislative process only in the summer of 2011, we do not expect plants to have strategically manipulated their electricity consumption that year to be declared eligible.[9]

[7]While larger plants, with an annual consumption of more than 10 GWh, need to provide environmental certification on the energy-efficiency potential, smaller plants are not subject to this requirement.

[8]It appears highly unlikely that many eligible firms did not apply for the exemption, as the exemption reduces total electricity costs by about 25% for the average treated plant. In fact, data from the Federal Office for Economic Affairs and Export Control (BAFA) shows that many plants sought the exemption even when they did not qualify. In 2012, about 19% of applicants have been rejected, which exceeds the rejection rates in previous years of 4-10%.

[9]Electricity is an intermediate input in the production process and highly dependent on output. It is furthermore unlikely that firms made capital investments to increase their level of electricity consumption in the same year based on the announcement of the law. We provide descriptive evidence of pre-treatment electricity trends at plant level

3 Data

Our analysis is based on a rich administrative dataset covering the German manufacturing industry (AFiD, Amtliche Firmendaten in Deutschland). The dataset is administered by the research data center of the Statistical Offices fo the Federal States and covers the universe of plants from the manufacturing sector with more than 20 employees. It contains around 40,000 plant-level observations per year and includes a variety of plant-level characteristics, such as sales, exports, employees, and wages. It also comprises detailed information on a plant's energy use for various energy inputs, most notably electricity, gas, and oil. Based on the disaggregate information on energy use, we are able to calculate CO_2 emissions using annual average emission coefficients of the respective fuel types for Germany obtained from the ministry of the environment. Finally, AfiD provides information on the energy cost and the gross value added at the firm level for a representative sample of firms. We observe this data at the annual frequency for the period 2007 to 2013.

We link this data with the full list of plants that are exempt from paying the EEG levy. This data is publicly available for the years 2010 to 2013 from the Federal Office for Economic Affairs and Export Control (BAFA). As these two datasets do not contain a common identifier, we rely on Bureau van Dijk identifiers, tax identification numbers, and official municipality keys to match records. This procedure allows us to match close to 80% of the plants that became newly exempt in 2013. The combined dataset permits us to observe plant-level outcomes for up to five years prior to the policy reform.

Table 1 presents summary statistics for three main groups of plants in the year 2013. The first column reports the plants that are non-exempt from the levy. Columns 2 and 3 refer to EEG exempt plants. While Column 2 shows summary statistic for the group of plants that were newly exempt in 2013 (1-10 GWh annual electricity consumption), Column 3 refers to all plants that were exempt from paying the levy in 2013. The table highlights the fact that the three groups are very different in terms of observable characteristics, which is not surprising, as the EEG levy exemption eligibility criteria is based on electricity consumption and closely related to plant size and energy-inputs. We are able to link 641 newly eligible plants belonging to the 1-10 GWh group. These plants are typically small and medium-sized manufacturing plants, with an average of 73

to contrast this hypothesis and for robustness estimate treatment effects based on the pre-announcement year 2010.

employees and 26 million Euros of sales. The exempt plants consume approximately 5.5 GWh of electricity in 2013 and their energy-mix is dominated by electricity (60%) and gas (28%). The table also presents electricity usage in 2011. While electricity in both the non-exempt group and the group of all exempt EEG plants decreased slightly over this period, we find that the group of newly eligible plants increased their electricity consumption from 5.1 GWh in 2011 to 5.4 GWh in 2013. This is first descriptive evidence that the policy reform might have led to additional electricity consumption of newly exempt plants. The next section elaborates on the empirical strategy to estimate the causal impact of the policy reform.

4 Research Design

We aim at identifying the causal impact of the EEG levy exemptions on energy input choices, CO_2 emissions, and competitiveness indicators for German manufacturing plants in 2013. In line with Rubin's (1974) potential outcomes framework, let D_{it} denote a treatment indicator that equals unity if plant i in year t is exempt and zero otherwise. Potential outcomes are denoted by $Y_{it}(1)$ if plant i is treated and $Y_{it}(0)$ if it is not treated, i.e. continues to pay the full EEG levy. The time subscripts t' and t denote pre-treatment and post-treatment observations, respectively. In addition, the vector $X_{it'}$ represents a set of covariates of plant i in year t' that are predetermined relative to the EEG levy exemption. We are interested in estimating the average treatment effect of the treated (ATT), given by $\alpha_{ATT} = E[Y_{it}(1) - Y_{it}(0) \mid D_{it} = 1]$, where $E[\cdot]$ denotes the expectations operator. The fundamental problem of causal inference (Holland 1986) is that only $Y_{it}(0)$ or $Y_{it}(1)$ can be observed, yet not both, so that we cannot directly estimate the ATT.

The most naive approach would be to compare EEG exempt plants with non-exempt plants in a difference-in-differences (DiD) framework. Yet, as the treatment status is based on plant characteristics related to plant size and energy-intensity, this would likely lead to biased estimates.[10] Rather, we rely on semi-parametric conditioning strategies and use a combined matching DiD estimator following recent work in the program evaluation literature (Calel and Dechezlepretre

[10]Using a conditional DiD framework in which we control for pre-treatment electricity consumption and plant demographics might lead to similar problems. Even assuming that we were able to control for all relevant covariates, the conditional DiD might lead to problems with limited overlap in the distribution of the covariate space. Also, this approach assumes equal weights for all control observations, not taking into account heterogeneity in match quality.

2016, Petrick and Wagner 2014, Fowlie et al. 2012), which we discuss next.[11]

4.1 Semi-parametric conditioning

To construct a credible counterfactual for the group of treated plants and to recover a consistent estimate of the treatment effect, we rely on an estimator that combines matching with a DiD approach. This approach allows us to exploit both the longitudinal structure of our dataset and the rich information on plant-level characteristics. By combining matching with DiD, the ATT can be identified under the weaker assumption of 'conditional independence' between changes in the outcome variables and treatment status, conditional on pre-treatment covariates $X_{it'}$ (Heckman et al. 1997). The ATT is given by the following expression:

$$\hat{\alpha}_{ATT} = \frac{1}{N_1} \sum_{i \in I_1} \left\{ (Y_{it}(1) - Y_{it'}(0)) - \sum_{k \in I_0} W_{N_0,N_1}(i,k)(Y_{kt}(0) - Y_{kt'}(0)) \right\}, \qquad (1)$$

where Y_{it} refers to the outcome of plant i in year t and Y_{i0} is the outcome variable in the base year. Furthermore, I_1 denotes the set of N_1 exempt plants, while I_0 and N_0 denote the corresponding control group values. The weight W with $\sum_{k \in I_0} W_{N_0,N_1}(i,k) = 1$ determines the weighting of counterfactual observation k.

We employ propensity score matching to construct a control group of non-exempt plants that closely match treated plants in terms of pre-treatment covariates $X_{it'}$. To pair treated and control plants, we use different matching algorithms based on nearest neighbor (NN) matching without replacement, NN matching with caliper and replacement, and one-to-many matching with caliper and replacement. We set the caliper to 25% of the standard deviation of the estimated propensity score (Rosenbaum and Rubin 1985). In case there is more than one control control plant matched to the treatment plant, more similar observations receive a higher weight W. We discuss the detailed matching procedure in Subsection 4.3.

[11] An alternative empirical strategy builds on a regression kink design. This approach compares plants facing different marginal tariffs close to the observed cutoffs. While our data allows us to observe the first eligibility criteria (annual electricity consumption at plant level) with precision, we observe the second criteria (electricity cost at the plant or firm level) only with error, which might be a threat to identification. This fact combined with the low number of data points close to the thresholds, might bias our estimates of interest and we refrain from using this approach.

The validity of the matching DiD estimator depends on three main identifying assumptions: conditional independence, overlap, and the stable unit treatment value assumption (SUTVA). First, conditional independence requires that the distribution of the control outcome $Y_{it}(0)$, conditional on observable plant and firm-level characteristics, is the same among plants that are exempt from the EEG levy and the group of control plants. Second, we require that the support of the distribution of the conditioning covariates overlaps for the treatment and control group. Finally, SUTVA requires that potential outcomes at one plant are independent of the treatment status of other plants. In practice this means that we rule out spillover effects and general equilibrium effects. While some of these assumptions are directly testable in the data, such as overlap, we will provide indirect evidence to show that both SUTVA and conditional independence are credible assumptions in the present context in 4.3, where we also elaborate on inference.

4.2 Heterogeneity

As plants depend to a different degree on electricity in their production processes, they are likely to be affected heterogeneously by the EEG levy exemption. Moreover, the original EEG motivated the exemption of industrial plants from the levy mainly with concerns about international competitiveness. To test for these channels we follow Fowlie et al. (2012) and estimate the following regression model that builds on the spirit of matching:

$$\Delta Y_i = \delta_j + \beta X_{it'} + \theta X_{it'} D_i + \alpha D_i + \varepsilon_i, \tag{2}$$

where $\Delta Y_i = Y_{it} - Y_{it'}$ denotes the difference in the outcome variable between the post-treatment year 2013 (t) and the pre-treatment year 2011 (t'), δ_j refers to fixed-effects for group j, which comprises plant j and its m_j closest matches. $X_{it'}$ denotes the predetermined covariate of plant i in year t' that we use for the estimation of treatment effects. To make the estimates comparable to our main results, we weight the observations as in the one-to-many matching DiD approach.[12]

[12] Counterfactual observations are weighted $1/M_j$, where M_j is the number of counterfactual obs. in group j.

4.3 Matching and assessment of identifying assumptions

This section discusses the detailed matching procedure applied in the empirical analysis as well as the main identifying assumptions concerning the matching DiD strategy. In a first step, we restrict our sample to manufacturing plants with an annual electricity consumption between 1 and 10 GWh in 2011. This initial data trimming assures that treated (newly EEG exempt in 2013) and control plants are of similar size and comparable electricity consumption. Figure A.2 illustrates how trimming and matching improves the covariate balance for the example of electricity.

To match treatment and control plants, we estimate two alternative propensity score specifications based on pre-treatment variables in 2011 that either directly determine the treatment status or that are pre-determined. In line with the EEG act, treatment eligibility is defined by electricity consumption at plant level and the share of electricity cost to gross value added at the firm level. As we do not observe the exact electricity expenditure at firm level, we rely on energy-related and economic variables to predict treatment status. Specification (1) conditions on baseline electricity use, number of employees, sales, export share, and average wage payments, both in linear and in quadratic terms. In addition, we exploit the longitudinal structure of our data and include lagged electricity consumption to the conditioning variables, which helps us to eliminate systematic differences in electricity use trend for treated and control observations.[13] Specification (1) includes furthermore dummies for two-digit sector classifications to capture potential differences at the sectoral level. Alternatively, Specification (2) uses strict matching on two-digit economic sub-sectors and includes as additional covariates the number of employees, sales, and electricity use in 2011, as well as lagged electricity use in 2009, 2010. Strict matching forces all treatment-control pair to be of the same sector, which might lead to worse balancing in terms of covariates, but ensures that differences in trends by sector cannot confound the estimates. As there is a limited number of treated observations in each manufacturing sub-sector, for the propensity score estimation, we regroup plants according to their average energy intensity in the pre-treatment period 2007-2011 into 5 sectors and estimate a separate logistic regression for each of the groups.[14] We estimate the propensity score by logistic regression. The propensity

[13] As electricity consumption is highly output related, conditioning on past electricity consumption allows us to match firms that share a similar economic history. The presence of the economic crisis in 2009-10 makes this feature especially desirable.

