

Germeshausen, Robert

Conference Paper

Effects of Attribute-Based Regulation on Technology Adoption - The Case of Feed-In Tariffs for Solar Photovoltaic

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Renewable Energies and Biodiversity, No. E15-V3

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Germeshausen, Robert (2016) : Effects of Attribute-Based Regulation on Technology Adoption - The Case of Feed-In Tariffs for Solar Photovoltaic, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel - Session: Renewable Energies and Biodiversity, No. E15-V3, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

This Version is available at:

<https://hdl.handle.net/10419/145712>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Effects of Attribute-Based Regulation on Technology Adoption - The Case of Feed-In Tariffs for Solar Photovoltaic

Abstract

Feed-in tariffs are a widely used policy instrument to support deployment of renewable energy technologies. The aim of this paper is to estimate the causal effect of a cut in feed-in tariffs on solar photovoltaic (PV) installations. I isolate this effect by a differences-in-differences approach using data on all grid-connected PV systems within Germany from 2009 until 2013 on a county level. A policy change of administrative size classes in 2012 provides exogenous variation in feed-in tariffs. I find that a cut in feed-in tariffs of five percent leads to a decrease in newly installed capacity of around 46 kilowatt (kW) in a county per month. This is equivalent to approximately three percent of the average annual solar PV deployment on a national level from 2009 to 2011. The re-evaluation of size classes implies de facto the introduction of attribute-based regulation for small installations. The design of differentiated rates incentivizes smaller individual capacity choices at the border of size classes. This leads to excess bunching at the ceiling of the smaller size class. Neglecting this leads to overestimating treatment effects by around double the size. This potential bias underlines the impact of attribute-based regulation on technology adoption for solar PV.

Keywords: Solar photovoltaic, differences-in-differences estimation, feed-in tariffs, renewable energy deployment, attribute-based regulation

JEL classification: O38, Q28, Q42

Preliminary draft, please do not cite or distribute
This version: February 29, 2016

1. Introduction

The diffusion of new technologies is often supported by policies aimed at initiating or accelerating this process. The choice of the specific instrument and its design are crucial for its efficacy, i.e., the achieved rate of diffusion, as well as for its economic efficiency. In this paper, I analyze a policy instrument that offers different financial incentives for adopters depending on characteristics of the deployed technology. An example of such a policy instrument is the German feed-in tariff system for renewable energy technologies. Within this system, the owner of an eligible renewable installation receives a fixed price (feed-in rate) per kilowatt hour (kWh) electricity produced.

The marginal feed-in rate depends on technology characteristics of the individual installation. Thus, this system is a form of differentiated or attribute-based regulation, which are widespread in practice. Spatially differentiated regulation (Tietenberg, 1978) and regulation differentiated by vintage of the respective technology (Gruenspecht, 1982; Nelson et al., 1993; Gray and Shadbegian, 2003; Stavins, 2006) have received the main attention in the economic literature on differentiated regulations so far. Recently, regulations depending on other characteristics or attributes of the underlying technology have also come under scrutiny (Ito and Sallee, 2014). In the case of technology adoption, the impacts of differentiated regulation is mainly discussed with respect to vintage differentiated (Gruenspecht, 1982; Bushnell and Wolfram, 2012), yet not so much for other forms of attribute-based regulation.

The rapid growth of solar photovoltaic (PV) deployment in Germany in recent years underlines the positive correlation between investment incentives generated by feed-in tariffs and installed capacity. However, additional factors may also explain partly this development, such as cost reductions in solar panels, (regional) end-use prices for electricity or other subsidy schemes. The existence of multiple influencing factors calls for disentangling the effect of feed-in tariffs on the deployment of solar PV from other factors. The correlation between feed-in tariffs and installations for solar PV has been documented before (Leepa and Unfried, 2013; Grau, 2014). The causal effect and especially its magnitude has not been identified yet. In this paper, I identify and estimate the causal effect of a cut in feed-in rates on the deployment of solar PV installations in Germany using data on all installations receiving feed-in tariffs from 2009 to 2013.

I separate the effect of feed-in tariffs from confounding factors using a differences-in-differences approach. Exogenous variation in feed-in tariffs stems from a policy change that includes a re-evaluation of size classes within the feed-in tariff system. The marginal feed-in rate is mainly dependent on the size of the individual installation (conditional on technology and type). Thereby it is not a continuous function of size but varies across administratively determined size classes and remains constant within these intervals. This creates unsteadiness of the marginal feed-in rate function with jumps for installation sizes just at the border of size classes. The amendment of the Renewable Energy Act in 2012 (PV Amendment) included a re-evaluation of size classifications of PV installations. I make use of this policy change and the respective change in the unsteadiness of the marginal feed-in rate function as exogenous variation.

This work is in a line of papers in which the diffusion of solar PV installations and the impact of policy instruments is investigated. Hughes and Podolefsky (2015) and Burr (2014) show that upfront rebates in California are a major determinant of solar PV adoption. Leepa and Unfried (2013) estimate an error correction model that shows the influence of a feed-in tariff on a nationwide level. Grau (2014) develops a simulation model of PV deployment based on profitability (net present value) on a weekly basis. The focus of the latter two analyses lies on detecting correlations but those studies do not draw upon causal inference. Both analyses are also on the national level. Deployment can be very heterogeneous geographically due to different solar radiation values

(Lamp, 2015), social effects (among others, Gillingham and Bollinger, 2012; Rode and Weber, 2012; Gillingham and Graziano, 2015) and other socio-economic aspects. These factors cannot be captured in a nationwide analysis. Hence, my analysis is conducted on the county level to better account for additional influencing factors varying on a regional level which may be correlated with feed-in tariff adjustments.

I find that the average treatment effect amounts to around -46 in the period until the end of 2013. This means that for a five percent cut of the feed-in rate the newly installed capacity within one month in a county drops by around 46 kilowatt (kW). Annualized and aggregated on the national level, this is equivalent to a reduction of new installations of about 220 Megawatt (MW), which is about three percent of the average annual capacity additions from 2009 to 2011. Further inspection of dynamic, i.e., time varying, treatment effects reveals that the effect persists until the end of 2013.

The re-evaluation of size classes includes de facto the introduction of attribute-based regulation for small installations. Thus, it provides an opportunity to identify the effect of attribute-based regulation on technology adoption. Before the amendment, installations up to 20 kW received the same marginal feed-in rate. Beyond the effect of a uniform reduction in feed-in rates across size classes, this specific design feature has also an additional impact on the distribution of installation sizes. The introduction of attribute-based regulation for small installations creates excess bunching at the upper border of the smaller size class. Neglecting this circumstance would lead to overestimating treatment effects by around double the size. This substantial difference underlines the impact of differentiated feed-in tariffs on technology adoption for solar PV. The design of the differentiated rates incentivizes smaller individual capacity choices at the border of the size classes to a capacity just at the ceiling of the smaller size class.

The paper is structured as follows: The institutional background and the identification strategy will be presented and discussed in Section 2. The data used in this analysis will be outlined in Section 3 and the empirical model will be specified in Section 4. Results of a naive differences-in-differences estimation, neglecting excess bunching, will be presented in Section 5. In Section 6, the issues with the naive approach will be addressed and treatment effects will be re-estimated. Section 7 concludes.

2. The PV Amendment 2012 and Identification Strategy

The feed-in tariff system specified in the Renewable Energy Act is the main (policy) instrument to foster the diffusion of renewable energy technologies in Germany. Eligible installations receive a fixed price (feed-in rate) for every kWh electricity produced. The rate of individual installations remains constant for 20 years beginning with the date of commissioning. Thereby the level of the feed-in rate is to be administratively determined, such that the rate shall on average enable an economic operation of renewable installations. Hence, feed-in rates are differentiated based

on installation characteristics, taking into account e.g., differences across renewable technologies, plant types and installation sizes. In the case of solar PV, feed-in tariffs are distinguished mainly by size and type (ground, rooftop etc.) of the individual installation. For example, all rooftop installations within a certain size range (size class) receive the same marginal feed-in tariff at a given time. Those rates are in general regularly adjusted to reflect changes and developments over time. In the past, however, there have been also additional interventions from the government in order to react to unforeseen events, such as fast cost reductions for PV systems. Tariff adjustments do only apply to new installations. Existing installations receive their initial fixed rate, regardless of any changes after their commissioning.

Since its introduction in the year 2000, the Renewable Energy Act has been subject to several amendments. From 2000 to 2009 feed-in rates were regularly (mainly annually) adjusted according to fixed degression factors. Beginning with the amendment in 2009, the reduction of feed-in rates depends on past deployment figures. The identification strategy in my analysis builds mainly on the so-called PV Amendment that came into force in April 2012. The most important change for my analysis is the re-evaluation of size classes that determine the marginal feed-in rates for newly build installations.¹ Given the more homogeneous technology and the higher probability to identify rooftop installations correctly, I concentrate on the change of size classes in the small installation segment.² Under the PV Amendment, the smallest size class for rooftop installations (up to 30 kW) was divided into two size classes (up to 10 kW and larger than 10 to 40 kW).

This change of size classes for small installations can serve as a quasi-experiment. Until the PV Amendment installations up to 30 kW received the same marginal feed-in rate. As depicted in Figure 1 the PV Amendment separates the marginal feed-in rates for installations from 0 to 10 kW and from larger than 10 to 30 kW. The larger size class experienced a deeper cut in the marginal feed-in rate compared to smaller units ranging from 0 to 10 kW. The difference is about five percent and can be used as a source of exogenous variation in feed-in rates. This larger cut is expected to change the relative deployment of installations within both size classes. Thus, the causal effect of a cut in marginal feed-in rates on PV capacity deployment can be identified by a differences-in-differences approach: the difference in deployment in the larger size class before the amendment and afterwards is compared to the deployment difference of smaller units.

