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

Robert Germeshausen[a,*]

[a] *Centre for European Economic Research, L 7, 1, 68161 Mannheim, Germany.*

Abstract

Production subsidies in the form of feed-in tariffs are a widely used policy instrument to support diffusion 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 a policy change of administrative size classes in Germany in 2012 for exogenous variation in feed-in tariffs. I find that a cut in marginal feed-in tariffs of five percent leads to a decrease in newly installed capacity of around 30 percent. Additionally, the re-evaluation of size classes implies de facto the introduction of attribute-based regulation for small installations. The differentiated rates incentivize smaller individual capacity choices at the border of size classes leading to excess bunching at the ceiling of the smaller size class. The net effect of excess bunching on deployment is negative indicating potential efficiency losses introduced by the design of the attribute-based regulation.

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

JEL classification: O38, Q28, Q42

Preliminary and incomplete draft, please do not cite or distribute
This version: 10 June 2016

* Corresponding author:
Email address: germeshausen@zew.de, +49 621 1235218 (Robert Germeshausen)

I would like to thank Kathrine von Grävenitz, Koichiro Ito, Goytom Abraha Kahsay, Andreas Löschel, Benjamin Lutz, Philipp Massier, Christiane Reif, Johannes Rode, Katrin Sommerfeld and Ulrich Wagner as well as participants at AURÖ Nachwuchsworkshop 2016, 21st Spring Meeting of Young Economists 2016, 5th Mannheim Energy Conference 2016, ZEW Mannheim and at the University of Münster for their helpful comments and suggestions. Data on regional end-user prices for electricity is kindly provided by ene't. Financial support by the Centre for European Economic Research (ZEW) Mannheim is gratefully acknowledged.

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, which is a production subsidy. Within this system, the owner of an eligible renewable installation receives a fixed amount (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 differentiation (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 for new installations 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, it rather 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. 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 learning (peer) effects (among others, Gillingham and Bollinger, 2012; Gillingham and Graziano, 2015; Rode and Weber, 2016) and other socio-economic aspects. These factors cannot be captured in a nationwide analysis. Hence, my analysis is conducted on the NUTS-3-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 -0.295 in the period until the end of 2013. This means that for the five percent cut of the marginal feed-in rate, the newly installed capacity within one month in a NUTS-3 area drops by around 30 percent. 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 (size-based) regulation for small installations. Thus, it provides an opportunity to identify the effect of attribute-based regulation on technology adoption. Before the PV Amendment, small installations up to 20 kilowatt (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. This design does not only change the absolute profitability of larger installations but also relatively to smaller installations. 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 almost double the size. 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. This leads to an additional negative net effect on PV deployment and underlines the impact of differentiated feed-in tariffs on technology adoption for solar PV.

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 deals with the net effect of excess bunching and Section 8 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 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

[1] Other 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.

[2] I 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.

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

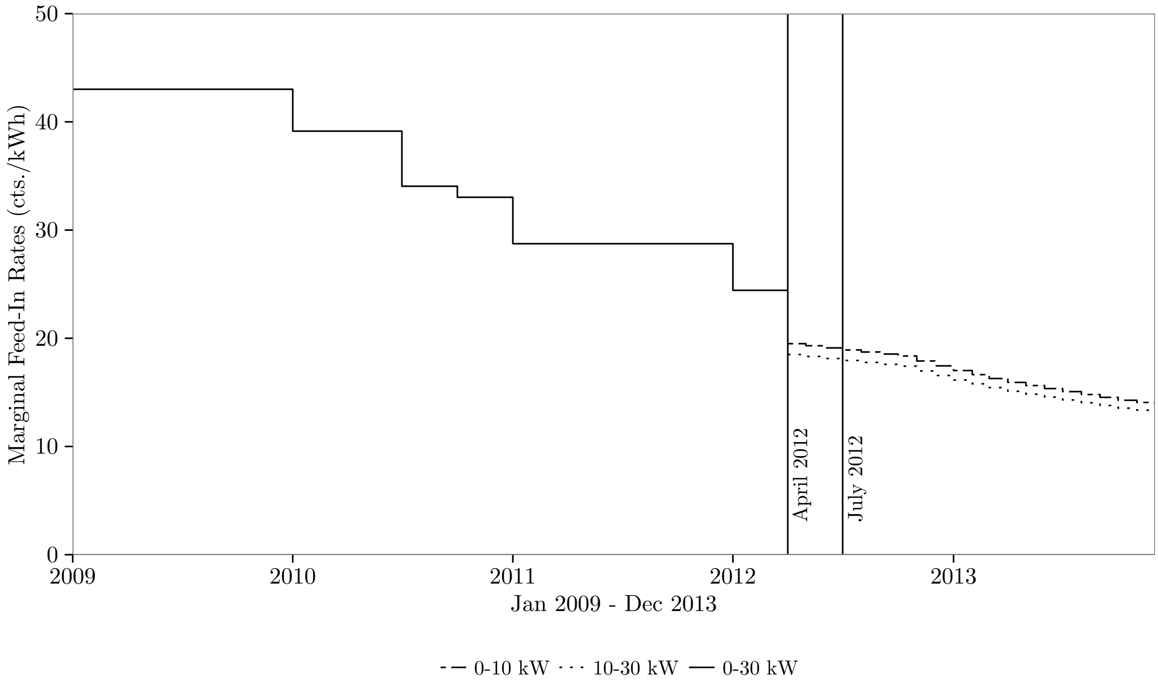

Figure 1: Development of Marginal Feed-in Rates for Rooftop Solar PV Installations

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

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.

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 NUTS-3 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.

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

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

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 NUTS-3 area 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 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 evolve quite similar, especially from mid year 2010 on until the treatment period starts.[5] 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 NUTS-3 level data to allow for more (regional) heterogeneity.

[5]The figure does hint at anticipation effects of the policy change as indicated by the spike in the month before. However, this might not interfere with the validity of the differences-in-differences approach as long as the anticipation effects are similar in both size classes.