[14] We provide robustness to this regrouping, estimating the two propensity scores on three digit sub-sectoral

score regression tables are presented in Tables A.9 and A.10 in the Appendix.

The validity of the semi-parametric DiD rests on the above discussed identifying assumptions: conditional independence, overlap, and SUTVA. First, for conditional independence to hold, we require changes in outcome variables to be independent of the treatment status, conditional on covariates X_{it}. This assumption is equivalent to the common trend assumption of the DiD model and is particularly plausible when conditioning on a rich set of covariates is possible. While untestable in principle, this assumption is more plausible if outcome trends are parallel in the years leading up to the policy intervention. We provide a visual inspection of the pre-treatment trends in Figure 3. The figure plots growth rates with respect to 2011 for a set of outcome variables for both the treated and control group and illustrates that there are no detectable differences in trends prior to 2011. The individual data points can be interpreted as growth rates with respect to the base-year 2011 that determines the EEG levy exemption eligibility. This result is confirmed when conducting statistical tests on trend differences by treatment status (Table 2). The table lists the mean difference for the treated (exempt) plants, as well as the two control groups following specifications (1) and (2). We then report the t-statistic and p-values for a pairwise mean-comparison between the treatment and control group. We find that none of the outcome variables in the control groups is statistically different from the treatment group when analyzing the differences in 2011-10 and only one is statistically different when considering the growth rates in 2010-09. This difference can likely be explained with differences in timing of recovery after the 2009 economic crisis.

Second, the overlap assumption requires that the propensity scores distribution of both treatment and control group observations overlaps, i.e. that there are no treated observations with propensity score values that are not reached by any control group observation. This assumption can easily be verified graphically and, as Figure A.3 shows, it is met in our application.

Third, SUTVA allows only for direct treatment effects on treated plants, but not for indirect effects on control group observations. Such indirect effects can occur for example when multiple

definitions (WZ 2008 definition). Also, given recent discussions on the use of 'pre-treatment' outcomes in a matching DiD framework (Chabé-Ferret 2017), we also experiment with a more parsimonious specification of the propensity score specification that strictly matches within economic sub-sector and only conditions on electricity intensity, measures as the 'electricity-to-sales' ratio in 2011. Our results are robust to the choice of the propensity score definition.

plants are operated by a single firm and production capacity is reallocated as it has been shown in other contexts (see for instance Martin et al. 2014b). In addition, we need to exclude general equilibrium effects of the policy. While there is no formal test for SUTVA, we present indirect evidence that these assumptions are likely to hold in our empirical setting. More precisely, we estimate our main treatment effect with a subset of firms that only own a single plant to exclude the possibility of intra-firm spillovers. On the other hand, given the EEG levy design, the exemption of some plants should lead to a higher levy for the remaining contributors by construction. However, the 2012 EEG reform removed some (non-manufacturing) sectors from the exemption that nearly offset the total amount of newly exempt electricity. The EEG reform increased the levy by only 0.04 Euro-cent / kWh in 2013, which is negligible and we will ignore in the remainder of this analysis.[15]

Finally, dealing with matching methods, we face a trade-off between efficiency and potential biases. Combining three different matching estimators with two propensity scores provides first robustness. In our main section, we rely on heteroskedasticity-consistent analytical standard errors as proposed by Abadie and Imbens (2006). To contrast these standard error estimates, we implement a regression version of our main matching DiD estimator for the nearest neighbor matching without replacement, that closely follows equation 2, and includes fixed-effects per matched group and clusters the standard errors at the group level. As pointed out by Abadie and Spiess (2016) this procedure will produce valid inference. Yet, this increase in precision comes at the cost of a smaller sample sizes. As we are concerned with the potential bias resulting from a small control group, as our main estimator of interest, we rely on one-to-many matching with caliper and replacement, as this approach allows us to have a better pool of control plants.

5 Main Results

Table 3 presents the main results for the *ATT*, following the two propensity score specifications and main matching algorithms. Each of the columns employs a distinct matching methodology for nearest neighbor matching, nearest neighbor matching with caliper and replacement, and one-to-many matching with caliper and replacement. We allow for up to 20 matched control firms

[15] Source: BMU (2013).

for each treated firm in Columns 3 and 6. The outcome variables are expressed in log differences between the treatment year (2013) and the year that determines the treatment eligibility (2011).[16] For ease of exposition, the table is grouped in three main sections of outcome variables: electricity & gas use (Panel A), fuel inputs and related carbon emissions (Panel B), and competitiveness indicators (Panel C).

Focusing on electricity use in Panel A, we find that the EEG exemption has led on an increase in electricity consumption of about 5.1-7.5% of the treated plants compared to the control plants. This effect is highly aligned across specifications and is significant at least at the 5% significance level. For an average 'treated plant' with 5.5 GWh electricity consumption in 2013, the levy exemption represents an approximate reduction of 23% in electricity input costs. The short-run price elasticity for electricity is hence to be estimated between -0.22 and -0.33. These estimates are roughly aligned with previous estimates in the literature that focus on short-run elasticity for electricity.[17] A 10% price reduction thus leads to an increase in electricity demand of approximately 2-3%. Panel A furthermore tests for differences in gas usage and the propensity for a plant to engage in own electricity generation. Electricity production in manufacturing is often a benefit of co-generation when gas units are employed. While the individual point estimates for gas show a similar magnitude as electricity, with a negative sign, estimates are not statistically significant. In fact, the large standard errors, indicate that there might be considerable heterogeneity in terms of gas usage in manufacturing sub-sectors. Finally, in line with the reduced gas usage in the treatment group, we find evidence that less firms engage in own electricity generation. The point estimates are all negative and significant in two out of six specifications.

In a second step, we evaluate the fuel input substitution and carbon emissions at the plant level. In line with the effects from Panel A, we find that the point estimates for the electricity share in the fuel mix of a plant is positive in all specifications. However, it only shows up to be significant in the one-to-many matching in Column 3. On the other hand, we find evidence

[16] Shares are expressed in level differences, as is investment. Own electricity generation is a dummy variable equal to one in case the plant reports positive electricity production.

[17] Studies that have aimed at identifying elasticities for fuel inputs and fuel substitution in the industry include Bernstein and Madlener (2015), Hyland and Haller (2018), Neenan and Eom (2008), Paul et al. (2009). These papers typically rely on time-series variation in energy prices and find a short-run elasticity for electricity of about -0.16 to -0.20 (higher in individual manufacturing sub-sectors).

that the gas share decreases for plants that are EEG exempt, with a similar magnitude of 1.5-2.1% and a negative sign. Oil, on the other hand, constitutes an interesting robustness check, as it is only an important fuel input in specific manufacturing sub-sectors and usage should not respond to changes in electricity prices due to the low substitutability between these two type of fuels. Finally, based on the individual energy inputs, we can calculate the difference of CO_2 emissions between the treated and control group. While the variable total CO_2 takes into account all type of fuels consumed by the plant (including electricity), 'direct CO_2 emissions' refers only to fossil fuels consumed at the plant level, such as oil, gas, and coal.[18] Given the observed fuel-substitution in treated plants, and the fossil-fuel dominated electricity mix in Germany, our estimates indicate that the average fuel emissions increase by 3.1-5.8%, representing a carbon elasticity of -.13 to -.25.[19]

As the EEG levy reform was originally motivated with concerns about 'international competitiveness' in the manufacturing industry and related job-loss, our third set of outcomes focuses on competitiveness indicators at the plant level. More precisely, we estimate the change in employment, sales, export share, and investment. We find that the EEG levy exemption has no significant impact on sales, export share or investment. We find a negative impact of the EEG levy exemption on employment that is significant in three out of the six specifications. According to our estimates, employment decreased by around 2-3% in exempt plants. This result can be likely explained by the reduction in own electricity generation of exempt plants. As the NN matching and the NN matching with caliper and replacement leads to almost identical results, in the remainder of this paper, we present matching estimators for NN matching and one-to-many

[18]To calculate CO_2 emissions for individual fuels we take into account the annual average emission factor of imported fuels in Germany (Federal Ministry of the Environment). For electricity, we rely on the average carbon factor of the German electricity fuel mix in each year. Ideally, we would be able to calculate the marginal emissions induced by the policy change. However, for this we would need to combine information on the marginal production technology in electricity markets with high-frequency data on electricity consumption changes at the plant level. This information is not available. Using the average carbon content of electricity likely provides us with conservative estimates for total carbon emission. In 2013 and 2014, the decrease in coal prices and weak electricity demand has led to 'hard coal' and 'lignite' plants to dominate the marginal price setting in Germany. Hence, these emissions would be higher than the average mix (Source: Timera Energy Blog, 20 October, 2014).

[19]Dussaux et al. (2018) find a carbon price elasticity in the same order of magnitude for manufacturing firms in France.

matching with caliper and replacement.

We re-estimate our main treatment effects with a reduced sample of plants that show positive electricity and gas consumption in both 2011 and 2013 for sensitivity, as these plants are more likely to substitute fuels (see Appendix, Table A.1). These selection reduces our sample to 348 treated plants and confirms our main results. While we do not find significant impacts on gas usage, we find a significant drop in gas shares of 1.5-2.7% and a similar increase in electricity shares of 1.1-1.3%. In this sub-sample, we also find stronger evidence for the reduction in own-electricity production and employment. Finally, as the main results in Table 3 refer to the difference between the outcome year 2013 and the year determining treatment eligibility, our overall findings can be either driven by a short-term response to the realized price change in 2013 or by a firm response to the expectation of electricity prices changes. To focus on the impact of a realized price change in 2013, we condition plants to be the same in 2012, and look at outcome differences for the years 2013-2012. The results are presented in Table A.2 in the Appendix. We find that the realized electricity price change accounts for at least the half (2.6% to 5%) of the observed increase in electricity for the treated plants compared to the control plants and thus explains a large portion of the observed electricity response.

5.1 Robustness

This section deals with potential threats to our identification strategy. First, we take on *anticipation* that might arise from the EEG reform announcement in 2011. Second, *SUTVA* might be affected by the possibility of firms reallocating production capacity between plants. Finally, we deal with possible *selection* that might arise from plant application to the program.

Table 4 takes into consideration the possibility that plants have anticipated the policy change in 2011 and strategically modified their electricity consumption in that year to be declared eligible for the exemption. To do so, we match the treatment and control group based on the pre-announcement year 2010. The outcome variables are still expressed as differences 2013-2011. The table confirms our main results for electricity use and CO_2 emissions, yet leads to slightly less precision.