Concerning the differences across installation sizes, the threshold value of 10 kW is fairly arbitrary chosen. IE Leipzig (2011) reports only small (cost) differences at the border of size classes. For example, size classes ranging up to 5 (or 15 kW) and larger than 5 to 35 kW (or 15

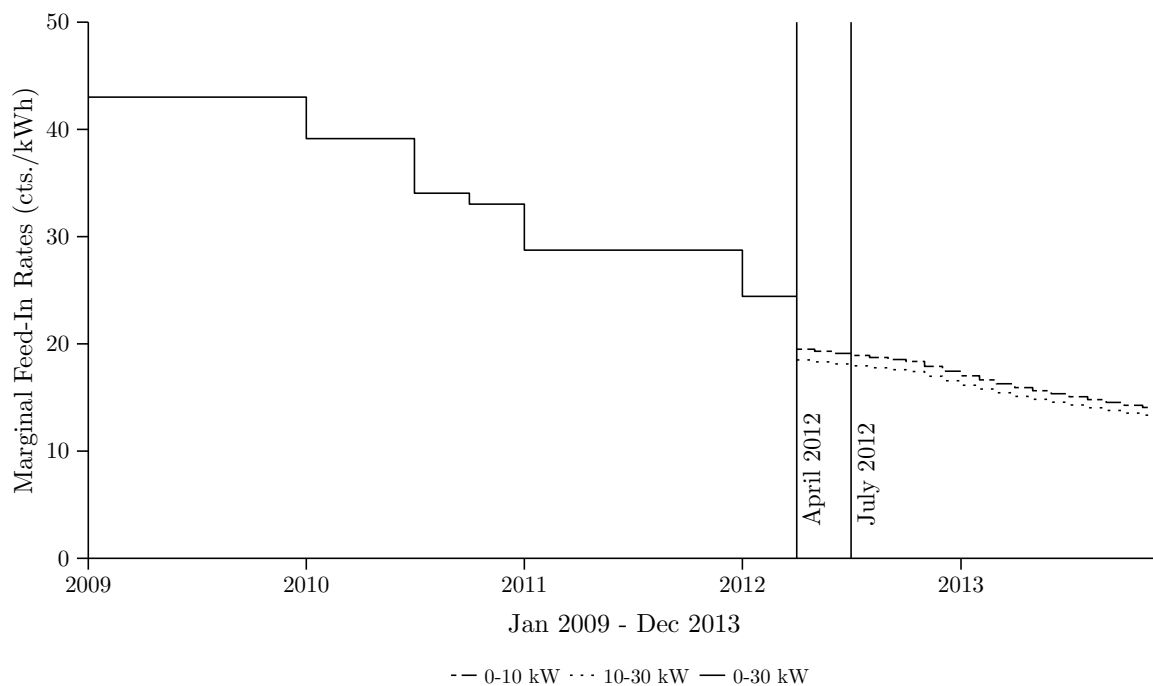
¹Other changes refer to more frequent adjustments of feed-in rates, a limit of 90 percent compensation for installations larger than 10 kW with the beginning of 2014, an overall 52 GW threshold from which on the feed-in system would be stopped and the requirement for all PV systems (existing and new ones) to be able to curtail production. I will comment on how these changes are important for my identification strategy below.

²I do not explicitly observe in the data whether an installation is mounted on a rooftop. However, free-standing PV systems are usually not smaller than 100 kW. Thus, I am convinced that I mainly observe rooftop installations in the data set focusing only on small installations.

to 35 kW) would have been also possible. Therefore, the precise definition of size classes can be assumed as random.

A first draft of the PV Amendment became known in February / March 2012. After reaching an agreement in the German Conciliation Committee (*Vermittlungsausschuss*), the amendment was passed in June 2012 with enactment taken place retrospectively in April 2012. The political process supports the claim that variation in feed-in tariffs induced by the change in size classes is indeed exogenous and cannot be easily anticipated. Before the draft of the PV Amendment reached the German Conciliation Committee, it specified size classes of up to 10 kW and from larger than 10 to 100 kW. The decision to include another size class for small installations ranging from larger than 10 to 40 kW has been made as one of the last adjustments. This impedes the exact anticipation of the changes in size classes and feed-in tariffs.

Figure 1: Development of Marginal Feed-in Rates for Rooftop Solar PV Installations



Source: Own illustration based on data from the German Federal Network Agency.

The identification of the treatment effect, i.e., the deeper reduction of the feed-in rate, relies crucially on the comparability of installations across the two size classes. I restrict the analysis to small rooftop installations up to 20 kW to enhance comparability as I argue in the following.³

Larger installations have smaller specific cost per unit capacity due to fixed cost degression. However, figures provided by IE Leipzig (2011) and ZSW (2014) indicate that this difference is not very large. In addition to cost differences, the decision of the installation size is also dependent on the available space, i.e., the rooftop size.⁴ Thus, the deployment of smaller and larger installations relies also on different building structures across regions, which can be regarded as fixed in the short- and medium-term. Time constant differences across regions do not hinder comparability and thus, do not interfere with the differences-in-differences approach. Furthermore, the average investor type in both size classes may be different. Private households mainly build installations up to 10 kW depending on the size of the respective rooftop. There are also installations larger than 10 up to 30 kW but household investment figures are fading out the higher the size of the respective installations is (IE Leipzig, 2011). However, restricting the analysis to installations up to 20 kW is expected to improve the comparability of investors as indicated in the literature. For example, Borenstein (2015) uses 20 kW as a cut-off value to define residential-based systems. I argue that investors can be distinguished to a certain degree by installed capacity since I do not have information about investor types in the data. This might not be a perfect proxy, but the correlation should be high and positive based on survey information from IE Leipzig (2011). As an additional check for comparability of the two size classes, I analyze pre-trends of the two groups and control for time constant differences across the size classes in the empirical analyses.

3. Data

I use data on all grid-connected solar installations in Germany for the period between January 2009 and December 2013. This data stems from the renewable energy register collected by the four German transmission system operators. The capacity of individual installations are aggregated on county level with monthly frequency for size classes up to 10 kW or larger than 10 to 20 kW. The capacity of the individual installation and the month of commission are relevant for the installation's feed-in rate. Positive capacity additions are observed in 399 counties within Germany during the observation period, which represent all but three counties in Germany.

Data on regional end-user prices for electricity are provided by Ene't. The prices are aggregated from individual price offers by computing the average offer price for each county and month. I restrict the individual offer prices to make sure that only price offers for households are included before calculating the average. Furthermore, special rates (e.g., block pricing, for electric heating

³I also estimated treatment effects with size classes up to 10 kW as control and larger than 10 to 30 kW as treatment group reaching similar conclusions.

⁴Capacity is only a rough indicator for the space needed.

etc.) are excluded. One limitation of this data is the lack of the exact prices individuals actually pay. It only provides price offers. However, the data base includes a comprehensive list of price offers valid in the specific region at the respective time. Offer prices should therefore be correlated with the actual prices. Thus, it can be expected to contain regional and time variation of actual end-use electricity prices.

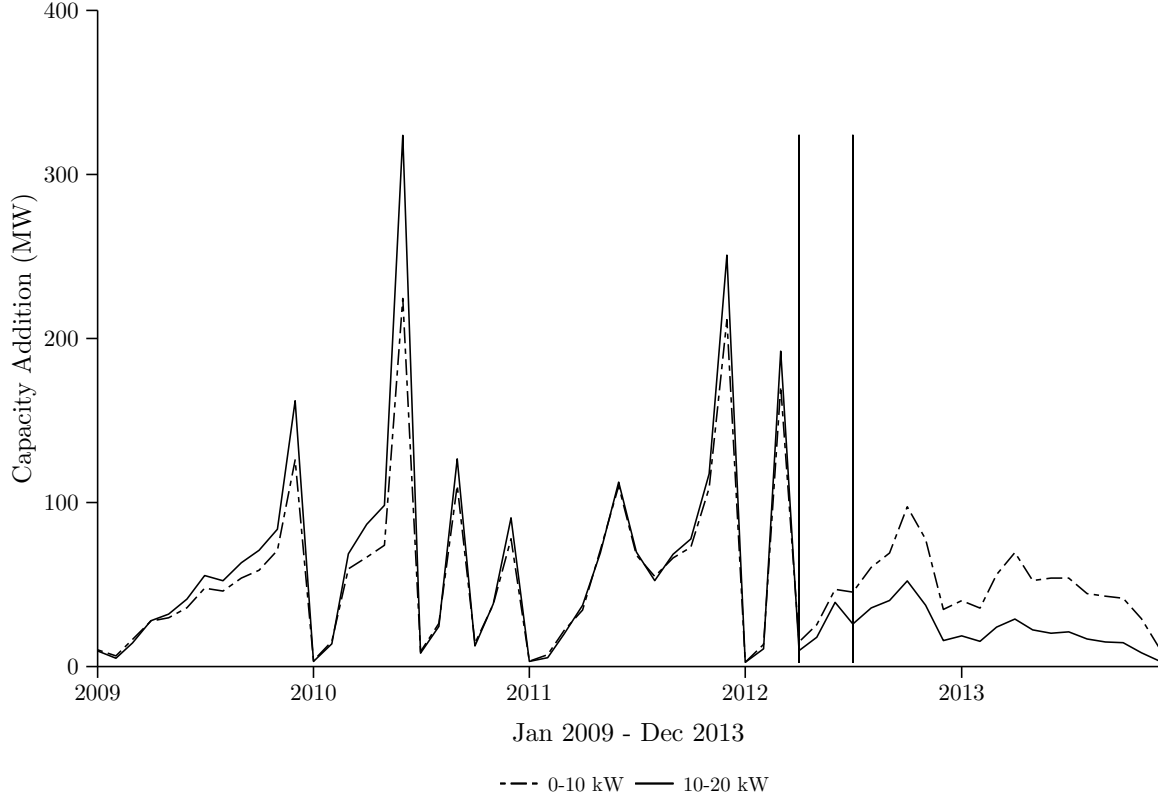
Summary statistics provided in Table 1 give an overview of the main variables used in this analysis.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Capacity Additions [kW]	132.757	233.608	0	6,457.100	47,880
for up to 10 kW					
- 2009 to 2013	136.597	187.027	0	2,886.320	23,940
- before April 2012	145.638	214.871	0	2,886.320	15,561
- after April 2012	119.806	117.329	0	1,243.481	8,379
- after July 2012	128.388	122.247	0	1,243.481	6,783
for 10 to 20 kW					
- 2009 to 2013	128.918	272.285	0	6,457.100	23,940
- before April 2012	167.281	326.359	0	6,457.100	15,561
- after April 2012	57.671	78.843	0	1,042.400	8,379
- after July 2012	57.578	77.539	0	1,042.400	6,783
Average End-use Price [cts./kWh]	20.03	1.82	15.95	25.25	47,880

The development of monthly deployment of solar PV installations within both size classes on a national level is depicted in Figure 2. The spikes in deployment are in the month before a downward adjustment of feed-in rates takes place as described by Leepa and Unfried (2013) and Grau (2014). The aggregated new installations for both size categories in Germany develop quite similar, especially from mid year 2010 on until the treatment period starts. The start of the treatment period is depicted by the first (April 2012) and second vertical line (July 2012), respectively. The national figures would imply a divergence in capacity additions of both groups with start of the treatment, but it remains unclear whether this result may also be driven by other factors on a regionally more disaggregated level. Thus, the following analysis uses county level data to allow for more (regional) heterogeneity.