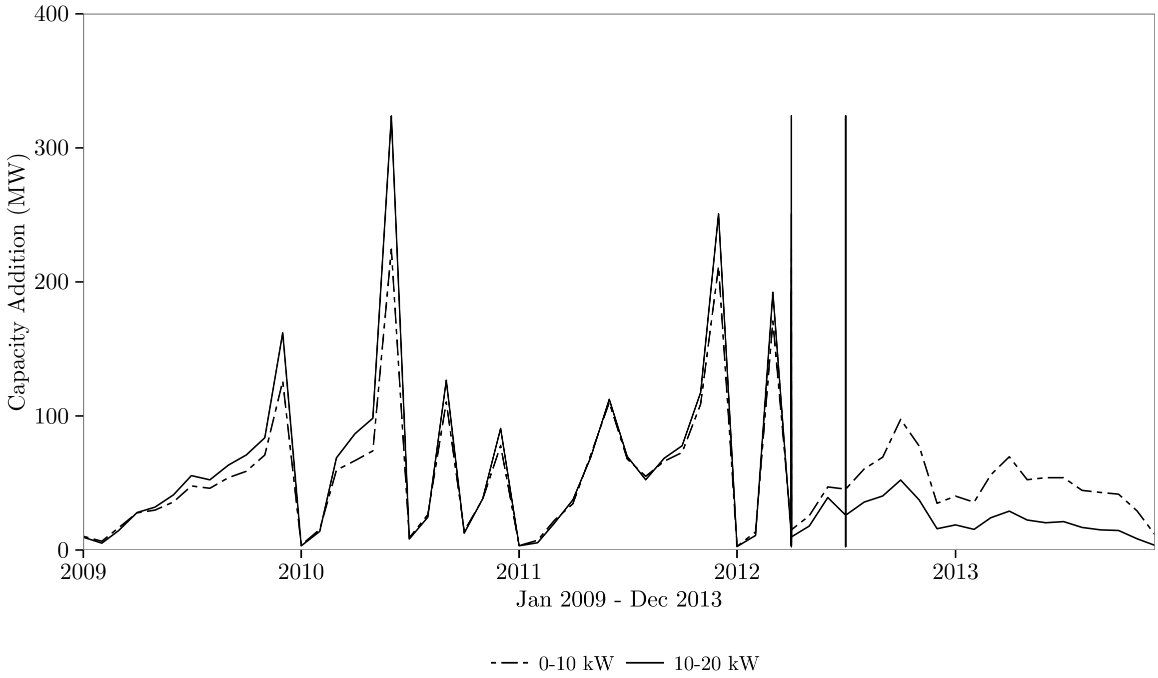

Figure 2: Monthly Deployment of Solar PV Capacity

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).

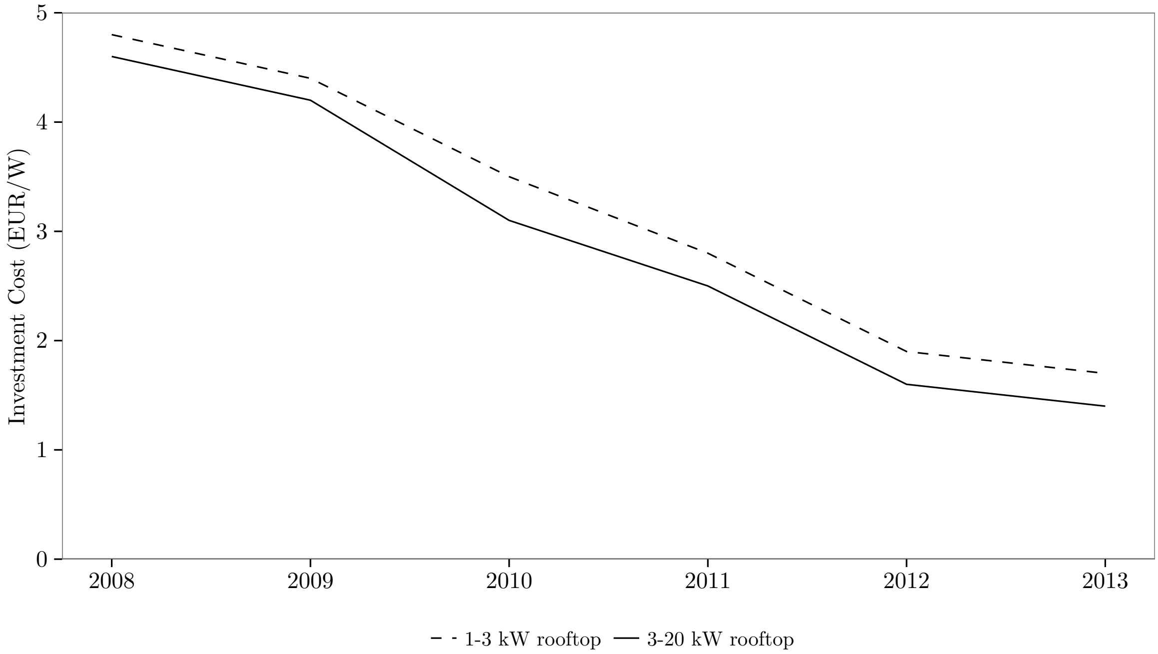

Figure 3: Cost Development for Modules and Inverters for Different Sizes in Italy

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. County-class fixed effects capture time constant differences in regional deployment of smaller and larger installations, e.g., different building structures across counties. The various fixed effects control for all effects that remain constant over time, are the same for all counties or vary on a NUTS-3 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 could occur within a year[6], are regionally differentiated and could also impact the decision to build a PV installation. Higher end-use electricity prices increase the incentive to

[6]The average price offer 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 changes in the average price offer occur more often than once a year.