Second, Table 5 tests for possible intra-firm spillovers and reallocation of productive capacities. As a result to the EEG levy, multi-plant firms might adjust their production processes and shift production to plants that are exempt from the levy. To test for this channel, we focus on single plant firms.[20] In our sample, we observe a total of 369 single-plant firms that have been newly exempt from the EEG levy in 2013. The point estimates for electricity are highly aligned with the ones found in the main section. We find a 4.9 to 7.7% increase in electricity consumption that is statistically significant at the 5% level in 3 out of 4 estimates.

Third, we provide indirect evidence on strategic selection into treatment. While first differencing allows us to control for permanent unobserved differences between the treatment and control group, this does not apply to selection into treatment based on growth expectations. To deal with this, we rely on the policy change as natural experiment. As eligibility is a necessary condition for being exempt, we focus on the newly eligible group of plants in 2013 and estimate a lower bound for the main treatment effect by comparing this group to a similar group of plants for which the incentives to apply did not change considerably in a standard DiD framework. More specifically, we compare the group of plants that consumed 5-10 GWh in 2011 (treated) to the group of plants that consumed between 10-20 GWh in 2011 that were already eligible for the levy exemption previously.[21] Section 8.2 in the Appendix provides more details on the estimation strategy. Figure A.4 and Table A.8 also show that the parallel trend assumption holds for these two groups before 2011. Taking advantage of the exogenous change in the eligibility criteria in 2012 allows us to estimate a lower bound effect for the ATT. More importantly, as the change in cutoff is policy induced, the DiD approach exploits a source of variation that is unrelated to firms' selection into treatment. The results are presented in Table 6. We find a lower bound effect of the EEG levy exemption of a 2.6% increase in electricity consumption, significant at the 10% level. By construction, this measure will lead to a less precise estimates. Yet, the finding helps us to bound our main treatment effect and we can exclude the possibility that the ATT is solely driven by selection into treatment.[22]

Finally, we provide additional robustness checks concerning the matching strategy and inference in Tables A.4 to A.6 in the Appendix. Table A.4 presents the results when refraining from

[20] Alternatively, we could also aggregate treatment status at the firm level, yet this approach would lead to less precise estimates, as we would need to pool plants of different sizes.

[21] For this group, the eligibility criteria changed only marginally concerning the definition of energy intensity.

[22] We contrast these results to our main specification in which we limit the sample to plants that consume between 5 and 10 GWh of electricity in 2011 (Table A.3). The results are highly aligned with our main findings.

sub-sector aggregations, i.e. we use 3-digit sub-sectoral definitions when estimating the propensity scores. Table A.5 shows the main results when relying on a more parsimonious propensity score estimation that only conditions on the electricity-to-sales ratio in 2011 and forces matches to be strict within economic sub-sector. Both tables support our main results. We perform additional robustness concerning inference in Table A.6, where we estimate the NN matching estimator for propensity score Specification (1) in a regression framework. This allows us to condition on match group specific fixed-effects and to cluster the standard errors at the match group, which will lead to valid inference (Abadie and Spiess 2016). This table focuses on the main fuel inputs and CO_2 emissions. We find that our main results are robust to the choice of the matching strategy and inference used.

5.2 Heterogeneity

As plants in the manufacturing sector are likely to be affected differently by the EEG levy exemption, in a next step we focus on heterogeneous treatment effects. In particular, we are interested in the heterogeneous impact of exempt plants with a high electricity-to-sales ratio that should benefit most from the EEG levy exemption, and plants that have a high export share, and that were at the center of the policy debate on EEG levy exemptions. We rely on one-to-many matching as outlined in Section 4 and define a dummy variable equal to one in case the average electricity-to-sales ratio (export share) at the plant level exceeds the median average electricity-to-sales ratio (export share) in the manufacturing sector in the pre-treatment period 2007-2011. We report this estimator for the main propensity score Specification (2), to rely on strict matches within economic sub-sector and match group fixed-effects can take into account all sector specific unobservables.[23] Each column in panels A and B of Table 7 refers to a separate regression, where the dependent variable is measured as differences in outcomes 2013-2011.[24]

Panel A focuses on plants with a high electricity-to-sales ratio. For each regression we report the main effects of being EEG exempt and belonging to the group of high electricity user, as well as the interaction term EEG $\times$ high electricity. The first four columns report heterogeneity in

[23]For completeness we report the results for propensity score estimation (1) in Table A.7 in the Appendix,.

[24]Similar to the main tables, electricity, total CO_2, employment, and sales are measured in log differences. Shares and investment are not transformed before taking differences.

treatment with respect to fuel inputs and carbon emissions, and the last four columns look at competitiveness indicators. Focusing first on fuel inputs, we find that the main effect of the EEG levy exemption on electricity use is mainly driven by plants that are highly electricity-dependent in their operation. The interaction term, EEG $\times$ high electricity, is positive and significant at the 5% level in Column 1, while the main effect is not any longer significant. The fuel switching becomes clear when looking at the fuel shares in Columns 2 and 3. While non-exempt plants that are highly electricity dependent increase their gas share by 1.6%, we find a similar increase for the electricity share for the interaction term EEG $\times$ high electricity. In line with the observed fuel changes, total CO_2 emissions increase for the group of EEG exempt plants that are high electricity consumers. The competitiveness indicators are in line with the main findings from Table 3. For employment, we find both main effects to be negative and significant. While the decrease in employment in EEG exempt plants is in line with the observed reduction in own generation capacities, plants that highly benefit from the EEG levy exemption do somewhat counteract this negative effect. We find similar results for investment.[25] While the average EEG exempt plant reduces investment compared to the control group, exempt plants that qualify as highly electricity intensive undo this effect. We do not find any significant differences for EEG exempt plants in sales and export share, indicating that the short-term impacts are limited to fuel switches.

Panel B, on the other hand, presents results for plants that face international competition, approximated by a high export share. This sample split reveals that the main effects are not influenced by the group of exporters that are EEG exempt. Rather, we find that plants with a high export share do increase their gas consumption more than their electricity consumption, as indicated by a positive and significant increase in the gas share. The marginal effects for the interaction term on electricity consumption and the electricity share is negative, indicating that EEG exempt plants in international competition did not particularly benefit from the exemption. It has been widely documented in the literature on firm productivity that exporting firms are different with respect to many characteristics (see for instance Bernard and Jensen 2004). As this paper focuses mainly on small and medium-sized manufacturing plants, it is likely that there is selection into export markets and that plants with a higher export share are using their fuel inputs more efficiently to begin with. Also production processes might be more standardized

[25]Note that the point estimates are not directly comparable as investment is measured in level differences.

(global value chain), making fuel-switching less attractive for these type of plants. In terms of competitiveness indicators, we do not find a clear heterogeneity pattern by export orientation. We find some evidence that the EEG levy helped plants with a high export share to increase this share further (interaction term in Column 7). Yet, as Column 6 shows, the effect on overall sales is negative. Investment shows the opposite sign as Panel A, indicating that the exempt plants with a high export share do not adjust their capital stock due to the exemption.

6 Discussion

Our main results show that the EEG levy exemption did lead to an increase in electricity consumption in the year of the policy introduction and that the main mechanism was fuel switching, i.e. exempt plants switch from gas to electricity and are moreover less likely to engage in own electricity production. As treated plants were first time receivers of the exemption, our results highlight the fact that plants in the manufacturing sector have possibilities of fuel switching in the short-run, which might impact CO_2 emissions. Our analysis does not find any short-run impacts on competitiveness indicators, such as sales or export share. We furthermore show that the policy design does favor mainly high electricity users and does not improve competitiveness of plants in international competition. These results indicate that the 2012 EEG reform was poorly targeted and led to a large shift in the burden for RES financing from the industry to commercial and residential accounts.[26] By extending the exemption criteria to energy-intensive plants consuming between 1 and 10 GWh, the total amount of exempt electricity increased by approximately 5,200 GWh (BMU 2013), representing around 190 Million Euros of direct rent transfer to the industry.[27] However, our findings highlight the fact that exempt firms have strong incentives to switch fuels and thus increase their electricity consumption further. This means that the true increase due to the policy change was likely underestimated by 300 - 400 MWh.

More broadly speaking, the EEG levy exemption in 2013 affected a total of 90,724 GWh of electricity in the manufacturing sector belonging to 1,667 plants.[28] Applying the 2013 EEG rules,

[26] Reguant (2018) describes this trade-off between charging residential versus industrial consumers at a broader scale to highlight distributional tensions between these groups.

[27] 5,200 GWh $\times$ EEG levy of 3.592 Euro-ct / kWh.

[28] BMU (2014).

this means that exempt plants only contributed with roughly 140 million Euros to the financing of renewables, while their full contribution would have implied a payment of 3.26 billion Euros.[29] This implies that the EEG levy for other electricity consumers could have been roughly one Eurocent per kWh (30%) less in 2013.

While we cannot fully generalize our results to the entire manufacturing sector, other work (Gerster 2017) leads to similar implications. Germany has been a leader in RES investment policies with very ambiguous climate change targets. Yet, due to the exemption of the energy-intensive industry, most price increases have fallen on smaller residential and commercial customers. A restructuring of the EEG levy exemptions could likely distribute the burden on a broader basis. One limitation to the current approach is that we are focusing only on the short-run impact of the policy exemption. Exempt plants might invest differently and optimize their production processes endogenously to the exemption, which might lead to competitiveness differences in the long-run. Also, other dynamic choices such as entry or plant exit are not taken into account in the present analysis.

7 Conclusion

This paper analyses the impact of electricity taxation on firm competitiveness and a broader set of plant-level outcomes. Using an exogenous variation in electricity prices resulting from a policy change in RES financing, we find that plants that are newly exempt from paying the EEG levy significantly increase their electricity consumption by 5 to 7.5% compared to a matched control group. The main mechanism behind this effect is fuel-switching from gas to electricity. Given the electricity-mix in Germany this switch is related to a significant increase in CO_2 emissions of about 5-6%. We run detailed robustness checks for our estimates. Taking advantage of the 2012 EEG levy reform as natural experiment, we estimate a lower bound for the main treatment effect at 2.6% increase in electricity consumption.

Our findings suggest that the EEG levy exemptions were not effective in strengthening the

[29] For simplicity we assume that all plants consume at least 10 GWh of electricity in 2013, of which the first GWh is non-exempt, electricity consumption between 2 and 10 GWh has to be paid with 10% of the levy, and the additional amount with 1%. The full EEG contribution without exemption is calculated by multiplying 90,724 GWh with the 2013 EEG levy rate.

competitiveness of firms, at least in the short run. We also find that targeting of the policy was poor, as less export-oriented plants reacted more strongly to being exempt, compared to more export-oriented plants. By contrast, the strong fuel substitution that we observe shows that firms respond to changes in energy prices. As electricity generation in Germany is carbon-intensive, mainly owing to large shares of coal and lignite in the electricity mix, this fuel substitution pattern may even be associated with increasing carbon emissions, thus counteracting the objective of the renewable energy support policies. By contrast, the EEG levy reform in 2012 resulted in substantial rent-transfers to newly exempt firms. While our analysis provides new evidence on the short-run impact of a large drop in electricity taxes on plant-level outcomes, our study disregards potential long-term impacts. This provides an interesting opportunity for future work.