Figure 2: Monthly Deployment of Solar PV Capacity



Note: The first vertical line depicts the PV Amendment in April 2012, whereas the second vertical line shows the end of the protection clause in July 2012.

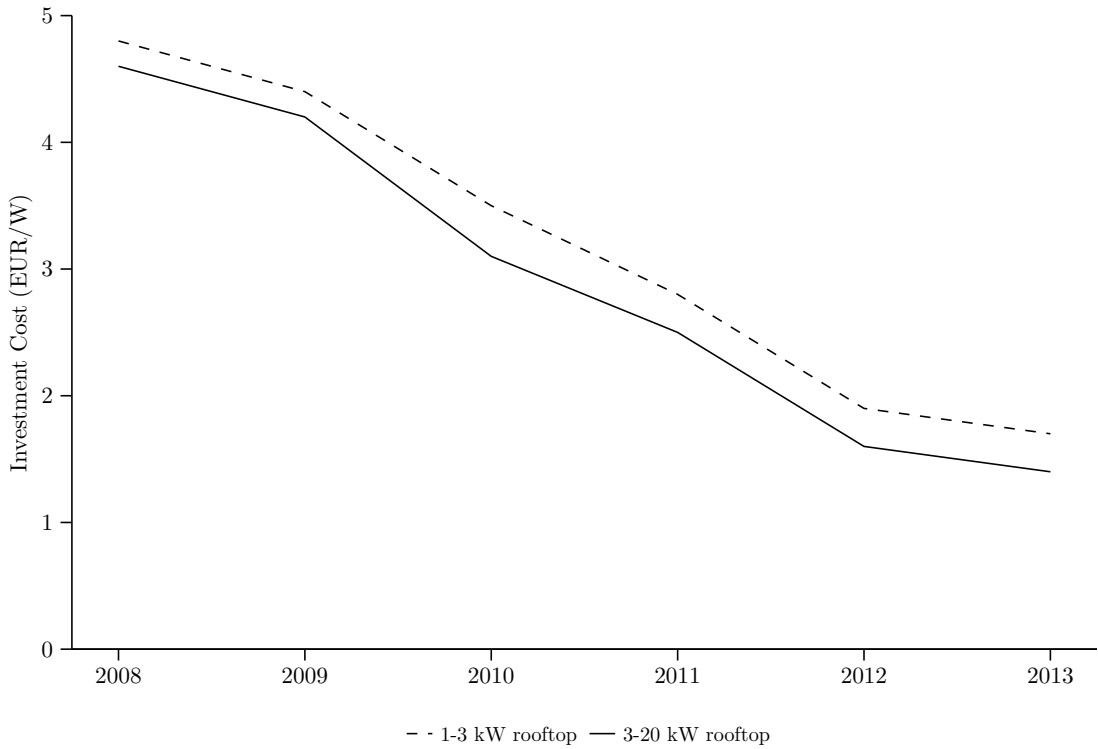
Source: Own illustration based on data from the four Transmission System Operators.

4. Empirical Model

The estimation strategy builds on a differences-in-differences design by comparing the difference in the deployment in the size class with installations ranging from 10 to 20 kW and deployment changes in the smaller size class up to 10 kW before and after the PV Amendment in 2012. I include a fixed effect for the larger size class to capture time constant differences in deployment between the two size classes. Furthermore, month-year fixed effects account for time effects that are the same for all regions and installation sizes. This includes e.g. the regulatory environment from the federal government, general macroeconomic effects and technological progress in the solar PV industry. The latter is only true under the assumption that technological progress does not

differ for installation sizes up to 20 kW. Evidence on this issue is provided by Benedetti (2014) with data for the Italian market. Especially module and inverter prices for different installation sizes experienced very similar developments in the recent past as given in Figure 3. These figures can also be transferred to the German market since module and inverter prices are pegged to world market prices (IE Leipzig, 2011; ZSW, 2014).

Figure 3: Cost Development for Modules and Inverters for Different Sizes in Italy



Source: Own illustration based on data from Benedetti (2014).

County-year fixed effects control for differences across regions on an annual level. The fixed effects capture not only time constant regional differences, but also year-on-year changes. Thus, factors such as socio-economic characteristics like income and population will also be controlled for by the inclusion of county-year fixed effects. The various fixed effects control for all effects that remain constant over time, are the same for all counties or vary on a county level only with annual frequency. The analysis is further expanded to include one additional within year varying regional effect, i.e., regional end-use electricity prices. Changes in these prices often occur within a year⁵,

⁵The average price changes in 55 percent, the minimum price in 22 percent of all observations across subsequent months. Assuming the price would only change once a year, the price would change in seven percent of all observations. These figures suggest that price changes occur more often than once a year.

are regionally differentiated and could also impact the decision to build a PV installation. Higher end-use electricity prices increase the incentive to self-consume electricity generated by the solar PV system. It can enhance the profitability of the installation, if the end-use price is larger than the respective feed-in rate.

The basic formulation of the empirical model is as follows:

$$C_{i,m,y,r} = \alpha + \mu_{i,y} + \mu_r + \mu_{m,y} + \beta D_{m,y,r} + \gamma' X + \epsilon_{i,m,y,r}, \quad (1)$$

where $C_{i,m,y,r}$ denotes the capacity additions in county i at month m in year y within size class r . r equals one for installations within the range of 10 to 20 kW indicating the larger size class. $\mu_{i,y}$, μ_r and $\mu_{m,y}$ are county-year, size class and month-year fixed effects, respectively. $D_{m,y,r}$ is a binary variable that is equal to one for deployment within the larger size class after the start of the treatment period. β is the parameter of interest indicating the average treatment effect. X denotes the monthly average end-user offer price for electricity prices in the respective county.

The most important assumption for the differences-in-differences estimation is the common trends assumption (Angrist and Pischke, 2009). This assumption states that the treatment group (in this case the larger size class) and the control group (the smaller size class) would exhibit the same trend in capacity additions in absence of the treatment (cut in feed-in tariff). Different levels of capacity additions across both size classes are not relevant as long as they are time constant. In this case the size class fixed effect controls for these differences. The estimated effect can only be interpreted as the causal effect, if this assumption holds. Otherwise the differences in trends will also be captured by the treatment dummy biasing the estimated treatment effect. The common trends assumption, however, cannot be tested. The investigation of trends for both size classes before the treatment starts (pre-trends) may only give support to this assumption. If both groups do not exhibit the same trend in the periods before the treatment, the common trends assumption might be more difficult to rely on. Therefore, I compare the pre-trends of both groups. This is tested by including a linear trend interacted with a binary variable indicating the larger size class in a regression using only the observations before the PV Amendment. The class-specific time trend for the larger size class is found to be statistically insignificant, supporting both size classes exhibit the same trend in monthly capacity additions before the PV Amendment.⁶

⁶Standard errors in all estimations are clustered at the county level to control for serial correlation, which is particularly important for differences-in-differences estimation as pointed out by Bertrand et al. (2004).

Table 2: Investigation of Parallel Pre-Trends of Capacity Additions

	(1)	(2)
Class-specific Trend	0.028 (0.100)	0.028 (0.100)
Large Class	21.089*** (4.998)	21.089*** (4.998)
Time Trend	51.921*** (2.232)	18.542*** (0.982)
Average End-use Price		2.084 (6.980)
Constant	-741.894*** (40.139)	-167.825 (142.275)
Observations	31,122	31,122
Time Fixed Effects	+	+
County-Year Fixed Effects	+	+

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Standard errors in parentheses and clustered at county level.

Related to the common trends assumption, another important assumption for the identification of the causal effect by a differences-in-differences estimation is random assignment into treatment and control group. Although there is a self-selection bias in the data, the policy design allows to estimate the magnitude of self-selection and to correct the bias to a certain degree. The next section presents naive estimation results neglecting self-selection. Comparing these results with the corrected estimates presented in Section 6 hints at the magnitude of the bias and illustrates the importance to take self-selection into consideration.

The design has potentially some further limits that need to be addressed to prevent biased estimates and to retain the causal interpretation. First, there is a clear pattern in the installation data that reveals anticipation effects of a change in the feed-in rates that have to be incorporated in the empirical model. This is illustrated by spikes of deployment in the month before tariff reduction in Figure 2. It is captured by the time fixed effects since the feed-in rates are determined on the federal level. Differences across groups may result in self-selection, which I will deal with in Section 6.

Second, the PV Amendment contains a protection clause. This permits installations to receive the older (and higher) tariff rates valid before the PV Amendment, if the grid connection request has been filed until February 24, 2012 and if the installation is commissioned before July 2012. Since I cannot observe the time at which the grid connection request was filed but only the commissioning date of the installation in the data, I have to solely rely on the second criteria. Therefore, I decided to use July 2012 instead of April 2012 as the start of the treatment period in the reference case. From July on, the protection clause does not hold any longer so that every new installation receives the feed-in rate in the respective month, in which the installation is commissioned. I drop

all observations within the period from April to June 2012 in the specifications with treatment starting in July 2012 since the treatment status of a larger installation from April to June is uncertain. As a robustness check I present the estimated effects with the treatment period starting in April 2012 along.

Third, aside from adjustments of feed-in rates the PV Amendment introduces further differences between the two size classes. Installations that are commissioned later than March 2012 and that are larger than 10 kW will receive their feed-in rate for only 90 percent of the produced electricity from January 2014 on. This means that from this time on, 10 percent of the electricity production has to be either sold privately or self-consumed. This should not provide a massive disadvantage for larger installations, given that households can easily achieve self-consumption rates up to 30 percent. Especially, I observe that from April 2012 on average end-use electricity prices are in all regions larger than the feed-in rates for installations up to 10 kW (and thus, also for installations up to 20 kW). Thus, self-consumption is profitable and superior to receive feed-in rates for the whole amount of produced electricity. I explicitly account for differences in the profitability of self-consumption across regions and time by including these time-varying regional end-use electricity prices.