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 dependent variable, capacity additions, is either positive or zero. For 14 per cent of all observations the dependent variable takes a value of zero. Furthermore, the model specification includes various fixed effects. To account for these data characteristics, I make use of the Poisson Pseudo-Maximum Likelihood (PPML) estimator, which has been applied for example by Santos Silva and Tenreyro (2006). Thus, the basic formulation of the empirical model in a log-linear specification is as follows:

$$C_{i,m,y,r} = \exp\left(\alpha + \mu_{i,y} + \mu_{i,r} + \mu_r + \mu_{m,y} + \beta\, D_{m,y,r} + \gamma\, X_{i,m,y}\right)\, \epsilon_{i,m,y,r}, \tag{1}$$

where $C_{i,m,y,r}$ denotes the capacity additions in NUTS-3 area 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. $\mu_{i,y}$, $\mu_{i,r}$, μ_r and $\mu_{m,y}$ are NUTS-3-year, NUTS-3-class, 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. $X_{i,m,y}$ denotes the monthly average end-user offer price for electricity prices in the respective NUTS-3 area and exp(.) is the exponential operator.

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 interactions of the size class dummy variable with time dummy variables, i.e., placebo treatment effects. The coefficients of the interaction terms are found to be statistically insignificant, supporting both size classes exhibit the same trend in monthly capacity additions before the PV Amendment.[7]

[7]Standard errors in all estimations are clustered at the NUTS-3-class level. Additionally, standard errors have been clustered on the NUTS-3 level to control for serial correlation, which is particularly important for differences-in-differences estimation as pointed out by Bertrand et al. (2004). However, those standard errors appear lower than the NUTS-3-class clustered standard errors. Therefore, I will use the NUTS-3-class clustered standard errors as the reference case.

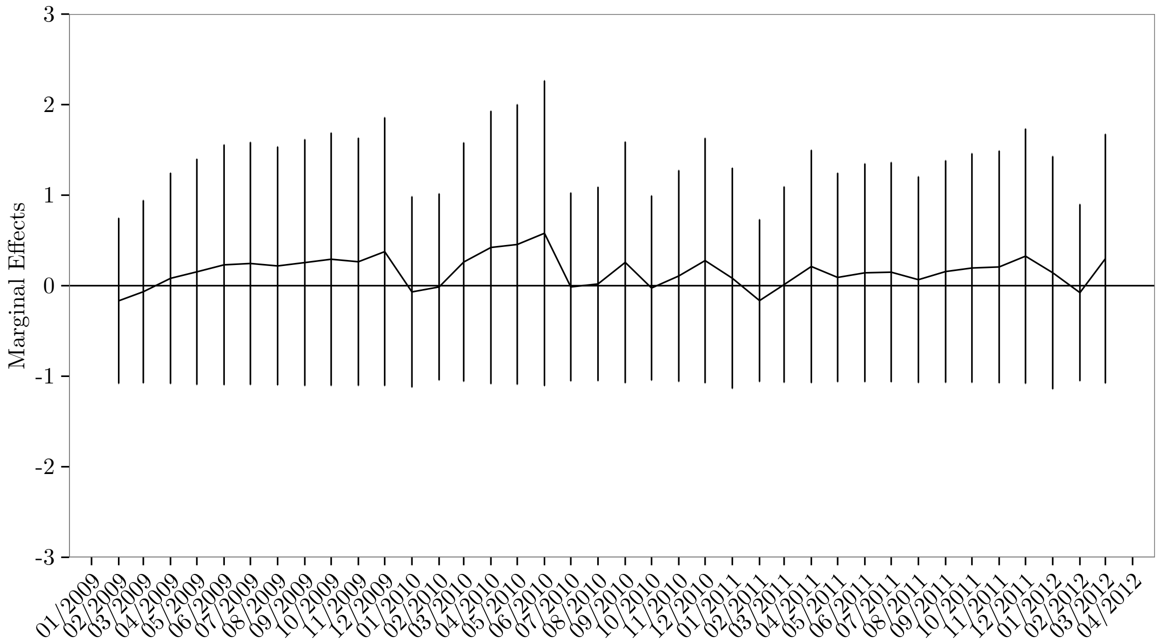

Figure 4: Parallel Pre-Trends in Capacity Additions

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 of taking 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. Furthermore, the pre-trend analysis may give credibility to the assumption of similar anticipation effects across groups. Differences across groups within the treatment period may result from 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 24 February 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 receiving 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 time-varying regional end-use electricity offer 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.[8] 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 are 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.

[8]The 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.

5. Results of the 'Naive' Approach

The estimated constant treatment effects are shown in Table 2.[9] In each specification, the monthly capacity additions in a NUTS-3 area within one of the two size classes are regressed on a binary variable indicating the larger size class, the average monthly end-use price offer in the respective NUTS-3 area as well as on a set of time 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 the five percent cut in marginal feed-in tariffs is found to be -0.57 for the treatment started in April 2012 and -0.59 for an start of the analysis in July 2012 (see column one and three in Table 2).[10] 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 NUTS-3 area decreases by 57 percent (April) or 59 percent (July), respectively. The range of 2 percentage points 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 confirmed in the empirical analyses.

Table 2: Summary of 'Naive' Treatment Effects on Capacity Additions

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Effect	-0.581^{***}	-0.581^{***}	-0.564^{***}	-0.604^{***}	-0.604^{***}	-0.587^{***}
	(0.007)	(0.011)	(0.006)	(0.006)	(0.011)	(0.006)
Observations	47,880	47,880	47,880	45,486	45,486	45,486
Time Fixed Effects	+	+	+	+	+	+
County-Year Fixed Effects	+	-	+	+	-	+
County-Class Fixed Effects	-	+	+	-	+	+
Treatment Start in	April	April	April	July	July	July

Notes: In this table the marginal effect of the treatment dummy obtained in a Poisson Pseudo-Maximum Likelihood regression of monthly capacity additions on NUTS-3-year, NUTS-3-class, size-class and month-year fixed effects as well as on monthly average end-user offer price for electricity in the respective area is shown. Standard errors are in parentheses and clustered at county-class level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 size class dummy variable with the time dummy variables within the treatment period. The coefficients of the interaction terms represent the treatment effects in the

[9]The full estimation results can be found in Appendix A.