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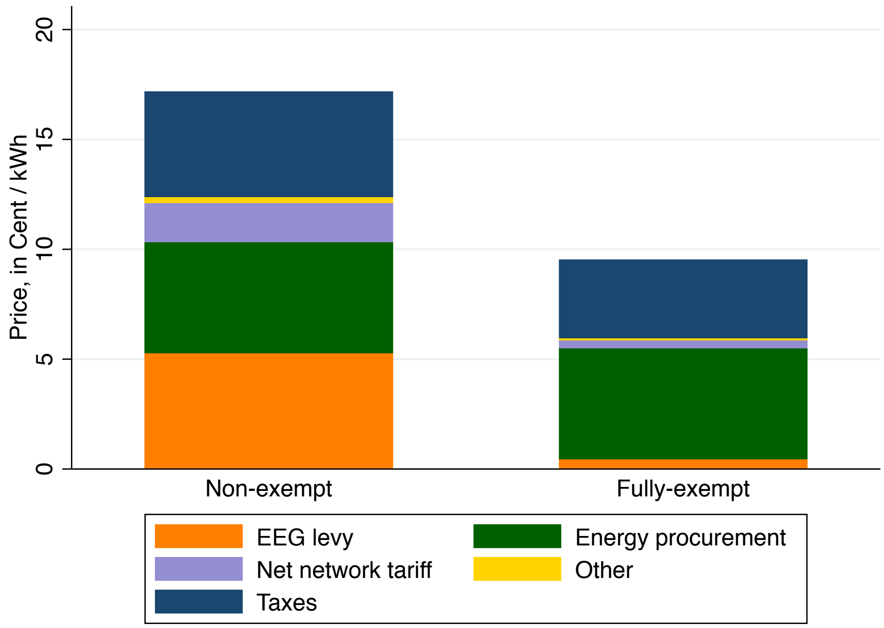
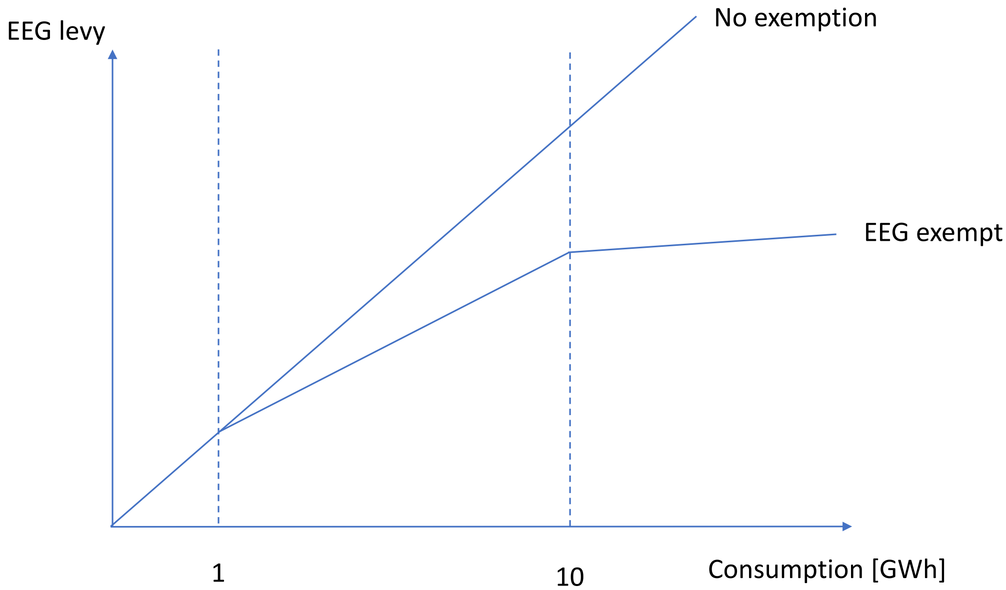
Figures & Tables

Figure 1: Average industry electricity prices in Germany 2013



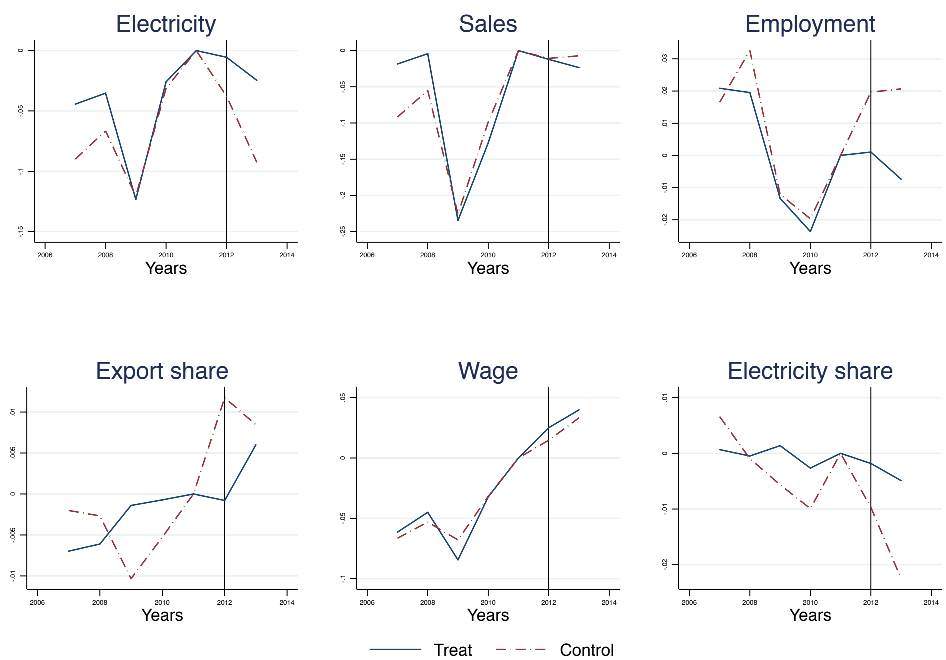
Notes: Average electricity prices in the German industry (quantity-weighted). Source: German federal network agency, Survey, April 2013. N= 206. The unweighted average electricity price is approximately 0.9 cent/kWh above the weighted mean of 17.17 cent / kWh for the non-exempt firms. Taxes include both value-added tax and electricity taxes. Other includes concession fees, metering and billing, and additional surcharges.

Figure 2: EEG levy payment schedule in 2013



Notes: EEG levy payment schedule as a function of electricity consumption. EEG exempt plants pay the full EEG levy for the first GWh electricity consumption, 10% of the levy for quantities between 1 and 10 GWh, and 1% above 10 GWh.

Figure 3: Common trends: matching difference-in-difference (plant-level)



Notes: Graphical analysis of parallel pre-treatment trends for treated plants (EEG exempt) and matched control plants. The control group is based on nearest neighbor matching, following propensity score Specification (2), as presented in Table A.10. The vertical line indicates the EEG reform in 2012. A formal test for mean-differences in pre-treatment growth rates 2011-2010 and 2010-2009 for both propensity score estimations is given in Table 2.

Table 1: Summary statistics

	Non-exempt plants			EEG exempt plants: 1-10GWh			All EEG exempt plants		
VARIABLE	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
Plant-level data									
Economic covariates									
Sales, in million €	37.265	453.930	39,045	26.527	69.815	641	79.284	219.216	1,458
Export share (of sales)	0.214	0.263	39,045	0.212	0.262	641	0.281	0.286	1,458
Number of employees	136	620	38,422	73	83	645	177	251	1,454
Investments, in million €	1.229	15.275	39,198	0.775	5.563	639	2.339	7.160	1,444
Average wage per employee, in thd. €	33.695	13.614	38,421	33.577	9.795	645	38.755	14.848	1,454
Energy-related covariates									
Electricity use, in GWh	3.652	48.653	38,917	5.474	4.360	630	52.280	164.919	1,429
Electricity use (2011), in GWh	3.768	46.610	36,693	5.135	2.350	608	56.096	192.672	1,431
Energy use (w/o electricity), in GWh	15.939	631.243	39,049	9.574	18.800	638	120.379	602.199	1,443
Own electricity generation, in %	0.089	0.285	40,755	0.085	0.279	659	0.129	0.335	1,482
Electricity use per sales	3.244	423.100	37,913	2.364	37.007	622	1.737	24.771	1,419
Electricity share in total energy	0.518	0.259	38,917	0.599	0.310	630	0.558	0.316	1,429
Gas share in total energy	0.297	0.292	38,917	0.281	0.307	630	0.281	0.301	1,429
Oil share in total energy	0.134	0.237	38,917	0.050	0.136	630	0.035	0.115	1,429
Coal share in total energy	0.005	0.063	38,917	0.010	0.086	630	0.031	0.134	1,429
Renewables share in total energy	0.047	0.161	38,917	0.061	0.194	630	0.094	0.229	1,429
Total CO_2 emissions, in 1,000 t	5540	181444	39,049	4707	4983	638	50328	181140	1,443
Direct CO_2 emissions, in 1,000 t	3862	175915	39,049	1692	4064	638	22876	139819	1,443
CO_2 intenisty of energy use, in g per kWh	408	121	38,917	416	132	630	395	141	1,429
Firm-level data									
Number of plants per firm	3.124	13.079	40,755	2.088	2.908	659	2.304	3.124	1,482
Gross value added, in million €	118.257	918.299	17,807	19.119	53.772	355	43.443	111.323	1,006
Sales, in million €	172.129	2073.110	40,755	87.524	355.118	659	175.171	512.104	1,482
Total energy cost, in million €	6.094	37.237	17,806	7.068	27.229	355	21.392	44.040	1,006

Notes: Descriptive statistics for the group of EEG exempt and non-exempt plants for the year 2013. Column 2, EEG exempt plants 1-10GWh, refers to the group of newly eligible plants, while Column 3 relates to all EEG exempt plants. Source: Research Data Centers of the Federal Statistical Offices and the Statistical Offices of the Länder: AFiD Panel Manufacturing Plants, AFiD Module Energy Use, and Cost Structure Survey, 2007-2013, own calculations.

Table 2: Balance of covariates: matching difference-in-difference (plant-level)

		Specification 1			Specification 2		
	Treat	Control	T-test		Control	T-test	
VARIABLE	mean	mean	t-stat	p-value	mean	t-stat	p-value
Differences: 2011-2010							
Electricity use	.026	.024	0.16	0.876	.058	-1.51	0.132
Sales	.130	.111	1.54	0.124	.109	1.19	0.236
Employment	.025	.020	0.61	0.543	.023	0	1
Wage	.032	.027	0.62	0.536	.032	-0.02	0.987
Export share	.001	.003	-0.56	0.572	.001	0.01	0.989
Differences: 2010-2009							
Electricity	.098	.10	-0.12	0.904	.091	0.32	0.749
Sales	.108	.144	-2.25	0.025**	.129	-1.34	0.181
Employment	-.0105	-.0025	-1.03	0.304	-.004	-0.77	0.443
Wage	.052	0.035	1.11	0.268	.036	0.99	0.322
Export share	.001	.004	-0.58	0.564	.006	-0.99	0.321

Note: Pre-treatment differences for the group of treated plants (EEG exempt in 2013) and two distinct control groups, based on nearest neighbor matching. All variables are in logs, except shares. Propensity score Specification (1) is presented in Table A.9, and Specification (2) in Table A.10. T-test for equality of means in growth rates 2011-2010 and 2010-2009. * p<.1 ,** p<.05, and ***p<.01.