Fourth, solar PV installations may receive subsidies additional to feed-in tariffs. Other subsidy programs for solar PV could potentially interfere with the presented design. Important for the validity of this design are only differences in subsidies across size classes and whether those change for pre- and post-treatment period. If subsidies within a program are provided regardless of the size of the installation or remains unchanged over the observation period, the differences-in-differences design might remain valid.⁷ I check whether there are subsidy programs from local utilities, federal state governments or agencies using a database from BINE (2015). This check reveals that there do not exist programs that either differentiate across size classes or do not change this differentiation around the time of the PV Amendment. In the latter case, those subsidies may interact with the treatment and may make self-selection more attractive. Furthermore, I cannot rule out that there a more special promotion offers by local actors on a deeper local level, which are not listed in this database. However, promotion offers existing on a lower regional level than counties will be averaged and may lose its importance in this analysis.

5. Results of the 'Naive' Approach

The estimated constant treatment effects are shown in Table 3.⁸ In each specification the monthly capacity additions in a county within one of the two size classes are regressed on a binary

⁷The propensity to actually take up these subsidies could potentially be increasing in installation size. The time constant part of this possible higher propensity in the larger size class is captured by the fixed effects for the larger size class.

⁸The full estimation results can be found in Appendix A.

variable indicating the larger size class, a linear time trend, the average monthly end-use price offer in the respective county as well as on a set of time and county-year fixed effects. A binary variable is included indicating the larger size class and the treatment period. The parameter of this variable is the average treatment effect of a cut in feed-in tariffs. In this basic specification the effect of a five percent cut in feed-in tariffs is found to be -83.777 for the treatment started in April 2012 and -91.222 for an start of the analysis in July 2012 (see column one and three in Table 3). Treatment effects are statistically significant at the one percent level in all four specifications. This means that the monthly capacity of new installations within a county decreases by 84 kW (April) or 91 kW (July), respectively. The range of almost seven kW (or around eight percent of the decrease) underlines the potential importance of the protection clause. From April to June 2012 the treatment group covers potentially also installations without treatment. Hence, the treatment effect starting in April 2012 is expected to be smaller in absolute terms than for the treatment starting in July 2012, which is also revealed by the empirical analyses. Furthermore, I include a class-specific linear time trend for larger installations as a robustness check. However, this leads only to small changes in treatment effects, with the class-specific trend being insignificant in both cases.

Table 3: Summary of 'Naive' Treatment Effects on Capacity Additions

	(1)	(2)	(3)	(4)
Treatment Effect	-83.777*** (5.642)	-79.612*** (6.397)	-91.222*** (5.901)	-94.827*** (6.975)
Observations	47,880	47,880	45,486	45,486
Time Fixed Effects	+	+	+	+
County-Year Fixed Effects	+	+	+	+
Class-Specific Trend	-	+	-	+
Treatment Start in	April	April	July	July

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

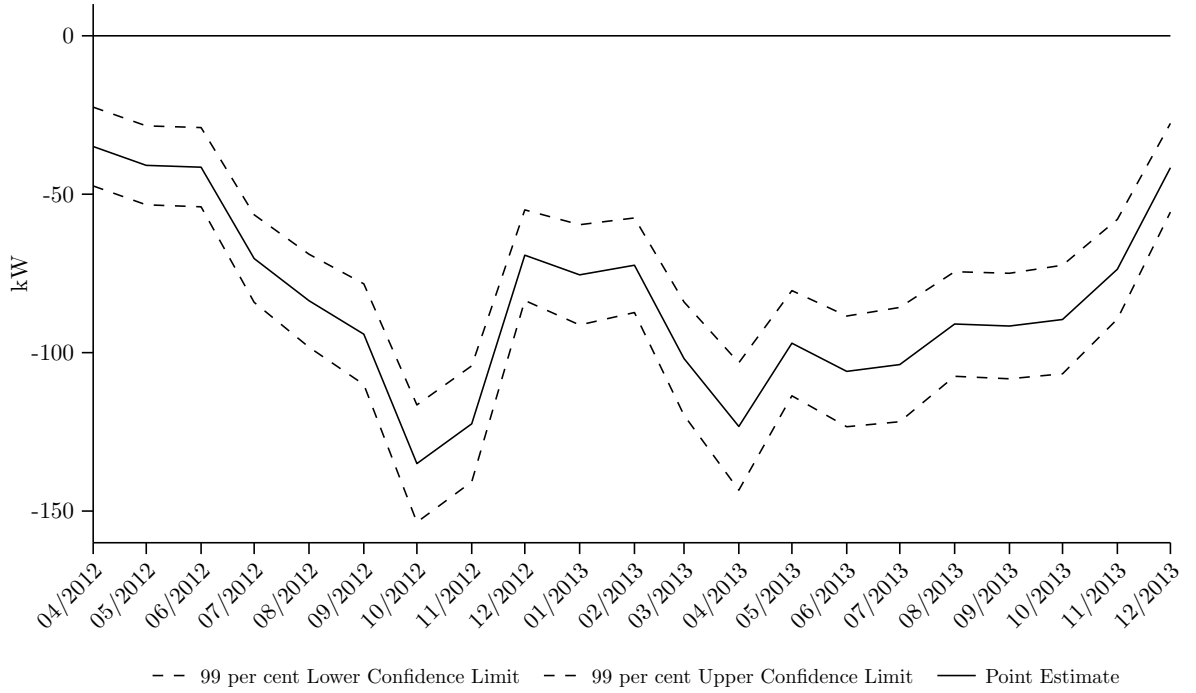
Standard errors in parentheses and clustered at county level.

In addition to the estimation of the average treatment effect over the treatment period, I also investigate how treatment effects develop over time. Instead of a single treatment variable, I include interactions of the treatment variable with the time fixed effects within the treatment period. The coefficients of the interaction terms represent the treatment effects in the respective month. The estimated variable treatment effects are shown in Figure 4.⁹ The absolute values of the treatment effects increase almost steadily until October, with larger jumps from June to July as well as from September to October. After a climax in October, the absolute values of treatment effects decrease. This illustrates considerable variation over time. It is also consistent with the estimated values

⁹The regression results of the other independent variables and the numerical values of treatment effects can be found in Appendix B.

for the average treatment effects. The jump from June to July could reflect the expiration of the protection clause. This may underline that a substantial amount of deployment within the larger class in the months from April to June 2012 had still the possibility to enjoy the higher rates before the PV Amendment, if the plant is commissioned until July 2012. I also include a class-specific linear time trend for the larger size class as a robustness check as in the case of the constant treatment effects. The deviations in treatment effects on a monthly level are also rather small.

Figure 4: Dynamic Treatment Effects

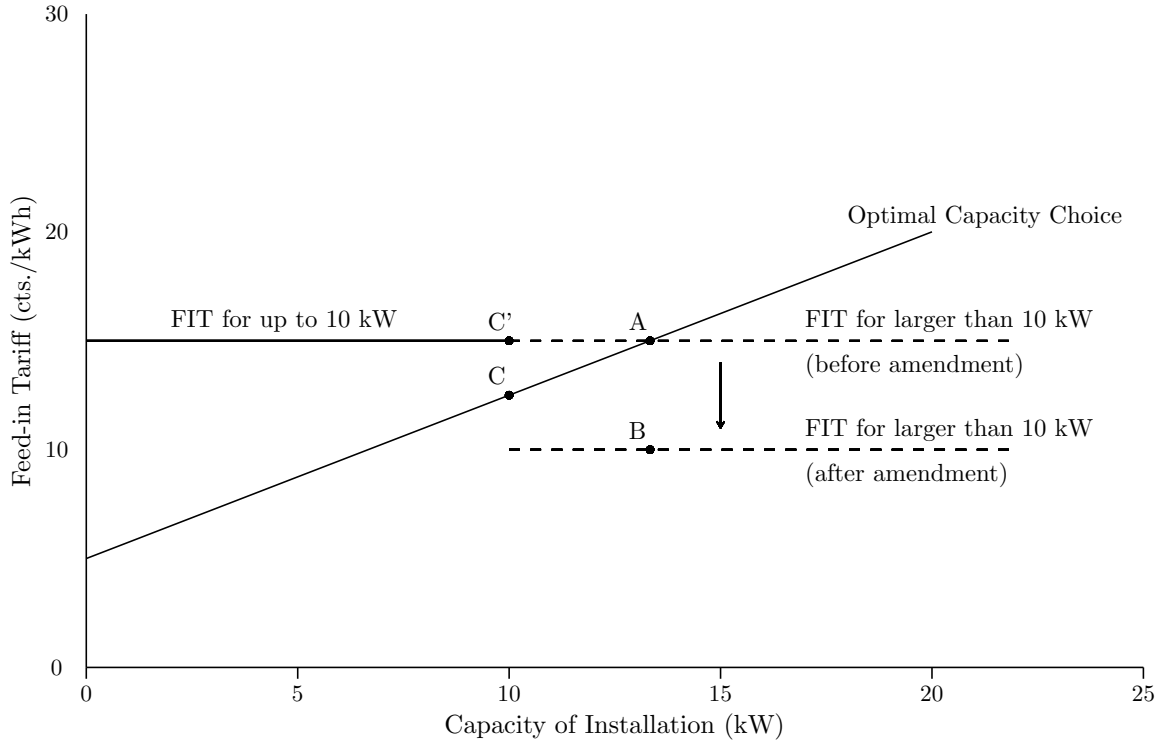


6. Self-selection and Excess Bunching

The differences-in-differences analysis relies crucially on common trends of treatment and control group. This assumption is likely to be violated if self-selection into treatment or control group is possible. In the case of solar PV, investors can choose the size of their installation and thus, can theoretically self-select into treatment or control group. Marginal feed-in rates are one (however an important) factor in determining the optimal installation size. Cost differences across installation sizes, different rooftop capacities or financing constraints represent other important determinants. A major impact of the introduction of different marginal feed-in rates for small installations can be expected at the border of the size classes. Threshold values at the boundaries of size classes create jumps in the marginal feed-in rate function. This implies an unsteady function that is unlikely to

represent exactly the differences across installation sizes, especially for small changes of installation sizes around the threshold values. This may offer one explanation for the excess bunching at the ceiling of the lower size class that can be observed in the data after the introduction of attribute-based regulation. The intuition of this can be explained using Figure 5, in which an upward sloping optimal capacity choice function dependent on the marginal feed-in rates and the valid marginal feed-in tariff rates are depicted.¹⁰ This figure can be used to illustrate an exemplary individual static adoption decision for a specific point in time.¹¹ Before the PV Amendment, all installations up to 20 kW receive the same marginal feed-in rate. In this example, the individual with this specific capacity choice curve would optimally install the related capacity at point A. However, with the respective feed-in tariff after the PV Amendment, the capacity choice in point A is not optimal any longer because now only point B can be achieved. The individual optimizes utility at point C, respectively point C', which is directly at the upper bound of the smaller installation category. This effect can lead to excess bunching of installations at a capacity of 10 kW.