[10]To obtain the marginal effect of the treatment dummy, the estimated coefficient β has to be adjusted by the following formula: $(\exp(\beta) - 1) * 100$ percent.

respective month. The estimated variable treatment effects are shown in Figure 5.[11] The absolute values of the treatment effects persist until the end of the observation period and increase almost steadily. 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.

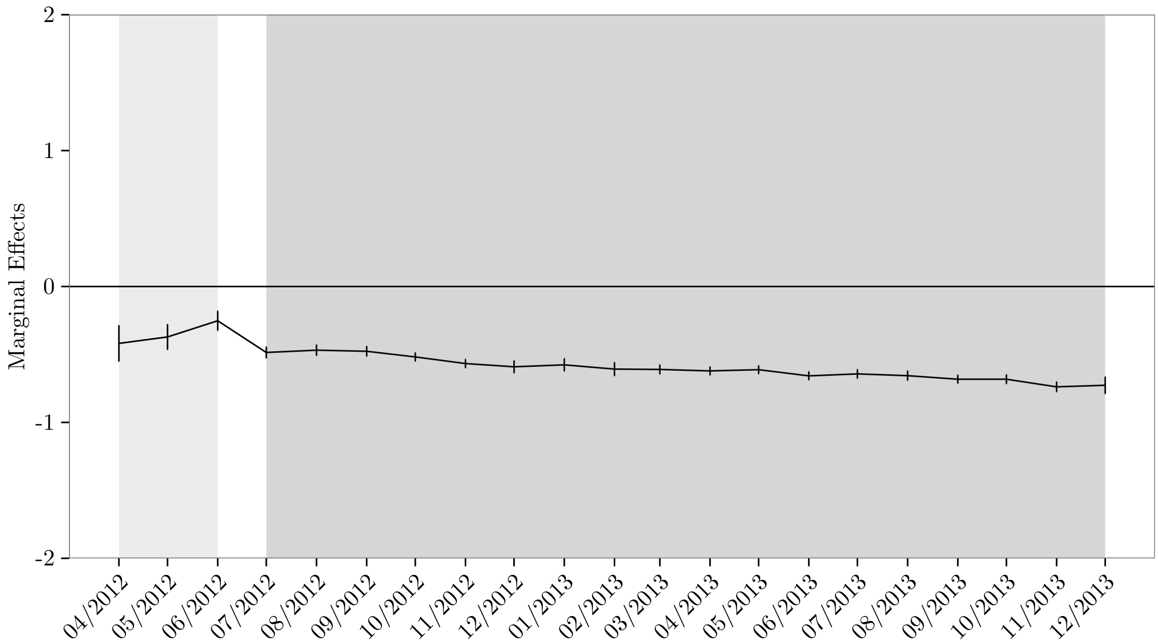

Figure 5: Dynamic Treatment Effects

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.

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

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 6, 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.[12] This figure can be used to illustrate an exemplary individual static adoption decision for a specific point in time.[13] 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.

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

[13]A 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 (dynamic) decision to adopt a solar PV system is made.

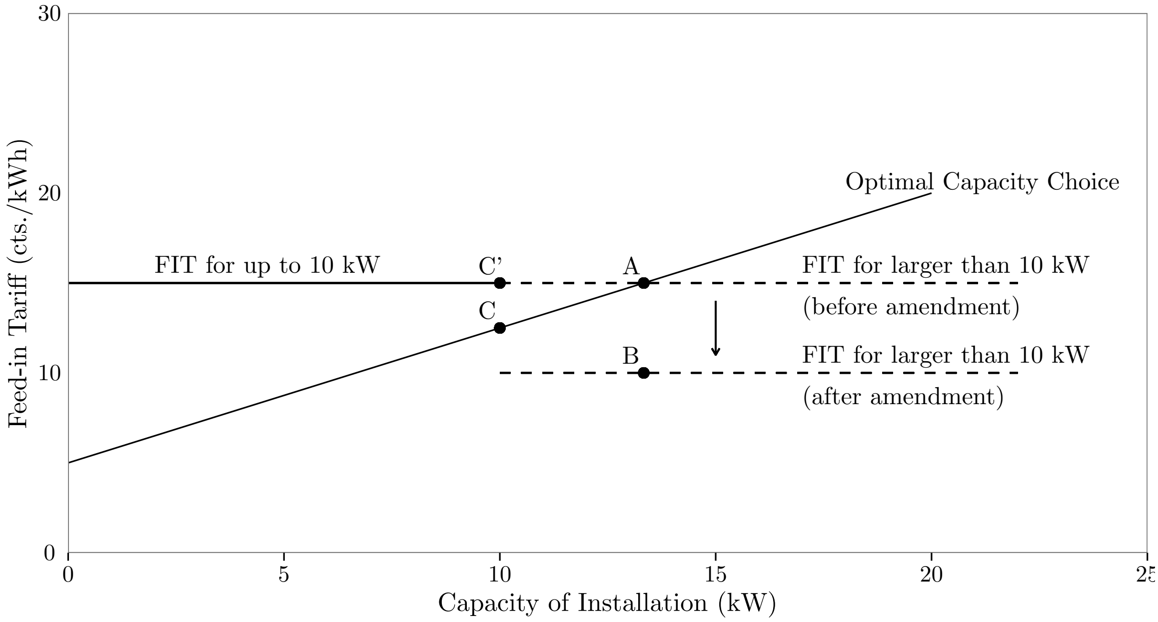

Figure 6: Effect of the Re-evaluation of Size Classes

First, in histograms of individual new PV installations excess bunching is revealed. In Figure 7 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).[14] 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.

[14] I 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.