Table 3: Results 2013-2011: matching difference-in-difference (plant level)

	Specification 1			Specification 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Matching algorithm	1:1	1:1 caliper	1:20 caliper	1:1	1:1 caliper	1:20 caliper
Panel A: *Electricity & gas use*						
Electricity use	0.075***	0.075***	0.051***	0.069**	0.071**	0.068***
	(0.024)	(0.024)	(0.018)	(0.031)	(0.029)	(0.023)
Gas use	-0.086	-0.066	-0.057	-0.056	-0.065	-0.044
	(0.063)	(0.064)	(0.054)	(0.073)	(0.082)	(0.061)
Own electricity generation	-0.012	-0.012	-0.01	-0.028*	-0.029*	-0.011
	(0.012)	(0.014)	(0.011)	(0.016)	(0.017)	(0.012)
Panel B: *Fuel inputs & carbon emissions*						
Electricity share in total energy	0.012	0.012	0.01*	0.012	0.013	0.009
	(0.008)	(0.009)	(0.006)	(0.008)	(0.008)	(0.007)
Gas share in total energy	-0.021**	-0.021**	-0.006	-0.016	-0.016	-0.015*
	(0.01)	(0.01)	(0.007)	(0.01)	(0.01)	(0.008)
Oil share in total energy	0.008	0.008	0	0.003	0.003	0.007
	(0.008)	(0.008)	(0.005)	(0.007)	(0.007)	(0.007)
Total CO_2 emissions	0.058**	0.058**	0.031**	0.029	0.031	0.052***
	(0.023)	(0.023)	(0.015)	(0.022)	(0.019)	(0.019)
Direct CO_2 emissions	-0.013	-0.004	-0.029	-0.03	-0.031	0
	(0.049)	(0.057)	(0.041)	(0.056)	(0.058)	(0.043)
Panel C: *Competitiveness indicators*						
Employment	-0.016	-0.016	-0.028**	-0.017	-0.023*	-0.031***
	(0.014)	(0.016)	(0.011)	(0.014)	(0.014)	(0.011)
Sales	-0.015	-0.015	-0.014	-0.001	-0.004	-0.026
	(0.022)	(0.021)	(0.018)	(0.02)	(0.02)	(0.018)
Export share	-0.002	-0.002	-0.009	-0.004	-0.006	-0.006
	(0.009)	(0.009)	(0.007)	(0.008)	(0.008)	(0.006)
Investment	-0.108	-0.111	-0.06	-0.12	-0.126	-0.044
	(0.108)	(0.103)	(0.093)	(0.117)	(0.117)	(0.11)
Observations	1,014	863	2,545	1,012	852	2,534
# treated plants	508	508	508	507	489	489
# control plants	506	355	2,037	505	363	2,045

Notes: Main outcome variables defined as log differences 2013-2011, except fuel shares, and investment (level differences). Own electricity is a dummy variable indicating a plant with own electricity production. Unit of observation is plant-year. Specification (1) is based on propensity score definition in Table A.9, while Specification (2) limits matches to be within the same industry sub-sector (Table A.10). Columns 1 and 4 employ nearest neighbor matching without replacement. Columns 2 and 5 use nearest neighbor matching with caliper (set to .25 of the standard deviation) and replacement, and Columns 3 and 6 use a 1:20 matching algorithm with caliper and replacement. Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens 2006) reported in parenthesis. * p<.1 ,** p<.05, and ***p<.01.

Table 4: Robustness: Anticipation to policy change (base year 2010)

	Specification 1		Specification 2	
	(1)	(2)	(3)	(4)
Matching algorithm	1:1	1:20 caliper	1:1	1:20 caliper
Panel A: *Electricity and gas use*				
Electricity use	0.057*	0.033*	0.025	0.034*
	(0.031)	(0.017)	(0.022)	(0.019)
Gas use	-0.081	-0.074	-0.067	-0.066
	(0.064)	(0.058)	(0.086)	(0.059)
Own electricity generation	0	-0.004	-0.015	-0.008
	(0.017)	(0.011)	(0.017)	(0.011)
Panel B: *Fuel inputs & carbon emissions*				
Electricity share in total energy	0.017**	0.012*	0.008	0.008
	(0.008)	(0.007)	(0.008)	(0.005)
Gas share in total energy	-0.014	-0.005	-0.016	-0.009
	(0.012)	(0.008)	(0.01)	(0.008)
Oil share in total energy	-0.004	-0.001	0.013*	0.006
	(0.01)	(0.006)	(0.008)	(0.007)
Total CO_2 emissions	0.042	0.028*	0.045**	0.041***
	(0.028)	(0.016)	(0.021)	(0.014)
Direct CO_2 emissions	-0.078	-0.06	-0.004	-0.005
	(0.05)	(0.044)	(0.059)	(0.039)
Panel C: *Competitiveness indicators*				
Employment	-0.019	-0.012	-0.01	-0.023**
	(0.014)	(0.012)	(0.014)	(0.012)
Sales	0.007	0.019	0.017	-0.006
	(0.027)	(0.018)	(0.023)	(0.018)
Export share	0	-0.002	0	-0.006
	(0.01)	(0.008)	(0.009)	(0.006)
Investment	-0.056	0.006	0.097	-0.064
	(0.147)	(0.112)	(0.176)	(0.121)
Observations	908	2,384	918	2,375
# treated plants	454	454	459	439
# control plants	454	1,930	459	1,936

Notes: Main outcome variables defined as log differences 2013-2011, except fuel shares, and investment (level differences). Own electricity is a dummy variable indicating a plant with own electricity production. Unit of observation is plant-year. Specification (1) is based on propensity score definition in Table A.9, while Specification (2) limits matches to be within the same industry sub-sector (Table A.10). Columns 1 and 4 employ nearest neighbor matching without replacement. Columns 2 and 5 use nearest neighbor matching with caliper (set to .25 of the standard deviation) and replacement, and Columns 3 and 6 use a 1:20 matching algorithm with caliper and replacement. Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens 2006) reported in parenthesis. * p<.1 ,** p<.05, and ***p<.01.

Table 5: Robustness: Spill-over (single-plant firms)

	Specification 1 (1)	Specification 1 (2)	Specification 2 (3)	Specification 2 (4)
Matching algorithm	1:1	1:20 caliper	1:1	1:20 caliper
Panel A: *Electricity and gas use*				
Electricity use	0.077**	0.049**	0.056	0.062**
	(0.034)	(0.021)	(0.039)	(0.025)
Gas use	-0.09	-0.069	-0.093	-0.055
	(0.078)	(0.071)	(0.091)	(0.07)
Own electricity generation	-0.024	-0.021	-0.019	-0.019
	(0.016)	(0.014)	(0.016)	(0.013)
Panel B: *Fuel inputs & carbon emissions*				
Electricity share in total energy	0.025**	0.013*	0.015	0.011
	(0.011)	(0.007)	(0.01)	(0.008)
Gas share in total energy	-0.011	-0.005	-0.012	-0.004
	(0.011)	(0.008)	(0.011)	(0.009)
Oil share in total energy	0.001	0.002	0.002	0.002
	(0.01)	(0.007)	(0.008)	(0.007)
Total CO_2 emissions	0.046	0.032*	0.009	0.049**
	(0.032)	(0.018)	(0.032)	(0.02)
Direct CO_2 emissions	-0.037	-0.033	-0.023	0.001
	(0.065)	(0.054)	(0.065)	(0.048)
Panel C: *Competitiveness indicators*				
Employment	-0.015	-0.014	-0.023*	-0.019*
	(0.015)	(0.011)	(0.013)	(0.011)
Sales	-0.003	-0.005	0.004	-0.008
	(0.027)	(0.021)	(0.023)	(0.02)
Export share	-0.003	-0.007	-0.011	-0.004
	(0.007)	(0.007)	(0.012)	(0.006)
Investment	0.004	0.006	-0.159	-0.01
	(0.114)	(0.098)	(0.13)	(0.14)
Observations	738	1,817	732	1,738
# treated plants	369	369	366	347
# control plants	369	1,448	366	1,391

Notes: Main outcome variables defined as log differences 2013-2011, except fuel shares, and investment (level differences). Own electricity is a dummy variable indicating a plant with own electricity production. Unit of observation is plant-year. Specification (1) is based on propensity score definition in Table A.9, while Specification (2) limits matches to be within the same industry sub-sector (Table A.10). Columns 1 and 4 employ nearest neighbor matching without replacement. Columns 2 and 5 use nearest neighbor matching with caliper (set to .25 of the standard deviation) and replacement, and Columns 3 and 6 use a 1:20 matching algorithm with caliper and replacement. Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens 2006) reported in parenthesis. * p<.1 ,** p<.05, and ***p<.01.

Table 6: Robustness: difference-in-difference 5-10 GWh vs. 10-20 GWh

OUTCOME	alpha_{LB}	std err.
Panel A: *Electricity use*		
Electricity use	0.026*	(0.016)
Electricity share	0.002	(0.003)
Own electricity generation	0.002	(0.007)
Panel B: *Competitiveness indicators*		
Employment	0.006	(0.007)
Sales	0.001	(0.013)
Export share	-0.001	(0.003)
Investment	-0.131	(0.237)
Obervations	3,585	
Constant	Yes	

Note: Regression results for the difference-in-difference model 3 comparing the group of eligible treatment plants (5-10 GWh) to the group of control plants (10-20 GWh). Each row corresponds to a separate regression of the corresponding outcome variable on a treatment indicator (eligible for EEG exemption in 2013). Outcome variables expressed in log-differences 2013-2011, except shares, investment, and own electricity (level-differences 2013-2011). Unit of observation: plant. Robust standard errors reported in parentheses. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