Figure 5: Effect of the Re-evaluation of Size Classes



¹⁰The capacity choice function is conditioned on other factors, such as rooftop or financing constraints, and is assumed to be linear only for illustrative reasons. The result holds for any other monotonically non-decreasing function.

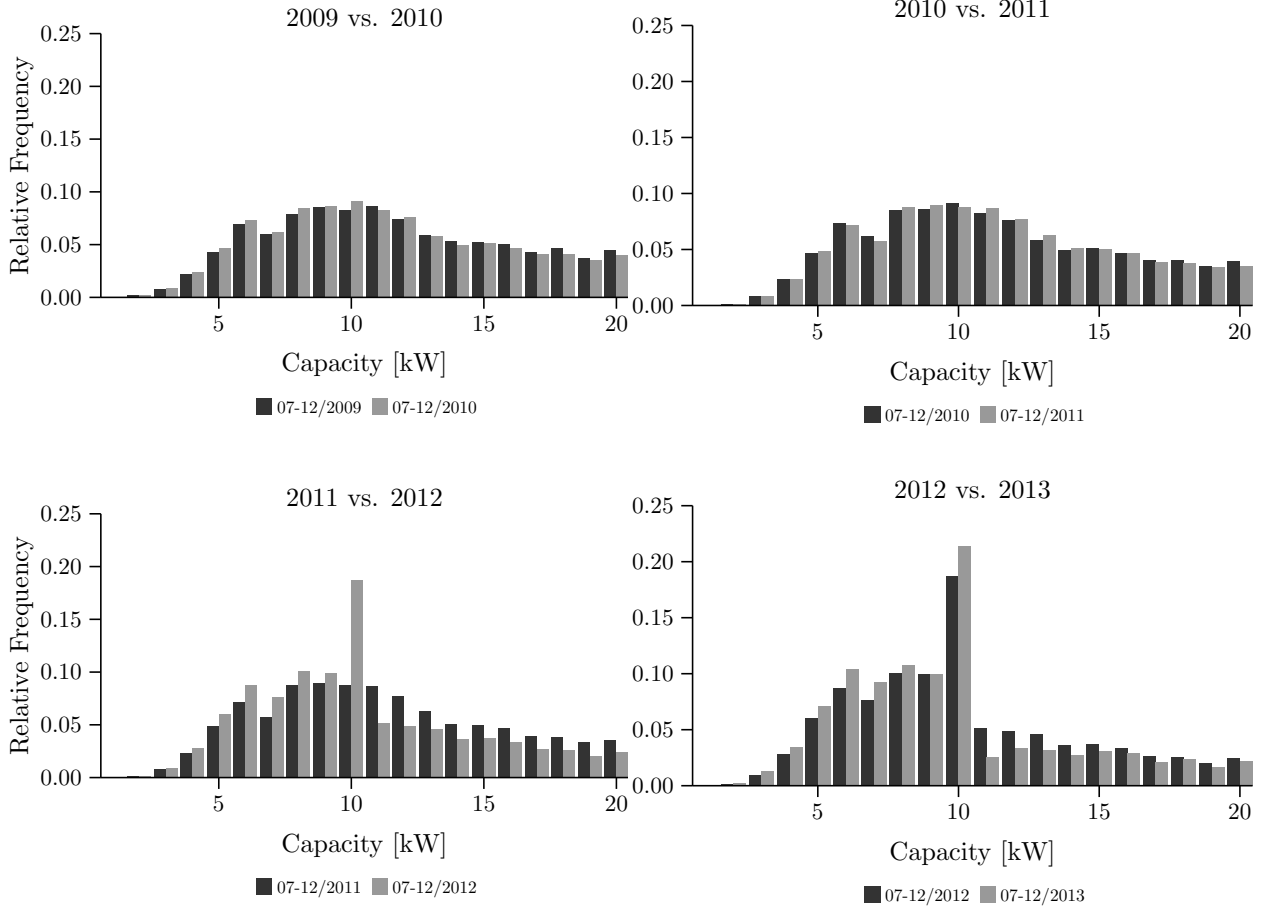
¹¹A static adoption decision is assumed for reasons of simplicity. The actual decision to adopt or not adopt in a given period may rather be a dynamic problem. However, in this case only the choice of the installation size is to be illustrated. This could be seen as the second stage after the decision to adopt a solar PV system is made.

First, in histograms of individual new PV installations excess bunching is revealed. In Figure 6 the distribution of sizes of new installations within 1 kW bins up to 20 kW within one year (from July to December) is compared to the distribution of sizes of new installations in the previous year (from July to December).¹² Before the PV Amendment, the distribution appears to be rather stable across years. After the change in size classes in 2012 a spike at the 10 kW bin is striking. New installations bunch exactly at the capacity threshold for the lower marginal feed-in rate. The comparison between the histograms of 2011 and 2012 indicates a shift from larger to smaller installations around the threshold value. This suggests that some PV installations in the smaller group would have likely been build larger without the introduction of a new size class.¹³

¹²I compare the installations within these months in order to control for possible seasonal effects. The same pattern is apparent using data from April to December in each year.

¹³Demand side explanation, could be an adjustment on the supply side, too. Higher demand leads to higher prices and shortages, larger spike in 2013 does not speak against this hypothesis.

Figure 6: Histogram of Individual Installations in a Year-on-Year Comparison



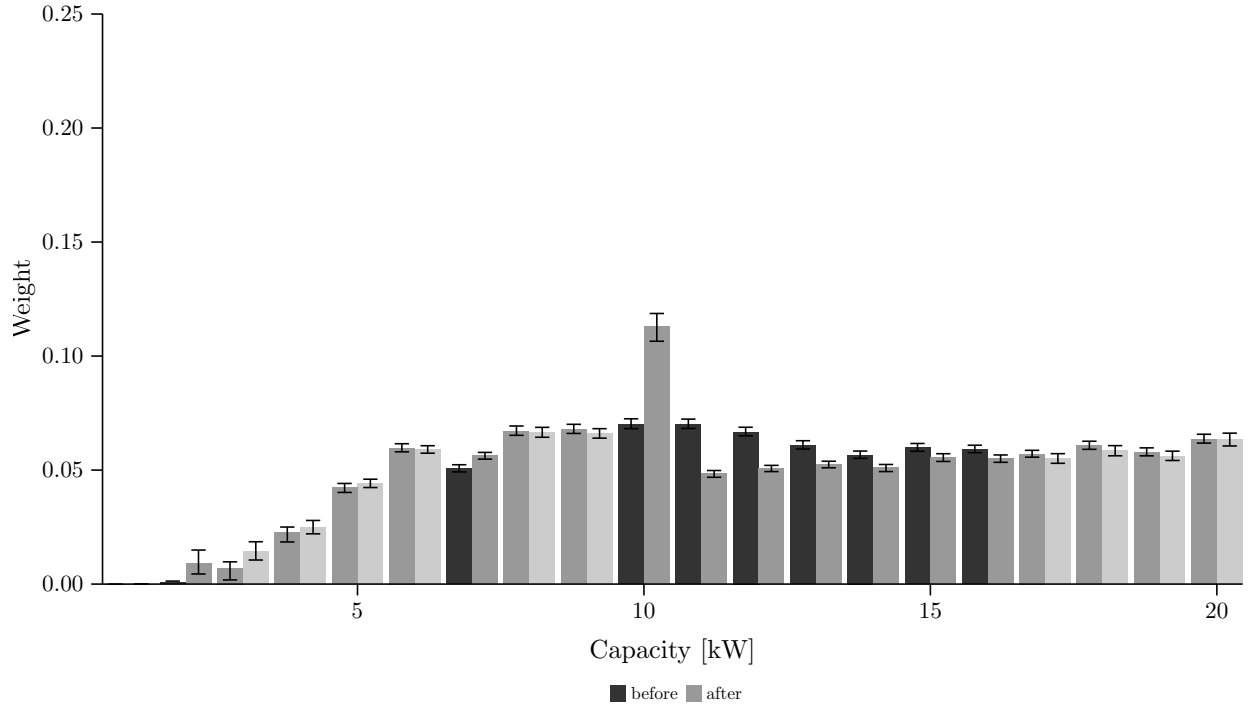
Second, I examine for which bins these changes are indeed statistically significantly different between pre-treatment and treatment period. I estimate the following equation for the period from January 2009 to April 2012 and from April 2012 to December 2013 separately:

$$C_{i,m,y,k} = \sum_{k=1}^{20} w_k + \mu_i + \mu_{m,y} + \epsilon_{i,m,y,k}, \quad (2)$$

where $C_{i,m,y,k}$ is the installed capacity in bin k in county i at time t and w_k are parameters for a set of binary variables indicating the 20 different one kW bins. μ_i and $\mu_{m,y}$ are county and month-year fixed effects, respectively. The parameter estimates \hat{w}_k are used to construct

weights of the different bins $((\hat{w}_k - \min(\hat{w}_k))/(\sum_{k=1}^{20} \hat{w}_k - \min(\hat{w}_k)))$ as shown in Figure 7.¹⁴ 99 percent confidence intervals for these point estimates are constructed by a wild bootstrap with 999 replications. The estimated weights for the bins exhibit a spike at 10 kW from April 2012 on and show smaller weights for bins larger than 10 kW compared to before. However, differences for bin weights before and after the PV Amendment are statistically significant only for the bins at two and seven kW as well as from 10 to 16 kW, with the largest differences being observed from 11 to 14 kW. The statistical analysis seems to support the hypothesis derived from visual inspection, i.e., bunching at 10 kW seems to occur from the right. In particular, this suggest that some of the 10 kW installations would have been most likely build larger (mainly up to 14 kW) in absence of the size class re-evaluation.

Figure 7: Bin Weights Before and After the PV Amendment



Note: Transparent bars are not statistically significantly different from each other at the one percent level.

If this selection is neglected, it will be implicitly assigned to the negative deployment effect of a cut in feed-in tariffs. The resulting (absolute) treatment effects are then likely to be overestimated.