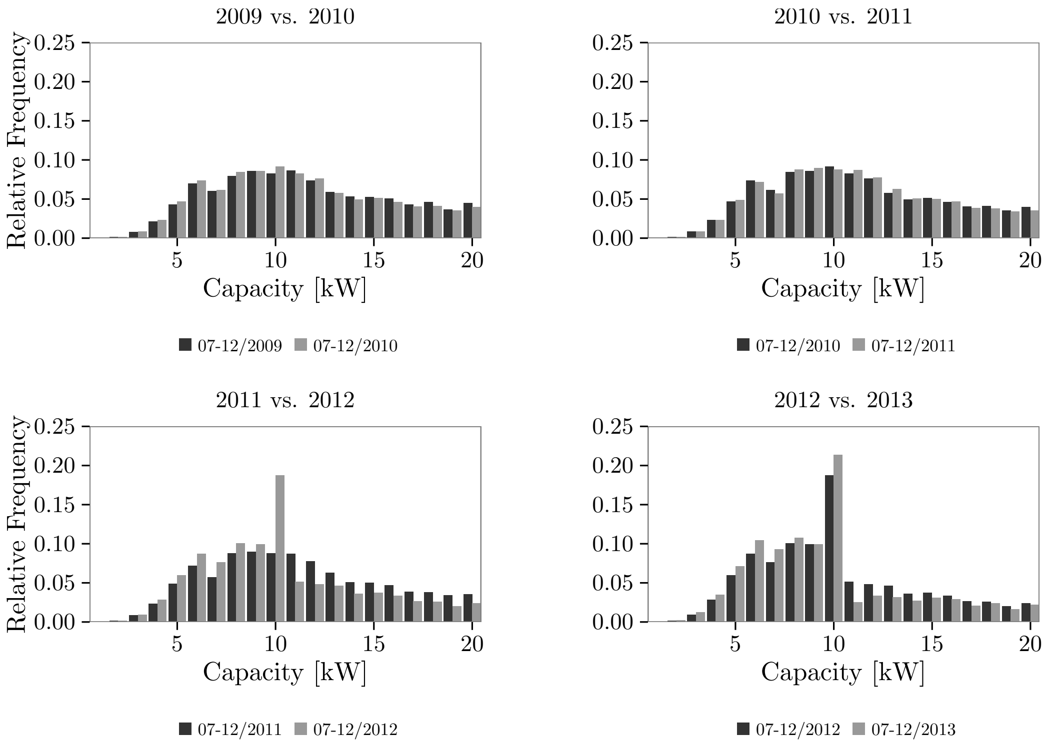

Figure 7: Histogram of Individual Installations in a Year-on-Year Comparison

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:

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

where $C_{i,m,y,k}$ is the installed capacity in bin k in NUTS-3 area 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 NUTS-3 and month-year fixed effects, respectively. The parameter estimates $\widehat{w}_k$ are used to construct weights of the different bins $((\widehat{w}_k - min(\widehat{w}_k))/(\sum_{k=1}^{20} \widehat{w}_k - min(\widehat{w}_k))$ as shown in Figure 8.[15] 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

[15]Weights are centered by the smallest estimate, which is the one kW bin with almost no deployment as can also be seen in Figure 7.

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.

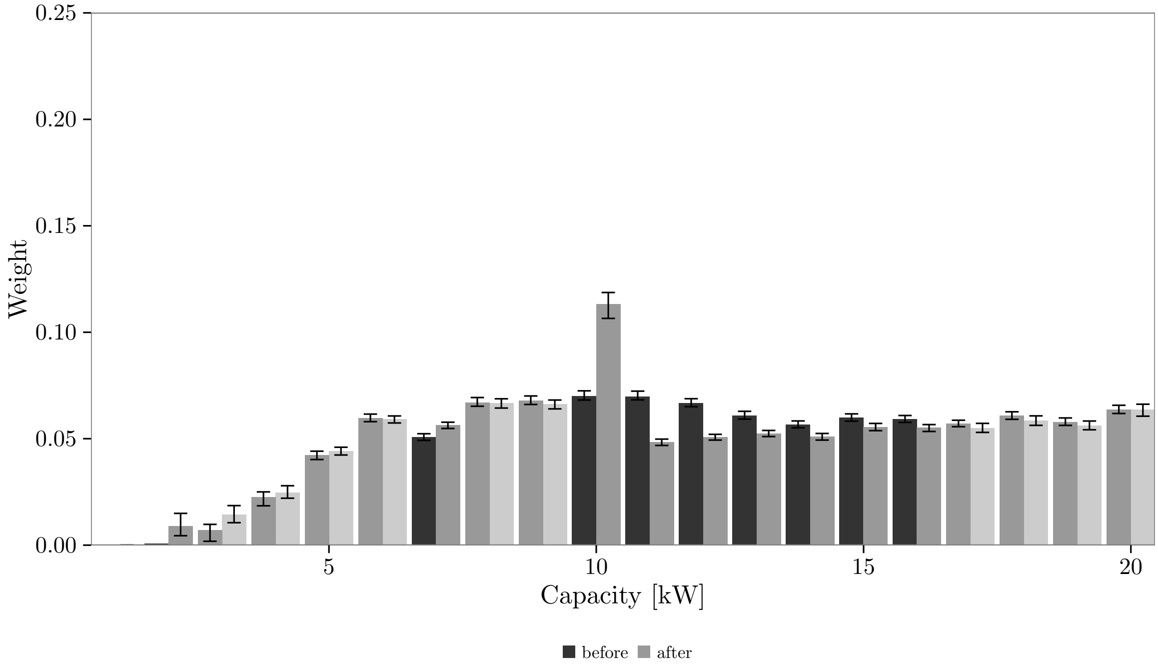

Figure 8: Bin Weights Before and After the PV Amendment

Note: Light grey 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. 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 7 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 8 strengthen further the credibility of this assumption.[16]

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):

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

where $S_{m,y,k}$ is the share of new installations within bin k in total new installations in month m and year y.[17] 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 ($\widehat{B}_{m,y}$) as the difference between the observed share ($S_{m,y,10}$) and the counterfactual share ($\widehat{S}_{m,y,10} - \widehat{\gamma}\, D_{10}$). However, the simple deduction of $\widehat{\gamma}\, D_{10}$ 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 shares in bins larger than 10 kW are scaled by the amount of excess bunching relative to the overall 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.