Table 7: Heterogeneous treatment effects

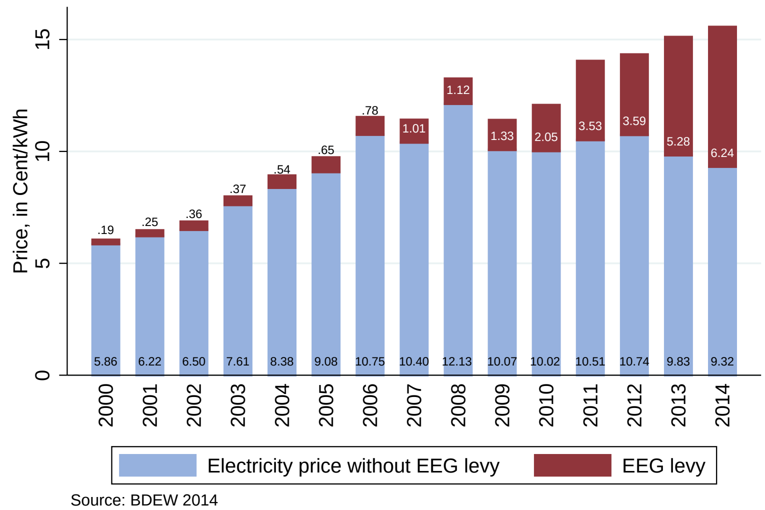
	Fuel inputs & carbon emissions				Competitiveness indicators			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME	Electricity	Electricity Share	Gas Share	Total CO_2	Employment	Sales	Export Share	Investment
Panel A: *High electricity-to-sales ratio*								
EEG exempt	0.032	0	-0.007	0.026	-0.056***	0.005	-0.008	-0.51**
	(0.021)	(0.007)	(0.012)	(0.02)	(0.034)	(0.006)	(0.23)	
High electricity	-0.102***	-0.008	0.016***	-0.09***	-0.029***	0.029	-0.008*	-0.146**
	(0.015)	(0.006)	(0.006)	(0.012)	(0.009)	(0.02)	(0.004)	(0.063)
EEG exempt × High electricity	0.06**	0.015*	-0.014	0.046*	0.038	-0.048	0.003	0.66***
	(0.028)	(0.009)	(0.013)	(0.026)	(0.023)	(0.037)	(0.008)	(0.239)
Group fixed effects	489	489	489	489	489	489	489	489
Obervations	9966	9966	9966	9966	9,934	9,936	9,936	9,739
R^2	0.162	0.191	0.239	0.198	0.304	0.366	0.22	0.225
Panel B: *High export share*								
OUTCOME	Electricity	Electricity Share	Gas Share	Total CO_2	Employment	Sales	Export Share	Investment
EEG exempt	0.093***	0.017***	-0.012	0.067***	-0.035***	0.001	-0.015***	0.181**
	(0.019)	(0.006)	(0.008)	(0.016)	(0.013)	(0.022)	(0.003)	(0.074)
High export share	0.042***	-0.003	0.016***	0.032***	-0.002	0.008	-0.011*	0.167***
	(0.009)	(0.003)	(0.003)	(0.008)	(0.005)	(0.007)	(0.002)	(0.051)
EEG exempt × High export share	-0.049*	-0.018*	-0.007	-0.026*	0.009	-0.064*	0.02**	-0.551***
	(0.028)	(0.01)	(0.011)	(0.026)	(0.02)	(0.037)	(0.01)	(0.193)
Group fixed effects	489	489	489	489	489	489	489	489
Obervations	9,966	9,966	9,966	9,966	9,934	9,936	9,936	9,739
R^2	0.158	0.192	0.24	0.193	0.302	0.367	0.221	0.224

Notes: Heterogeneous treatment effects for fuel inputs and competitiveness indicators for plants with a high electricity-to-sales ratio (Panel A) and plants with a high export share (Panel B). Main outcome variables defined as log differences (2013-2011) but shares, and investment (level-differences). Each column in Panel A and Panel B refers to a separate regression. Main estimator: 1:20 matching with replacement and caliper (set to .25 of the standard deviation) following propensity score estimation (2). Control observations weighted $1/M_j$, where M_j is the group size. Unit of observation: plant. EEG exempt: dummy variable indicating plant is exempt from the EEG levy in 2013. High electricity (export share) is a dummy variable indicating that the plant's mean electricity-to-sales ratio (export share) in the pre-treatment period 2007-2011 is above the median of the manufacturing industry. Regression controls for match specific fixed-effects (group FE). Robust standard errors clustered at the match (group)-level in parenthesis. * p<.1 ,** p<.05, and ***p<.01.

8 Appendix

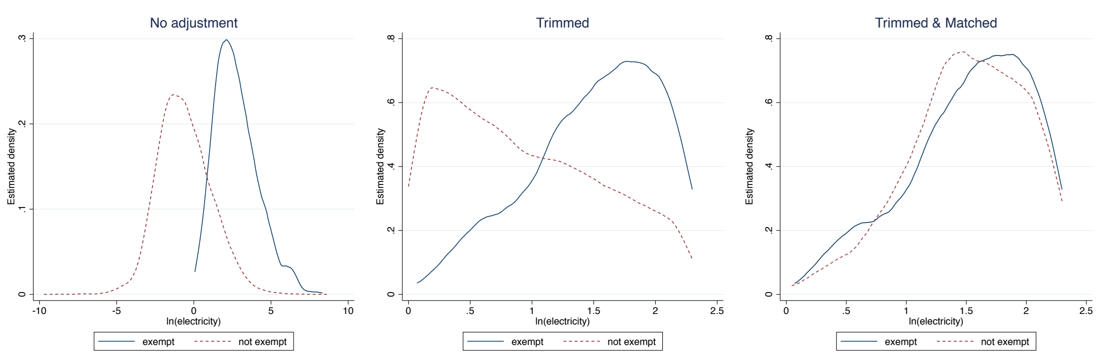
8.1 Additional figures and tables

Figure A.1: Average electricity prices and EEG levy in the industry



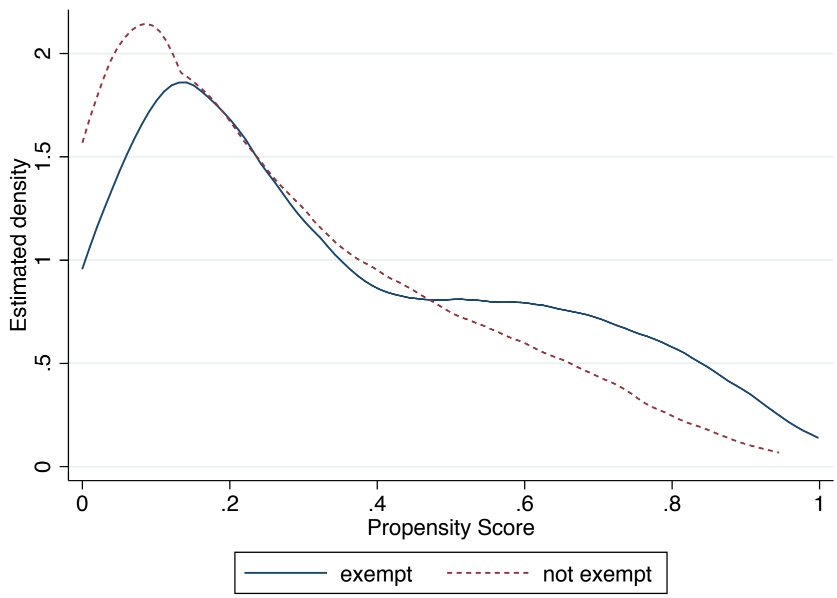
Notes: Average electricity prices in German industry and share of EEG levy over time.

Figure A.2: Overlap: electricity



Notes: Density distribution of log electricity for exempt plants and non-exempt plants, without adjustment (Panel a), with trimming to 1-10 GWh (Panel b), and with trimming and matching (Panel c).

Figure A.3: Overlap: propensity score



Notes: Overlap of the propensity score following Specification (2). Main estimator: nearest neighbor matching without replacement.

Table A.1: Robustness: electricity & gas

	Specification 1		Specification 2	
	(1)	(2)	(3)	(4)
Matching algorithm	1:1	1:20 caliper	1:1	1:20 caliper
Panel A: *Electricity and gas use*				
Electricity	0.042*	0.038*	0.03	0.042*
	(0.025)	(0.02)	(0.023)	(0.024)
Gas	-0.051	-0.055	-0.081	-0.046
	(0.066)	(0.055)	(0.058)	(0.059)
Own electricity generation	-0.026*	-0.022*	-0.026*	-0.019
	(0.014)	(0.012)	(0.013)	(0.013)
Panel B: *Fuel inputs & carbon emissions*				
Electricity share in total energy	0.013*	0.011**	0.013*	0.009
	(0.008)	(0.005)	(0.007)	(0.007)
Gas share in total energy	-0.016	-0.015*	-0.027**	-0.015*
	(0.01)	(0.008)	(0.009)	(0.008)
Oil share in total energy	-0.006	0.002	0.008	0.003
	(0.005)	(0.005)	(0.006)	(0.006)
Total CO_2 emissions	0.02	0.017	0.012	0.03
	(0.024)	(0.018)	(0.02)	(0.022)
Direct CO_2 emissions	-0.056	-0.057	-0.063	-0.031
	(0.056)	(0.043)	(0.047)	(0.047)
Panel C: *Competitiveness indicators*				
Employment	-0.02	-0.028**	-0.021	-0.033**
	(0.017)	(0.013)	(0.018)	(0.015)
Sales	-0.006	-0.001	-0.023	-0.021
	(0.028)	(0.024)	(0.031)	(0.022)
Export share	-0.021	-0.008	-0.012	-0.004
	(0.016)	(0.01)	(0.012)	(0.007)
Investment	-0.09	-0.041	-0.012	-0.043
	(0.138)	(0.121)	(0.165)	(0.155)
Observations	696	1756	694	1745
# treated plants	348	348	346	327
# control plants	348	1,408	348	1,418

Notes: Main outcome variables defined as log differences 2013-2011, except fuel shares, and investment (level differences). Own electricity is a dummy variable indicating a plant with own electricity production. Unit of observation is plant-year. Specification (1) is based on propensity score definition in Table A.9, while Specification (2) limits matches to be within the same industry sub-sector (Table A.10). Columns 1 and 4 employ nearest neighbor matching without replacement. Columns 2 and 5 use nearest neighbor matching with caliper (set to .25 of the standard deviation) and replacement, and Columns 3 and 6 use a 1:20 matching algorithm with caliper and replacement. Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens 2006) reported in parenthesis. * p<.1 ,** p<.05, and ***p<.01.