¹⁴Weights are centered by the smallest estimate, which is the one kW bin with almost no deployment as can also be seen in Figure 6.

To reconcile this problem, I would ideally need the distribution of capacity additions that would have occurred without the re-evaluation of size classes. Since this is unobservable, I estimate a counterfactual distribution using a bunching approach as in Chetty et al. (2011). The identifying assumption for inference is that the capacity distribution from 1 to 20 kW would have been smooth without the re-evaluation of size classes. As shown in Figure 6 the distribution remains rather stable across years before the change of size classes. The number and location of bins with insignificant differences in their estimated weights depicted in Figure 7 strengthen further the credibility of this assumption.¹⁵ The following procedure is based on Chetty et al. (2011), who estimate the counterfactual distribution by fitting a polynomial up to a power of q and including a binary variable to control for excess bunching. I estimate the following equation by ordinary least squares (OLS):

$$S_{m,y,k} = \sum_{i=0}^q \alpha_i (bin_k)^i + \gamma D_{10} + \mu_{m,y} + \epsilon_{m,y,k}, \quad (3)$$

where $S_{m,y,k}$ is the share of newly installed capacity within bin k in total capacity additions in month m and year y .¹⁶ bin_k is the respective bin of the installed capacity. D_{10} is a binary variable that is equal to one for the 10 kW bin after the enactment of the PV Amendment. $\mu_{m,y}$ are month-year fixed effects.

Following Chetty et al. (2011), I define the excess bunching at the 10 kW bin ($\hat{B}_{m,y}$) as the difference between the observed capacity share ($S_{m,y,10}$) and the counterfactual capacity share ($\hat{S}_{m,y,10} - \hat{\gamma} D_{10}$). However, the simple deduction of $\hat{\gamma} D_{10}$ would not yield the same space under the counterfactual distribution as under the original distribution (Chetty et al., 2011). Thus, the dependent variable is adjusted in an iterative manner such that the fitted values fulfill the "integration constraint". In this case the sum of fitted values must be equal to one in each period. Therefore, the capacity shares in bins larger than 10 kW are scaled by the amount of excess bunching relative to the overall capacity share of the larger size class in the respective period. This assumes that the distribution is shifted from the right, which is supported by the preceding statistical analysis of weights.

$$S_{m,y,k} \left(1 + \mathbb{1}[k > 10] \frac{\hat{B}_{m,y}}{\sum_{k=11}^{20} S_{m,y,k}} \right) = \sum_{i=0}^q \alpha_i (bin_k)^i + \gamma D_{10} + \mu_{m,y} + \epsilon_{m,y,k} \quad (4)$$

This procedure differs to Chetty et al. (2011) to some extent taking into account the characteristics of the underlying data. Given the discrete nature of PV installations and that investors

¹⁵Note that a change in relative deployment between the two size classes, and thus, also a movement of proportions from large to small installations is expected and part of the actual treatment effects to be estimated. This analysis focuses only on the spike at 10 kW.

¹⁶I conduct the analysis on a national level to obtain sufficient number of observations in each capacity bin and thus, get a realistic estimate of the distribution.

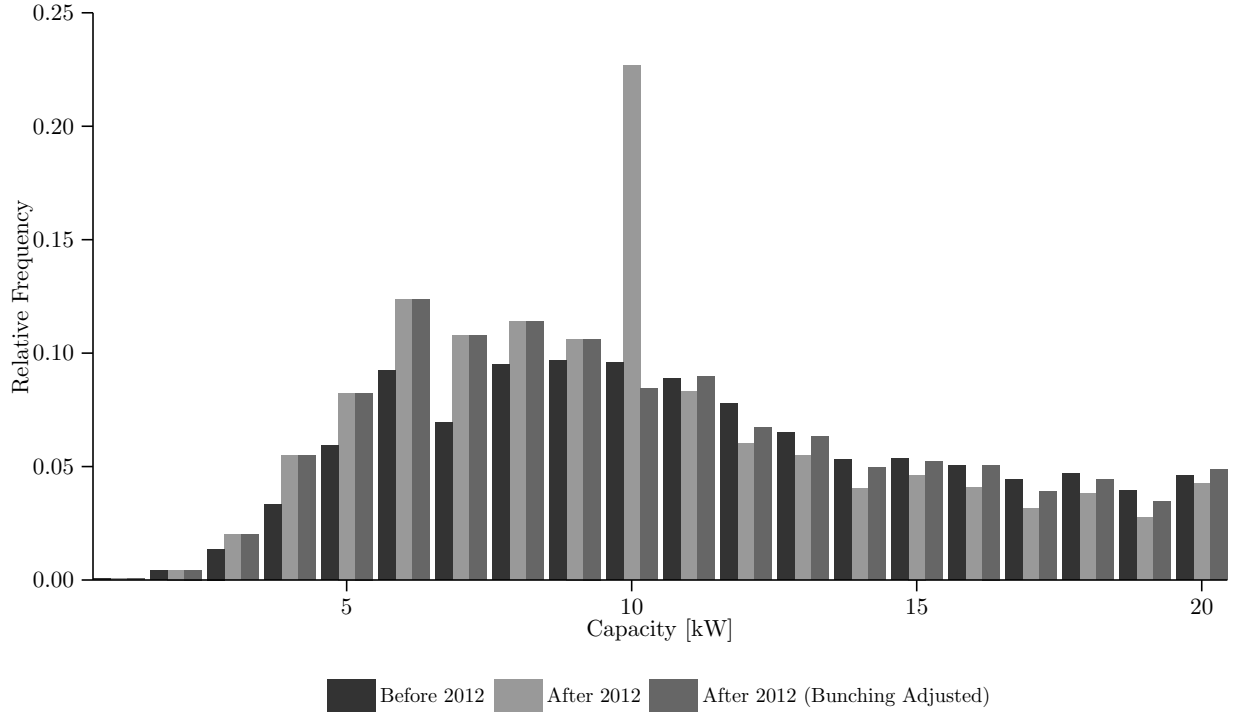
can (almost) perfectly control installation size, excess bunching appears rather to be a point mass (in contrast to the case of income as in Saez (2010) and Chetty et al. (2011)). In the empirical setting, bins with the size of one kW yield the best fit. To enhance precision in estimating the counterfactual distribution, I exploit time and cross-sectional variation.

The sample of county-month-size class observations is adjusted for excess bunching as follows. The capacity of all bins before the change of size classes remain unchanged. After the PV Amendment monthly capacity additions within bins larger or equal to 10 kW are adjusted. For the 10 kW bin the excess mass has to be deducted and for the larger than 10 kW bins this excess mass will be added. The estimate of the excess mass at the 10 kW bin is the difference of actual and estimated capacity in this bin in this period.¹⁷ The latter is calculated by multiplying the total capacity additions within a month and county by the respective fitted value from Equation 4 subtracted by $\hat{\gamma}D_{10}$. The estimated excess mass at 10 kW is then equally distributed on the installation bins larger than 10 kW.¹⁸ This procedure leads to the excess bunching adjusted distribution of installation sizes as shown in Figure 8.

¹⁷Only positive excess mass will be considered since I want only identify excess bunching. If the difference between observed and estimated capacity in the respective county and time period is smaller than zero, the capacity will remain unchanged. Thus, this procedure leads to a lower bound of treatment effects.

¹⁸Note that it does not matter whether the excess mass is equally distributed or with any other weights because in the empirical analysis the comparison is based on more aggregate groups, i.e., up to 10 kW and larger than 10 up to 20 kW. Hence, the distribution within a size class does not impact the estimated treatment effects.

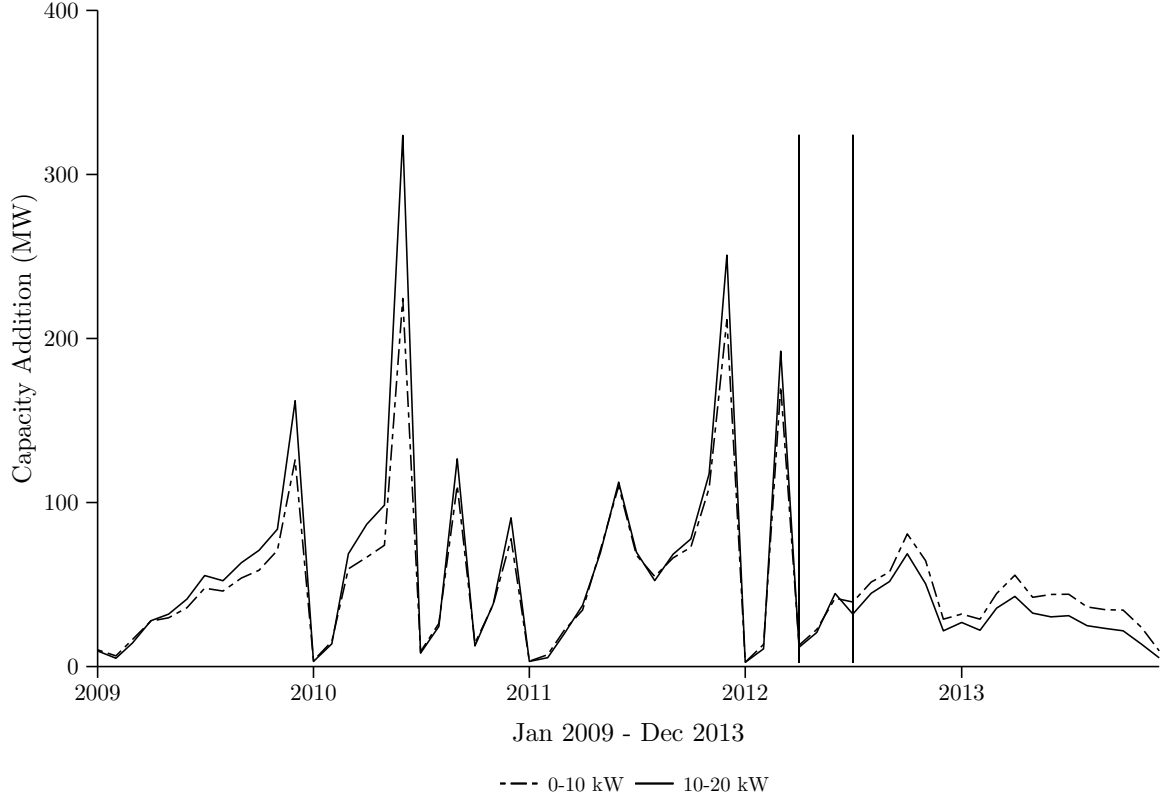
Figure 8: Histogram of Individual Installations Adjusted to Excess Bunching



The aggregate deployment is shown in Figure 9. Compared to the actual values observed in the data in Figure 2, adjusting for excess bunching leads to a smaller gap between the two size classes with beginning of the treatment period. The pre-treatment deployment development remains the same.¹⁹ The direction of this change, i.e., a smaller gap, is not surprising considering the construction of the adjusted sample. Only the magnitude is illustrative in this figure and hints already at a rather large impact of excess bunching on the gap after the PV Amendment and thus on treatment effects.