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

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 can control installation size (conditional on available roof area), 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 and a polynomial with degree seven ($q = 7$) yield the best fit. To enhance precision in estimating the counterfactual distribution, I exploit time and cross-sectional variation.

The sample of NUTS-3-month-size class observations is adjusted for excess bunching as follows. The capacity of all bins before the size class change remains the same. After the PV Amendment,

[16] Note 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.

[17] I 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.

monthly capacity additions within bins larger or equal to 10 kW are adjusted. For the 10 kW bin the excess mass is deducted and for the larger than 10 kW bins this excess mass is added. The estimate of the excess mass at the 10 kW bin is the difference of actual and estimated number of installations within this bin in this period.[18] The latter is calculated by multiplying the total number of installations within a month and NUTS-3 area by the respective fitted value from Equation 4 subtracted by $\widehat{\gamma}\, D_{10}$. The estimated counterfactual number of observations multiplied by 10 is the estimated counterfactual capacity addition within the 10 kW bin. The estimated excess number of installations at 10 kW is then redistributed on the installation bins larger than 10 kW according to the share of fitted values from Equation 4. The number of additional installations are multiplied by the respective size in each bin (e.g., for the 12 kW bin, the number of additional installations is multiplied by 12) to generate the additional newly build capacities. This procedure leads to the excess bunching adjusted distribution of installation sizes as shown in Figure 9.

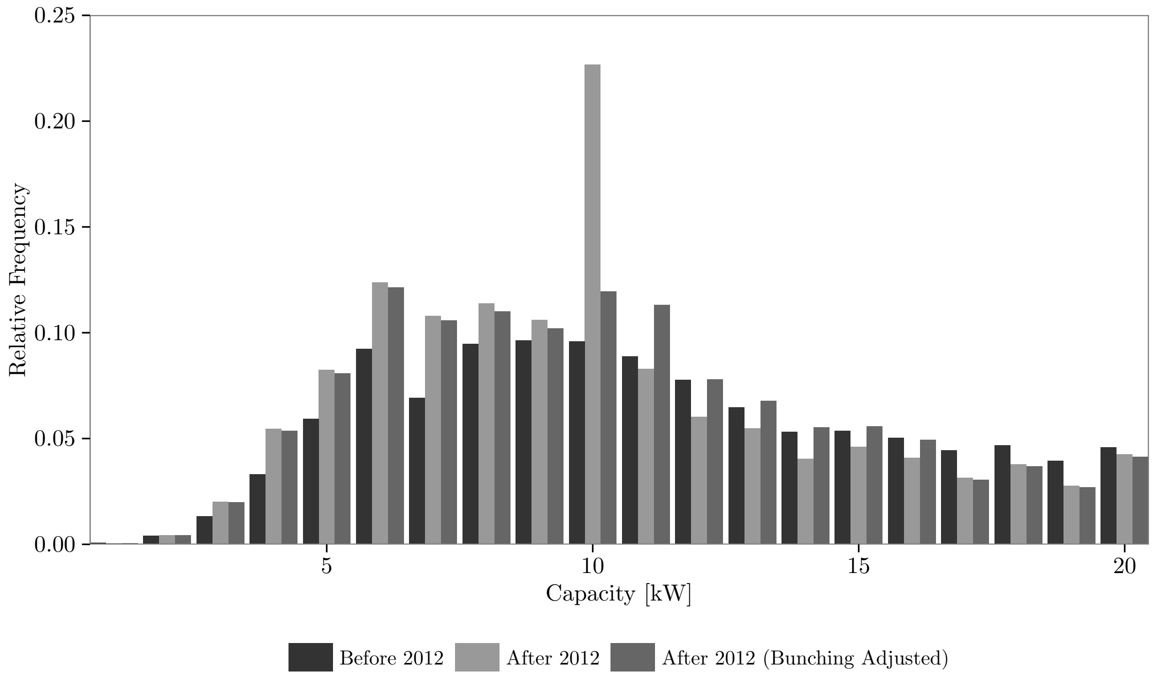

Figure 9: Histogram of Individual Installations Adjusted to Excess Bunching

The aggregate deployment is shown in Figure 10. Compared to the actual values observed in the data in Figure 2, adjusting for excess bunching leads to a smaller gap between the two

[18]Only positive excess mass will be considered since I want only identify excess bunching. If the difference between observed and estimated (counterfactual) number of installations in the respective NUTS-3 area and time period is smaller than zero, the capacity will remain unchanged. Thus, this procedure leads to a lower bound of treatment effects.

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.