Table A.2: Results 2013-2012: Short-run impact of realized price changes

	Specification 1		Specification 2	
	(1)	(2)	(3)	(4)
Matching algorithm	1:1	1:20 caliper	1:1	1:20 caliper
Panel A: *Electricity and gas use*				
Electricity	0.026	0.027**	0.05*	0.041**
	(0.017)	(0.014)	(0.026)	(0.017)
Gas	-0.044	-0.039	-0.034	-0.043
	(0.044)	(0.044)	(0.058)	(0.041)
Own electricity generation	-0.004	-0.009	-0.013*	-0.017***
	(0.014)	(0.007)	(0.007)	(0.006)
Panel B: *Fuel inputs & carbon emissions*				
Electricity share in total energy	0.012*	0.011**	0.02**	0.014**
	(0.007)	(0.005)	(0.008)	(0.006)
Gas share in total energy	-0.015**	-0.009*	-0.014*	-0.011**
	(0.008)	(0.005)	(0.007)	(0.005)
Oil share in total energy	0.007	0	-0.005	-0.003
	(0.006)	(0.004)	(0.003)	(0.003)
Total CO_2 emissions	0.02	0.013	0.026	0.021
	(0.017)	(0.013)	(0.022)	(0.015)
Direct CO_2 emissions	-0.036	-0.051	-0.059	-0.062
	(0.035)	(0.033)	(0.038)	(0.03)
Panel C: *Competitiveness indicators*				
Employment	-0.02**	-0.011	-0.005	-0.004
	(0.01)	(0.009)	(0.009)	(0.011)
Sales	-0.027	-0.026*	-0.01	-0.01
	(0.017)	(0.015)	(0.019)	(0.015)
Export share	0.011	0.006	0.009	0.011**
	(0.008)	(0.006)	(0.007)	(0.005)
Investment	0.006	0.131	0.067	0.023
	(0.093)	(0.113)	(0.17)	(0.099)
Observations	1,060	2659	1,058	2674
# treated plants	530	530	529	505
# control plants	530	2,129	529	2,169

Notes: Main outcome variables defined as log differences 2013-2011, except fuel shares, and investment (level differences). Own electricity is a dummy variable indicating a plant with own electricity production. Unit of observation is plant-year. Specification (1) is based on propensity score definition in Table A.9, while Specification (2) limits matches to be within the same industry sub-sector (Table A.10). Columns 1 and 4 employ nearest neighbor matching without replacement. Columns 2 and 5 use nearest neighbor matching with caliper (set to .25 of the standard deviation) and replacement, and Columns 3 and 6 use a 1:20 matching algorithm with caliper and replacement. Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens 2006) reported in parenthesis. * p<.1 ,** p<.05, and ***p<.01.

Table A.3: Robustness: 5-10 GWh plants

	Specification 1 (1)	Specification 1 (2)	Specification 2 (3)	Specification 2 (4)
Matching algorithm	1:1	1:20 caliper	1:1	1:20 caliper
Panel A: *Electricity and gas use*				
Electricity	0.028	0.055*	0.079**	0.047**
	(0.031)	(0.032)	(0.034)	(0.023)
Gas	-0.184*	-0.111	-0.085	-0.082
	(0.101)	(0.079)	(0.093)	(0.083)
Own electricity generation	-0.012	-0.002	-0.02	0.007
	(0.033)	(0.016)	(0.019)	(0.018)
Panel B: *Fuel inputs & carbon emissions*				
Electricity share in total energy	0	0.001	-0.003	0.001
	(0.009)	(0.007)	(0.008)	(0.007)
Gas share in total energy	-0.007	-0.016	-0.02	-0.021**
	(0.013)	(0.01)	(0.015)	(0.01)
Oil share in total energy	0.001	0.01	0.009	0.011
	(0.009)	(0.008)	(0.01)	(0.009)
Total CO_2 emissions	0.007	0.035	0.06	0.04*
	(0.033)	(0.031)	(0.037)	(0.023)
Direct CO_2 emissions	-0.062	-0.067	-0.005	-0.029
	(0.094)	(0.058)	(0.067)	(0.064)
Panel C: *Competitiveness indicators*				
Employment	0.006	0.01	0.01	0.007
	(0.019)	(0.017)	(0.019)	(0.015)
Sales	-0.027	-0.009	0.006	-0.014
	(0.037)	(0.029)	(0.032)	(0.028)
Export share	0.001	-0.011	0.001	-0.006
	(0.016)	(0.011)	(0.015)	(0.009)
Investment	-0.197	-0.193	-0.449*	-0.209
	(0.19)	(0.169)	(0.272)	(0.214)
Observations	506	827	498	885
# treated plants	253	253	249	240
# control plants	253	574	249	645

Notes: Main outcome variables defined as log differences 2013-2011, except fuel shares, and investment (level differences). Own electricity is a dummy variable indicating a plant with own electricity production. Unit of observation is plant-year. Specification (1) is based on propensity score definition in Table A.9, while Specification (2) limits matches to be within the same industry sub-sector (Table A.10). Columns 1 and 4 employ nearest neighbor matching without replacement. Columns 2 and 5 use nearest neighbor matching with caliper (set to .25 of the standard deviation) and replacement, and Columns 3 and 6 use a 1:20 matching algorithm with caliper and replacement. Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens 2006) reported in parenthesis. * p<.1 ,** p<.05, and ***p<.01.

Table A.4: Robustness: 3-digit grouping (WZ3)

	Specification 1		Specification 2	
	(1)	(2)	(3)	(4)
Matching algorithm	1:1	1:20 caliper	1:1	1:20 caliper
Panel A: *Electricity and gas use*				
Electricity	0.075***	0.051***	0.034	0.043*
	(0.024)	(0.018)	(0.034)	(0.024)
Gas	-0.086	-0.057	-0.057	-0.072
	(0.063)	(0.054)	(0.075)	(0.067)
Own electricity generation	-0.012	-0.01	-0.02	-0.036**
	(0.012)	(0.011)	(0.016)	(0.014)
Panel B: *Fuel inputs & carbon emissions*				
Electricity share in total energy	0.012	0.01*	0.013	0.006
	(0.008)	(0.006)	(0.009)	(0.007)
Gas share in total energy	-0.021**	-0.006	-0.001	-0.008
	(0.01)	(0.007)	(0.011)	(0.009)
Oil share in total energy	0.008	0	-0.002	0.005
	(0.008)	(0.005)	(0.009)	(0.007)
Total CO_2 emissions	0.058**	0.031**	0.007	0.033*
	(0.023)	(0.015)	(0.028)	(0.018)
Direct CO_2 emissions	-0.013	-0.029	-0.105**	0.005
	(0.049)	(0.041)	(0.048)	(0.047)
Panel C: *Competitiveness indicators*				
Employment	-0.016	-0.028**	-0.03*	-0.031**
	(0.014)	(0.011)	(0.015)	(0.012)
Sales	-0.015	-0.014	-0.032	-0.023
	(0.022)	(0.018)	(0.024)	(0.018)
Export share	-0.002	-0.009	0.017**	0.002
	(0.009)	(0.007)	(0.008)	(0.005)
Investment	-0.108	-0.06	0.116	-0.026
	(0.108)	(0.093)	(0.158)	(0.119)
Observations	1,016	2545	1,008	1866
# treated plants	508	508	504	369
# control plants	508	2,037	504	1,497

Notes: Main outcome variables defined as log differences 2013-2011, except fuel shares, and investment (level differences). Own electricity is a dummy variable indicating a plant with own electricity production. Unit of observation is plant-year. Specification (1) is based on propensity score definition in Table A.9, while Specification (2) limits matches to be within the same industry sub-sector (Table A.10). Columns 1 and 4 employ nearest neighbor matching without replacement. Columns 2 and 5 use nearest neighbor matching with caliper (set to .25 of the standard deviation) and replacement, and Columns 3 and 6 use a 1:20 matching algorithm with caliper and replacement. Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens 2006) reported in parenthesis. * p<.1 ,** p<.05, and ***p<.01.

Table A.5: Robustness: Propensity Score (minimal specification)

	(1)	(2)
Matching algorithm	1:1 caliper	1:20 caliper
Panel A: *Electricity and gas use*		
Electricity	0.063***	0.062***
	(0.02)	(0.014)
Gas	-0.064	-0.044
	(0.067)	(0.049)
Own electricity generation	-0.018	-0.008
	(0.014)	(0.009)
Panel B: *Fuel inputs & carbon emissions*		
Electricity share in total energy	0.013*	0.009*
	(0.007)	(0.005)
Gas share in total energy	-0.007	-0.011*
	(0.007)	(0.005)
Oil share in total energy	-0.003	0
	(0.006)	(0.005)
Total CO_2 emissions	0.046**	0.046***
	(0.018)	(0.013)
Direct CO_2 emissions	-0.041	0.008
	(0.052)	(0.036)
Panel C: *Competitiveness indicators*		
Employment	-0.015	-0.008
	(0.014)	(0.011)
Sales	-0.009	-0.034**
	(0.024)	(0.017)
Export share	0.007	-0.001
	(0.006)	(0.004)
Investment	-0.068	-0.166
	(0.157)	(0.125)
Observations	1,040	4163
# treated plants	564	564
# control plants	476	3,599

Notes: Main outcome variables defined as log differences 2013-2011, except fuel shares, and investment (level differences). Own electricity is a dummy variable indicating a plant with own electricity production. Unit of observation is plant-year. Propensity score (matching) based on minimum specification: plants matched strict within subsector on electricity-to-sales ratio in the year 2011. Columns 1 employs nearest neighbor matching with caliper (set to .25 of the standard deviation) and replacement and Column 2 uses a 1:20 matching algorithm with caliper and replacement. Heteroskedasticity-consistent analytical standard errors (Abadie and Imbens 2006) reported in parenthesis. * p<.1 ,** p<.05, and ***p<.01.

Table A.6: Robustness: Inference Propensity Score (1)

	(1) Unweighted	(2) Weighted
Panel A: *Electricity*		
EEG exempt	0.075^{**}	0.078^{**}
	(0.029)	(0.029)
Constant	-0.100^{***}	-0.101^{***}
	(0.014)	(0.010)
Match Group FE	Y	Y
Observations	1,016	1,016
Panel B: *Gas*		
EEG exempt	-0.066	-0.088
	(0.106)	(0.110)
Constant	0.120^{*}	0.148^{***}
	(0.052)	(0.033)
Match Group FE	Y	Y
Observations	716	716
Panel C: *Total CO_2*		
EEG exempt	0.058^{*}	0.057^{*}
	(0.028)	(0.029)
Constant	-0.049^{***}	-0.046^{***}
	(0.014)	(0.010)
Match Group FE	Y	Y
Observations	1,016	1,016

Note: Linear regression of log electricity, gas, and CO_2 emissions on treatment dummy (EEG exempt in 2013) and constant. Each regression is based on nearest neighbor matching without replacement and includes matching group fixed effects. Weights in Column 2 based on matching. Robust standard errors clustered at the matching group reported in parentheses. $p < 0.1$ (*), $p < 0.05$ (**), $p < 0.01$ (***).