¹⁹From this follows that the statement regarding pre-trends does not change for an analysis taking excess bunching into account.

Figure 9: Monthly deployment of National Solar PV Capacity Adjusted to Excess Bunching



Note: The first vertical line depicts the PV Amendment in April 2012, whereas the second vertical line shows the end of the protection clause in July 2012.

Source: Own illustration based on data from the four Transmission System Operators.

Given the adjusted sample at hand, I re-estimate the empirical model outlined in Section 5. The estimated constant treatment effects are statistically significant, but considerably smaller, i.e. approximately half the size, compared to the treatment effects without taking excess bunching into account. The constant treatment effect starting in July is around -0.46.²⁰ This means that a five percent cut in feed-in tariffs leads on average to a reduction of monthly new installed capacity in a county of 46 kW. Thus, the smaller gap on the aggregate level in Figure 9 is mirrored by estimation results on the county level.

²⁰Observed capacity is adjusted to bunching by parameters that are random variables. Hence, the regression is with an estimated dependent variable. Note that the coefficient estimates remain unbiased, however standard errors are larger. Correcting standard errors illustrates that the differences are negligible.

Table 4: Summary of Treatment Effects on Capacity Additions

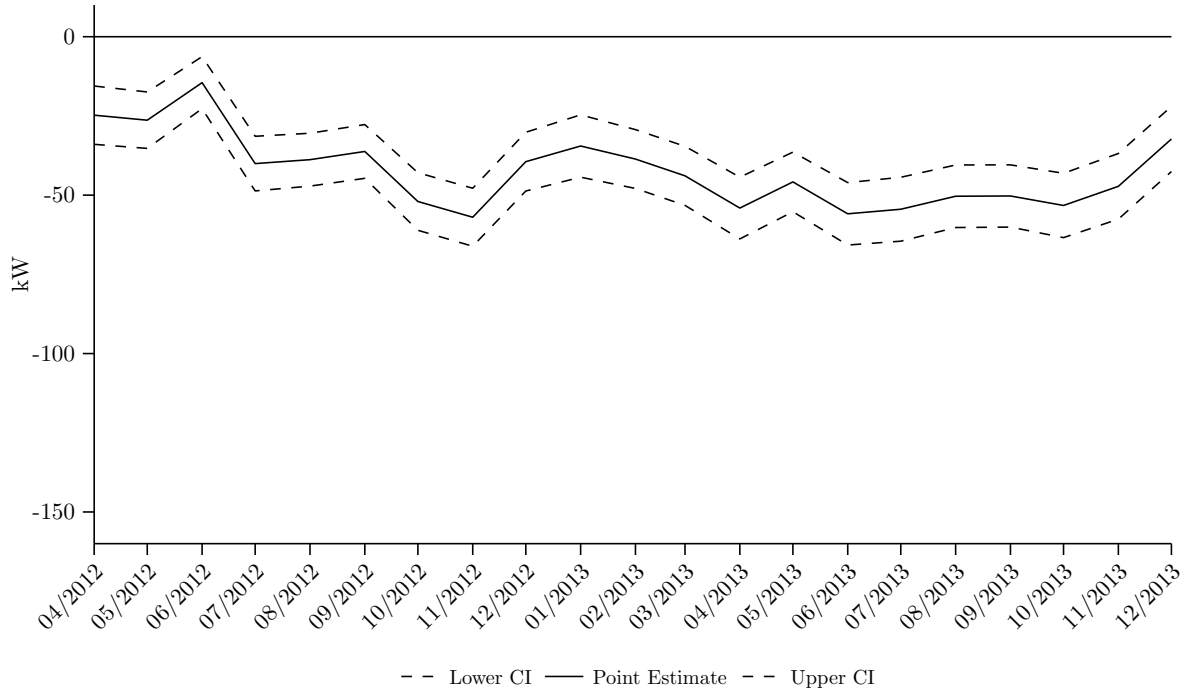
	(1)	(2)	(3)	(4)
Treatment Effect	-42.371*** (4.229)	-38.745*** (5.022)	-45.788*** (4.297)	-45.470*** (5.203)
Observations	47,880	47,880	45,486	45,486
Time Fixed Effects	+	+	+	+
County-Year Fixed Effects	+	+	+	+
Class-Specific Trend	-	+	-	+
Treatment Start in	April	April	July	July

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Standard errors in parentheses and clustered at county level.

The variable treatment effects range from -15 in June 2012 to -56 in June 2013. The comparably lower treatment effects before July 2012 and especially in June 2012 hints again at the effect of the expiration clause. In total, the evolution of variable treatment effects are rather similar to the estimation without taking bunching into account. However, the level of effects are substantially smaller. This is in line with the results for constant treatment effects.

Figure 10: Dynamic Treatment Effects



7. Conclusion

In this paper I explore the impact of one specific influencing factor for the deployment of (residential) solar PV systems. Feed-in tariffs are a widely used policy instrument to support the diffusion of renewable energy technologies by means of a production subsidy. Renewable energy and other environmental or so-called green technologies are to reduce (negative) environmental impacts. It is considered as an option to combat climate change by mitigating greenhouse gas emissions in electricity generation. Therefore, understanding the diffusion process of those technologies is key to tailor future and improve current (environmental) policies.

Using quasi-experimental variation, I identify the causal effect of feed-in rates on solar PV deployment in Germany. I disentangle this effect from other influencing factors by a differences-in-differences approach using data for all PV installations receiving feed-in tariffs within Germany from 2009 until 2013 on a county level. I find that a cut of feed-in rates by five percent leads to a decrease in newly installed capacity of about 46 kW on a county level within one month. This is equivalent to about 220 MW on a national level within one year, which is about three percent of average annual capacity additions from 2009 to 2011. In this paper I concentrate on isolating a single effect. Thus, no conclusion can be drawn about the relative importance of feed-in tariffs compared to other influencing factors (such as cost reductions or social learning). The investigation of these and possible interaction effects from feed-in tariffs with other determinants is left to future research.

The policy design provides an opportunity to study the effect of attribute-based regulation on PV deployment of small installations. Differentiated rates with respect to installation size introduce kinks in the marginal feed-in rate function. This provides incentives for installations to bunch exactly at those kinks. I show that the introduction of attribute-based regulation leads to smaller individual capacity choices at the border of size classes. Estimated treatment effects neglecting excess bunching are almost double the size (in absolute values) compared to the bunching adjusted effects. The magnitude of this difference underlines the economic significance of the policy design change. It indicates an additional negative effect on deployment triggered by the introduction of differentiated rates compared to a hypothetical uniform reduction in feed-in tariffs. A final conclusion regarding its impact on economic efficiency is subject to further analyses, which are still work in progress. Overall, this work adds empirical evidence on the effectiveness of policy instruments aimed at supporting technology diffusion.

References

- Angrist, J., Pischke, J.-S., 2009. *Mostly Harmless Econometrics*. Princeton University Press.
- Benedetti, L., 2014. Developing a Comprehensive Renewable Cost Data Collection Process to Support Italian Policy Makers. *Gestore Servizi Energetici (GSE)*.
- Bertrand, M., Duflo, E., Mullainathan, S., 2004. How Much Should We Trust Differences-in-Differences Estimates? *Quarterly Journal of Economics* 119 (1), 249–275.
- BINE, 2015. Förderung Erneuerbare Energien und Energieeinsparung. <http://www.energiefoerderung.info>, retrieved in Spring 2015.
- Borenstein, S., 2015. The Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives and Rebates. NBER Working Paper.
- Burr, C., 2014. Subsidies, Tariffs and Investments in the Solar Power Market. Working Paper, University of Colorado, Boulder.
- Bushnell, J., Wolfram, C., 2012. Enforcement of Vintage Differentiated Regulations: The Case of New Source Review. *Journal of Environmental Economics and Management* 64, 137–152.
- Chetty, R., Friedman, J., Olsen, T., Pistaferri, L., 2011. Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records. *Quarterly Journal of Economics* 126, 327–354.
- Gillingham, K., Bollinger, B., 2012. Peer Effects in the Diffusion of Solar Photovoltaic Panels. *Marketing Science* 31 (6), 900–912.
- Gillingham, K., Graziano, M., 2015. Spatial Patterns of Solar Photovoltaic System Adoption: The Influence of Neighbors and the Built Environment. *Journal of Economic Geography*.
- Grau, T., 2014. Responsive Feed-in Tariff Adjustment to Dynamic Technology Development. *Energy Economics* 44, 36–46.
- Gray, W. B., Shadbegian, R. J., 2003. Plant Vintage, Technology, and Environmental Regulation. *Journal of Environmental Economics and Management* 46 (3), 384–402.
- Gruenspecht, H. K., 1982. Differentiated Regulation: The Case of Auto Emissions Standards. *American Economic Review* 72 (2), 328–331.
- Hughes, J. E., Podolefsky, M., 2015. Getting Green with Solar Subsidies: Evidence from the California Solar Initiative. *Journal of the Association of Environmental and Resource Economists* 2 (2), 235–275.
- IE Leipzig, 2011. Vorbereitung und Begleitung der Erstellung des Erfahrungsberichts gemäß § 65 EEG - Vorhaben IIc Solare Strahlungsenergie. Endbericht, Leipziger Institut für Energie GmbH.
- Ito, K., Sallee, J. M., 2014. The Economics of Attribute-Based Regulation: Theory and Evidence from Fuel-Economy Standards. NBER Working Paper.
- Lamp, S., 2015. The Impact of Short-Lived Weather Outliers on Household Investment. Working paper; http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2463570.
- Leepa, C., Unfried, M., 2013. Effects of a Cut-Off in Feed-In Tariffs on Photovoltaic Capacity: Evidence from Germany. *Energy Policy* 56, 536 – 542.
- Nelson, R. A., Tietenberg, T., Donihue, M. R., 1993. Differential Environmental Regulation: Effects on Electric Utility Capital Turnover and Emissions. *Review of Economics and Statistics* 75 (2), 368–373.
- Rode, J., Weber, A., 2012. Does Localized Imitation Drive Technology Diffusion? A Case Study on Solar Cells in Germany. Working Paper; http://www.stadtforschung.tu-darmstadt.de/media/loewe_eigenlogik_der_staedte/dokumente_download/artikel/Rode_Weber_2012.pdf.
- Saez, E., 2010. Do Taxpayers Bunch at Kink Points? *American Economic Journal: Economic Policy* 2 (3), 180–212.
- Stavins, R. N., 2006. Vintage-Differentiated Environmental Regulation. *Stanford Environmental Law Journal* 25:29, 29–63.
- Tietenberg, T., 1978. Spatially Differentiated Air Pollutant Emission Charges: An Economic and Legal Analysis. *Land Economics* 54 (3), 265–277.