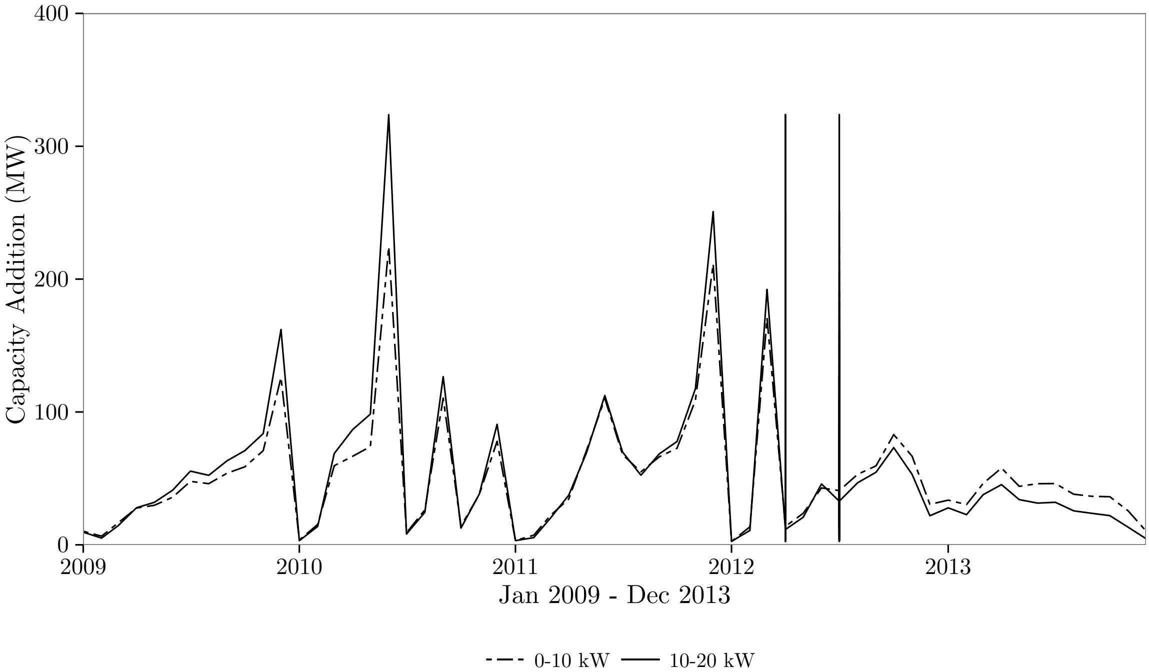

Figure 10: Monthly deployment of National Solar PV Capacity Adjusted to Excess Bunching

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., about half the size, compared to the treatment effects without taking excess bunching into account. The constant treatment effect starting in July is around -0.295.[20] This means that the five percent

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

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

cut in marginal feed-in tariffs leads on average to a reduction of monthly new installed capacity in a NUTS-3 area of around 30 percent. Thus, the smaller gap on the aggregate level in Figure 10 is mirrored by estimation results on the NUTS-3 level.

Table 3: Summary of Treatment Effects on Capacity Additions - Adjusted for excess bunching

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Effect	-0.315^{***}	-0.315^{***}	-0.279^{***}	-0.332^{***}	-0.332^{***}	-0.295^{***}
	(0.010)	(0.018)	(0.009)	(0.010)	(0.019)	(0.009)
Observations	47,880	47,880	47,880	45,486	45,486	45,486
Time Fixed Effects	+	+	+	+	+	+
County-Year Fixed Effects	+	-	+	+	-	+
County-Class Fixed Effects	-	+	+	-	+	+
Treatment Start in	April	April	April	July	July	July

Notes: In this table the marginal effect of the treatment dummy obtained in a Poisson Pseudo-Maximum Likelihood regression of monthly capacity additions (adjusted to excess bunching as described in the main text) on NUTS-3-year, NUTS-3-class, size-class and month-year fixed effects as well as on monthly average end-user offer price for electricity in the respective area is shown. Standard errors are in parentheses and clustered at county-class level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.

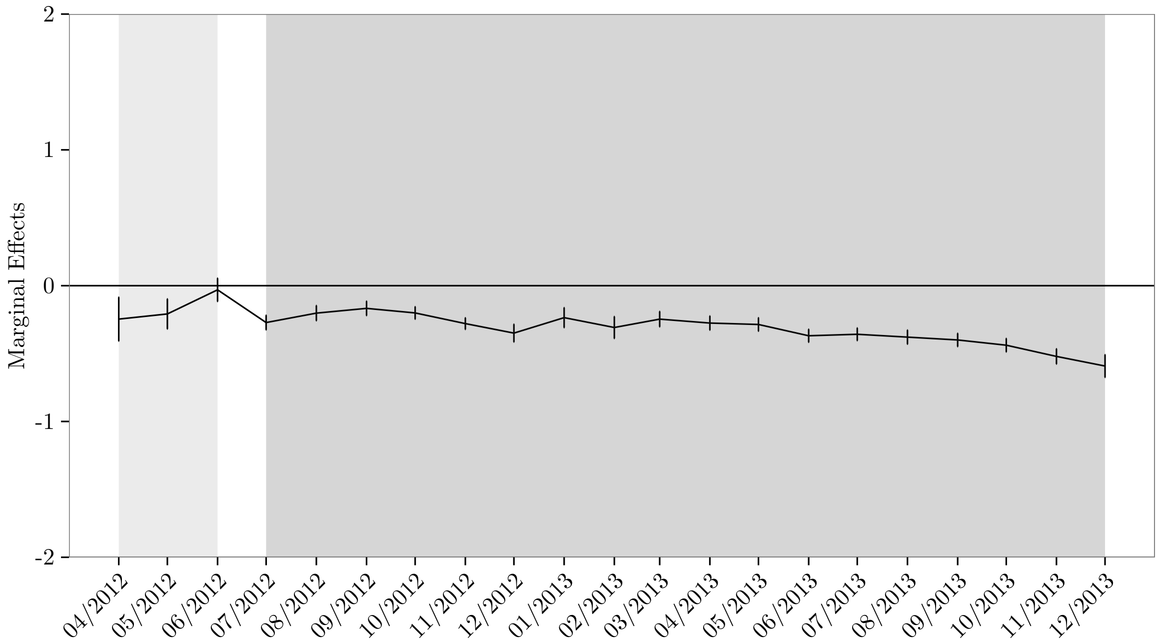

Figure 11: Dynamic Treatment Effects

7. The Net Effect of Excess Bunching

The PV Amendment contains a re-evaluation of size classes in the feed-in tariff system that leads to a steeper reduction of the marginal feed-in tariff for larger installations compared to smaller ones. This change has two implications. First, it reduces the profitability of larger PV systems, resulting in a reduction of newly installed capacity corresponding approximately to a uniform cut in the feed-in rate. Second, there is the impact of attribute-based regulation on the deployment of PV systems, i.e., small installations become relatively more attractive compared to larger ones. This leads to a shift in the capacity distribution of installations as discussed in the previous section, which implies both a change in the control group (capacity increase of smaller installations) and a change in the treatment group (capacity decrease in larger size class). Both changes point in the same direction, but are just reflecting the switch from larger to smaller installation size. The effect of attribute-based regulation on deployment is not identified by the difference of the "Naive" and the "Bunching adjusted" estimation since this would result in double counting.