Table A.7: Heterogeneity: Propensity Score (1)

	Fuel inputs & carbon emissions				Competitiveness indicators			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OUTCOME	Electricity	Electricity Share	Gas Share	Total CO_2	Employment	Sales	Export Share	Investment
Panel A: *High electricity-to-sales ratio*								
EEG exempt	0.04*	0.013*	0.01	0.016	-0.054**	0.011	-0.002	-0.403*
	(0.021)	(0.007)	(0.012)	(0.019)	(0.021)	(0.036)	(0.006)	(0.222)
High electricity	-0.038***	0.004	0.014***	-0.023**	-0.02***	0.003	-0.002	-0.018
	(0.013)	(0.004)	(0.004)	(0.011)	(0.007)	(0.01)	(0.003)	(0.055)
EEG exempt × High electricity	0.019	-0.003	-0.026**	0.024	0.035	-0.045	-0.011	0.474**
	(0.025)	(0.009)	(0.014)	(0.024)	(0.024)	(0.039)	(0.008)	(0.227)
Group fixed effects	508	508	508	508	508	508	508	508
Obervations	10,124	10,124	10,124	10,124	10,100	10,077	10,077	9,949
R^2	0.192	0.22	0.275	0.214	0.321	0.359	0.191	0.306
Panel B: *High export share*								
OUTCOME	Electricity	Electricity Share	Gas Share	Total CO_2	Employment	Sales	Export Share	Investment
EEG exempt	0.063***	0.017***	-0.002	0.034**	-0.033**	-0.005	-0.017***	-0.033
	(0.019)	(0.006)	(0.008)	(0.016)	(0.014)	(0.022)	(0.003)	(0.061)
High export share	0.025***	-0.005*	0.003	0.02**	-0.008*	-0.022***	-0.01***	-0.085*
	(0.009)	(0.003)	(0.003)	(0.008)	(0.004)	(0.006)	(0.002)	(0.045)
EEG exempt × High export share	-0.022	-0.011	-0.013	-0.003	0.005	-0.031	0.015*	-0.096
	(0.027)	(0.009)	(0.011)	(0.025)	(0.019)	(0.033)	(0.009)	(0.145)
Group fixed effects	508	508	508	508	508	508	508	508
Obervations	10,124	10,124	10,124	10,124	10,100	10,077	10,077	9,949
R^2	0.192	0.222	0.273	0.214	0.319	0.36	0.191	0.303

Notes: Heterogeneous treatment effects for fuel inputs and competitiveness indicators for plants with a high electricity-to-sales ratio (Panel A) and plants with a high export share (Panel B). Main outcome variables defined as log differences (2013-2011) but shares, and investment (differences in levels). Each column in Panel A and Panel B refers to a separate regression. Main estimator: 1:20 matching with replacement and caliper (set to .25 of the standard deviation) following propensity score estimation (1). Control observations weighted $1/M_j$, where M_j is the group size. Unit of observation: plant. EEG exempt: dummy variable indicating plant is exempt from the EEG levy in 2013. High electricity (export share) is a dummy variable indicating that the plant's mean electricity-to-sales ratio (export share) in the pre-treatment period 2007-2011 is above the median of the manufacturing industry. Regression controls for match specific fixed-effects (group FE). Robust standard errors clustered at the match (group)-level in parenthesis. * $p<.1$,** $p<.05$, and ***$p<.01$.

8.2 Policy change as natural experiment

As a robustness check, we exploit the exogenous shift in the eligibility criteria from 10 GWh to 1 GWh in a classic difference-in-differences (DiD) framework, which yields an intention-to-treat (ITT) estimate and provides us with a lower bound estimator for the ATT. As the change in cutoff is policy induced, the DiD approach exploits a source of variation that is unrelated to firms' selection into treatment. To increase the similarity of treated and control plants, we focus on the group of plants with 5-10 GWh annual electricity consumption in 2011, 'treated', and those with 10-20 GWh electricity consumption in 2011, as 'control' plants. While the treated group became newly eligible from 2013 onwards, the control group consists of similar plants that have been eligible already before that year so that their eligibility status does not change.

We identify the ITT by estimating $\hat{\alpha}_{ITT}$ from the following DiD regression:

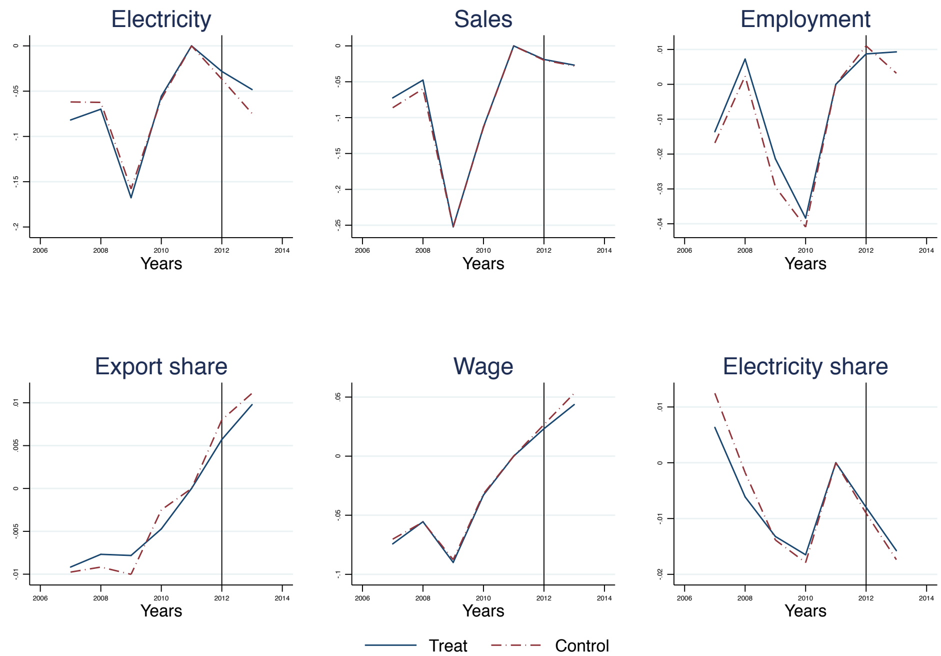
$$Y_{it} = \alpha_{ITT} Z_{it} + \theta_i + \gamma_t + \epsilon_{ijt}, \tag{3}$$

where Y_{it} denotes the outcome variable for plant i belonging in year t. We additionally include time fixed-effects, γ_t and group fixed-effects θ_j; ϵ_{it} represents an idiosyncratic error term. Identification rests on the common trends assumption which posits that outcome trends are the same for the group of newly eligible plants and the group of control plants.

Figure A.4 assess the common trends assumption graphically and finds supporting evidence as the trends for both groups of plants are very similar prior to 2011. We formally test for the differences in pre-treatment growth rates in the two-years leading up to the policy change (2011-2010 and 2010-2009) in Table A.8. The table confirms the graphical evidence and shows that the growth rates are very similar. In fact, we only find a statistically difference between the two groups in employment growth two years prior to the treatment, but not thereafter.

Table 6 lists the ITT estimates for electricity use and competitiveness indicators, which correspond closely to the results that we have discussed in the main text. We find that the EEG levy exemption leads to an increase in electricity use of 2.6% in the year following the exemption. In line with this result, we find that the ITT on the electricity share in total energy use is positive, yet not statistically significant. Finally, we find that no ITT estimate on one of our competitiveness indicators – including employment, sales, export share, and investment – is statistically significant.

Figure A.4: Common trends: difference-in-difference (2 groups)



Notes: Graphical analysis of parallel pre-treatment trends for the group of newly eligible plants for the EEG levy exemption (5-10 GWh in 2011, treated) and control group (10-20 GWh electricity consumption in 2011). Individual variables are normalized with respect to the year 2011. The vertical line indicates the EEG reform in 2012. A formal test for mean-differences in pre-treatment growth rates 2011-2010 and 2010-2009 is given in Table A.8.

Table A.8: Balance of covariates: difference-in-difference (groups)

	Treat	Control	T-test	
VARIABLE	mean	mean	t-statistic	p-value
Differences: 2011-2010				
Electricity	.056	.059	0.76	0.95
Sales	.113	.114	-0.08	0.933
Employment	.038	.041	-0.54	0.586
Wage	.033	.032	0.30	0.762
Export share	.005	.003	0.90	0.369
Differences: 2010-2009				
Electricity	.115	.104	0.85	0.394
Sales	.145	.151	-0.73	0.466
Employment	-.011	-.000	-2.59	0.01**
Wage	.057	.055	0.74	0.460
Export share	.004	.007	-1.05	0.292

Note: Pre-treatment differences for group of newly eligible plants for EEG levy exemption (5-10GWh in 2011, treated) and control group (10-20 GWh in 2011). All variables are in logs, except for shares. T-test for equality of growth rates 2011-10 and 2010-09. * p<.1 ,** p<.05, and ***p<.01.

8.3 Propensity score estimates

Table A.9: Propensity score: logit model, Specification (1)

Exempt 2013	beta	std err.
Electricity 2011	3.005***	(0.556)
Electricity 2010	.680**	(0.319)
Electricity 2009	.445*	(0.259)
Electricity 2008	.348*	(0.211)
Sales	-.548**	(0.239)
Employment	.638	(0.923)
Wage	4.197	(3.255)
Electricity × electricity	-.448**	(0.173)
Sales × sales	.015	(0.042)
Employment × employment	-.341**	(0.111)
Wage × wage	-.855*	(0.480)
Export share	-.323	(0.675)
Export share × export share	-.267	(0.868)
Constant	Y	
Observations	9,064	
Pseudo R^2	.42	
2-digit sector FE	17	

Note: Main dependent variable: EEG exempt 2013. Logit regression. Sample trimmed to plants with 1-10 GWh electricity consumption in 2011. All dependent variables refer to the base year, 2011. Unit of observation: plant. All variables are in logs, except for shares. Regression controls for manufacturing sub-sectors with 2-digit specific fixed-effects. * p<0.1, **p<0.05, and ***p<0.01.

Table A.10: Propensity score: logit model, Specification (2)

Exempt 2013	Sub-sector 1	Sub-sector 2	Sub-sector 3	Sub-sector 4	Sub-sector 5
Electricity 2011	1.897**	3.141***	1.959*	1.514	1.626***
	(0.952)	(0.693)	(1.143)	(1.426)	(0.318)
Electricity 2010	0.15	0.282	1.287	0.698	0.817**
	(1.187)	(0.509)	(1.107)	(1.853)	(0.351)
Electricity 2009	0.079	-0.128	-0.238	-0.376	1.359***
	(1.306)	(0.481)	(0.769)	(1.424)	(0.433)
Electricity 2008	0.376	-0.144	0.358	1.33	0.317
	(1.079)	(0.226)	(0.87)	(0.835)	(0.376)
Sales	0.377**	-1.139***	-2.229***	-0.456*	-1.38***
	(0.164)	(0.206)	(0.349)	(0.246)	(0.153)
Employment	-2.46***	-1.422***	-0.736**	-2.542***	-2.063***
	(0.209)	(0.216)	(0.341)	(0.327)	(0.24)
Observations	1,419	1,881	973	867	4,069
Pseudo R^2	0.4	0.3	0.4	0.35	0.51

Note: Main dependent variable: EEG exempt 2013. Logit regression. Sample trimmed to plants with 1-10 GWh electricity consumption in 2011. All dependent variables refer to the base year, 2011. Unit of observation: plant. All variables are in logs, except for shares. Each column refers to a separate logit estimation of the propensity score (matches forced to be within same sub-sector). Sub-sectors defined according to the mean energy intensity (original WZ 2008 definition in parenthesis) sector 1: food (WZ 10,11), sector 2: chemicals & pharmaceuticals (WZ 19,20,21,22), sector 3: paper & cement (WZ 17,23), sector 4: metal, electrical equipment, machinery and cars (WZ 24,25,26,27,28,29,30,33), and sector 5: textiles, leather, wood processing and miscellaneous (WZ 13,14,15,16,18,31,32). BBGG algorithm, bootstrapped standard errors in parentheses. * p<0.1, **p<0.05, and ***p<0.01.