ZSW, 2014. Vorbereitung und Begleitung der Erstellung des Erfahrungsberichts 2014 gemäß § 65 EEG - Vorhaben
IIc Solare Strahlungsenergie. Zentrum für Sonnenenergie- und Wasserstoff-Forschung.

Appendix A Results - Without adjustment for bunching

Table 5: Results - Capacity

	(1)	(2)	(3)	(4)
Treatment Effect	-83.777*** (5.642)	-79.612*** (6.397)	-91.222*** (5.901)	-94.827*** (6.975)
Large Class	21.643*** (5.237)	24.420*** (5.186)	21.643*** (5.237)	19.354*** (5.088)
Time Trend	18.572*** (0.971)	18.641*** (0.969)	18.545*** (0.974)	18.487*** (0.968)
Average End-use Price	2.367 (6.243)	2.367 (6.243)	1.890 (6.429)	1.890 (6.429)
Class-specific Trend		-0.139 (0.084)		0.114 (0.088)
Constant	-489.572*** (138.719)	-543.370*** (140.592)	-481.633*** (143.401)	-457.247*** (145.645)
Observations	47,880	47,880	45,486	45,486
Time Fixed Effects	+	+	+	+
County-Year Fixed Effects	+	+	+	+
Class-Specific Trend	-	+	-	+
Treatment Start in	April	April	July	July

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Standard errors in parentheses and clustered at county level.

Table 6: Results - Capacity

	(1)	(2)	(3)	(4)
April 2012	-34.954*** (4.805)	-35.507*** (5.730)		
May 2012	-40.896*** (4.814)	-41.477*** (5.741)		
June 2012	-41.475*** (4.830)	-42.083*** (5.609)		
July 2012	-70.305*** (5.339)	-70.941*** (6.231)	-70.305*** (5.338)	-70.941*** (6.231)
August 2012	-83.608*** (5.667)	-84.272*** (6.396)	-83.608*** (5.666)	-84.272*** (6.396)
September 2012	-94.183*** (6.138)	-94.875*** (6.934)	-94.183*** (6.138)	-94.875*** (6.934)
October 2012	-135.014*** (7.152)	-135.733*** (7.767)	-135.014*** (7.152)	-135.733*** (7.767)
November 2012	-122.467*** (7.072)	-123.214*** (7.963)	-122.467*** (7.072)	-123.214*** (7.963)
December 2012	-69.239*** (5.523)	-70.014*** (6.700)	-69.239*** (5.523)	-70.014*** (6.700)
January 2013	-75.449*** (6.112)	-76.251*** (7.398)	-75.449*** (6.112)	-76.251*** (7.398)
February 2013	-72.416*** (5.767)	-73.246*** (7.159)	-72.416*** (5.767)	-73.246*** (7.159)
March 2013	-101.868*** (6.904)	-102.726*** (8.143)	-101.868*** (6.904)	-102.726*** (8.143)
April 2013	-123.299*** (7.768)	-124.185*** (8.910)	-123.299*** (7.768)	-124.185*** (8.910)
May 2013	-97.024*** (6.413)	-97.937*** (7.836)	-97.024*** (6.413)	-97.937*** (7.836)
June 2013	-105.919*** (6.749)	-106.859*** (8.176)	-105.919*** (6.749)	-106.859*** (8.176)
July 2013	-103.770*** (6.968)	-104.738*** (8.336)	-103.770*** (6.968)	-104.738*** (8.336)
August 2013	-90.964*** (6.377)	-91.960*** (7.936)	-90.964*** (6.377)	-91.960*** (7.936)
September 2013	-91.607*** (6.433)	-92.631*** (8.100)	-91.607*** (6.433)	-92.631*** (8.099)
October 2013	-89.545*** (6.621)	-90.596*** (8.426)	-89.545*** (6.621)	-90.596*** (8.425)
November 2013	-73.674*** (6.079)	-74.753*** (8.038)	-73.674*** (6.079)	-74.753*** (8.038)
December 2013	-41.642*** (5.410)	-42.749*** (7.641)	-41.642*** (5.409)	-42.749*** (7.641)
Large Class	21.643*** (5.238)	21.089*** (4.999)	21.643*** (5.238)	21.089*** (4.999)
Time Trend	18.572*** (0.971)	18.558*** (0.964)	18.545*** (0.975)	30.316*** (1.777)
Average End-use Price	2.367 (6.244)	2.367 (6.244)	1.890 (6.430)	1.890 (6.430)
Class-specific Trend		0.028 (0.100)		0.028 (0.100)
Constant	-513.159*** (140.404)	-494.789*** (142.563)	-543.234*** (145.284)	-819.565*** (120.510)
Observations	47,880	47,880	45,486	45,486
Time Fixed Effects	+	+	+	+
County-Year Fixed Effects	+	+	+	+

* p < 0.10, ** p < 0.05, *** p < 0.01.

Standard errors in parentheses and clustered at county level.

Appendix B Results - Bunching adjusted

Table 7: Results Bunching Adjusted - Capacity

	(1)	(2)	(3)	(4)
Treatment Effect	-42.371*** (4.229)	-38.745*** (5.022)	-45.788*** (4.297)	-45.470*** (5.203)
Large Class	21.648*** (5.237)	24.065*** (5.169)	21.648*** (5.237)	21.850*** (5.153)
Time Trend	18.572*** (0.971)	18.633*** (0.968)	18.545*** (0.974)	30.335*** (1.780)
Average End-use Price	2.375 (6.243)	2.375 (6.243)	1.898 (6.429)	1.898 (6.429)
Class-specific Trend		-0.121 (0.084)		-0.010 (0.086)
Constant	-493.869*** (138.756)	-547.435*** (140.621)	-412.940*** (143.787)	-857.286*** (119.618)
Observations	47,880	47,880	45,486	45,486
Time Fixed Effects	+	+	+	+
County-Year Fixed Effects	+	+	+	+
Class-Specific Trend	-	+	-	+
Treatment Start in	April	April	July	July

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Standard errors in parentheses and clustered at county level.

Table 8: Results Bunching Adjusted - Capacity

	(1)	(2)	(3)	(4)
April 2012	-24.768*** (4.682)	-25.318*** (5.599)		
May 2012	-26.349*** (4.528)	-26.926*** (5.468)		
June 2012	-14.501*** (4.175)	-15.105*** (4.844)		
July 2012	-40.049*** (4.386)	-40.681*** (5.287)	-40.049*** (4.385)	-40.681*** (5.287)
August 2012	-38.813*** (4.241)	-39.472*** (4.947)	-38.813*** (4.241)	-39.472*** (4.947)
September 2012	-36.213*** (4.317)	-36.900*** (4.900)	-36.213*** (4.317)	-36.900*** (4.900)
October 2012	-52.011*** (4.622)	-52.725*** (4.757)	-52.011*** (4.622)	-52.725*** (4.756)
November 2012	-56.978*** (4.656)	-57.720*** (5.443)	-56.978*** (4.656)	-57.720*** (5.443)
December 2012	-39.436*** (4.718)	-40.205*** (5.856)	-39.436*** (4.718)	-40.205*** (5.856)
January 2013	-34.499*** (5.006)	-35.296*** (6.229)	-34.499*** (5.006)	-35.296*** (6.229)
February 2013	-38.614*** (4.722)	-39.438*** (6.045)	-38.614*** (4.722)	-39.438*** (6.045)
March 2013	-43.907*** (4.741)	-44.759*** (5.958)	-43.907*** (4.741)	-44.759*** (5.958)
April 2013	-54.080*** (4.956)	-54.960*** (6.135)	-54.080*** (4.956)	-54.960*** (6.134)
May 2013	-45.833*** (4.784)	-46.740*** (6.110)	-45.833*** (4.784)	-46.740*** (6.109)
June 2013	-55.898*** (5.012)	-56.832*** (6.380)	-55.898*** (5.012)	-56.832*** (6.380)
July 2013	-54.453*** (5.130)	-55.415*** (6.549)	-54.453*** (5.130)	-55.415*** (6.548)
August 2013	-50.352*** (5.020)	-51.341*** (6.559)	-50.352*** (5.020)	-51.341*** (6.559)
September 2013	-50.267*** (4.998)	-51.284*** (6.689)	-50.267*** (4.998)	-51.284*** (6.689)
October 2013	-53.264*** (5.163)	-54.308*** (7.054)	-53.264*** (5.162)	-54.308*** (7.054)
November 2013	-47.223*** (5.269)	-48.294*** (7.240)	-47.223*** (5.269)	-48.294*** (7.240)
December 2013	-32.288*** (5.227)	-33.387*** (7.464)	-32.288*** (5.227)	-33.387*** (7.464)
Large Class	21.648*** (5.238)	21.098*** (4.999)	21.648*** (5.238)	21.098*** (4.999)
Time Trend	18.572*** (0.971)	18.559*** (0.964)	30.330*** (1.786)	30.317*** (1.777)
Average End-use Price	2.375 (6.244)	2.375 (6.244)	1.898 (6.430)	1.898 (6.430)
Class-specific Trend		0.027 (0.100)		0.027 (0.100)
Constant	-520.392*** (140.466)	-498.869*** (142.592)	-826.806*** (120.451)	-826.386*** (120.592)
Observations	47,880	47,880	45,486	45,486
Time Fixed Effects	+	+	+	+
County-Year Fixed Effects	+	+	+	+

* p < 0.10, ** p < 0.05, *** p < 0.01.

Standard errors in parentheses and clustered at county level.