To identify the net effect of attribute-based regulation, I concentrate on three different cases. First, the naive estimation neglects the issue of excess bunching ("Naive"). Second, the excess mass is only deducted from the 10 kW bin, but is not redistributed on bins larger than 10 kW ("Excess

Mass"). Third, the estimation with bunching adjustment as in Section 6 is conducted ("Bunching"). Those three cases help to identify the net effect of excess bunching. The effect of a reduction in feed-in rate of five percent can be identified as described in the previous section and equals the treatment effect of the "Bunching" model ($\delta_{bunching} = -0.295$). This effect is around 30 percent. The positive effect on smaller installations can be identified by the difference in treatment effects between the "Excess Mass" and the "Naive" specification ($\delta_{excess} - \delta_{naive} = (-0.511) - (-0.587) = 0.076$). This represents the differences in treatment effects with and without the deduction of the excess mass, which is equal to the positive deployment effect of the smaller size class. The negative effect on larger installations can be disentangled by the amount of redistribution of excess mass on the larger size class , i.e., the difference in treatment effects between the "Excess Mass" and "Bunching" specification ($\delta_{excess} - \delta_{bunching} = (-0.511) - (-0.295) = -0.216$). This effect is around 22 percent and hence, almost in the same order of magnitude as the "uniform reduction" effect.

Table 4: Summary of Treatment Effects on Capacity Additions

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Effect	-0.564^{***}	-0.487^{***}	-0.279^{***}	-0.587^{***}	-0.511^{***}	-0.295^{***}
	(0.006)	(0.006)	(0.009)	(0.006)	(0.007)	(0.009)
Observations	47,880	47,880	47,880	45,486	45,486	45,486
Time Fixed Effects	+	+	+	+	+	+
County-Year Fixed Effects	+	+	+	+	+	+
County-Class Fixed Effects	+	+	+	+	+	+
Treatment Start in	April	April	April	July	July	July
Model	Naive	Excess Mass	Bunching	Naive	Excess Mass	Bunching

Notes: In this table the marginal effect of the treatment dummy obtained in a Poisson Pseudo-Maximum Likelihood regression of monthly capacity additions on NUTS-3-year, NUTS-3-class, size-class and month-year fixed effects as well as on monthly average end-user offer price for electricity in the respective area is shown. Standard errors are in parentheses and clustered at county-class level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

However, the total effect or net effect of the excess bunching on overall deployment is the sum of the positive and the negative bunching effect:

$$\begin{aligned} \widehat{\delta}_{net} &= (\widehat{\delta}_{excess} - \widehat{\delta}_{naive}) + (\widehat{\delta}_{excess} - \widehat{\delta}_{bunching}) \\ &= 0.076 + (-0.216) \\ &= -0.14 \end{aligned} \tag{5}$$

The positive effect on deployment on the small class amounts to around 8 percent and the negative effect on the larger size class amounts to approximately 22 percent. Thus, excess bunching leads to a lower overall deployment by around 14 percent of the larger size class installations. This means that the introduction of this kind of attribute-based regulation leads to additional lower deployment. Furthermore, this lower deployment is also on average more expensive in terms of average feed-in rate per kW. Given that specific installation costs (cost per kW installed) are similar at the border of the size class, this highlights potential efficiency losses introduced by the design of the attribute-based regulation.

8. 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 the NUTS-3 level. I find that the cut of marginal feed-in rates by five percent leads to a decrease in newly installed capacity of about 30 percent on the NUTS-3 level within one month. 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 this 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 size class border. The net negative effect on deployment in the larger group due to excess bunching amounts to 14 percent. 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. Including additional size classes could be promising way to investigate its (overall) impact on economic efficiency of the policy change. However, in this case it has to be examined whether comparability of the different size classes can be sustained. This area is 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, BINE Informationsdienst.

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., 2016. Does Localized Imitation Drive Technology Adoption? A Case Study on Rooftop Photovoltaic Systems in Germany. Journal of Environmental Economics and Management 78, 38–48.

Saez, E., 2010. Do Taxpayers Bunch at Kink Points? American Economic Journal: Economic Policy 2 (3), 180–212.

Santos Silva, J. M. C., Tenreyro, S., 2006. The Log of Gravity. Review of Economics and Statistics 88 (4), 641–658.

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)	(5)	(6)
Treatment Effect	-0.581^{***}	-0.581^{***}	-0.564^{***}	-0.604^{***}	-0.604^{***}	-0.587^{***}
	(0.007)	(0.011)	(0.006)	(0.006)	(0.011)	(0.006)
Large Class	0.149^{***}	-0.585^{***}	-0.582^{***}	0.149^{***}	-0.590^{***}	-0.585^{***}
	(0.024)	(0.003)	(0.001)	(0.024)	(0.002)	(0.001)
Average End-use Price	0.046^{***}	-0.027^{**}	0.045^{***}	0.045^{***}	-0.025^{*}	0.044^{***}
	(0.016)	(0.013)	(0.016)	(0.016)	(0.013)	(0.016)
Constant	1.015^{**}	5.373^{***}	0.892^{***}	1.035^{**}	5.124^{***}	0.386^{**}
	(0.423)	(1.727)	(0.328)	(0.431)	(1.667)	(0.155)
Observations	47,880	47,880	47,880	45,486	45,486	45,486
Time Fixed Effects	+	+	+	+	+	+
County-Year Fixed Effects	+	-	+	+	-	+
County-Class Fixed Effects	-	+	+	-	+	+
Treatment Start in	April	April	April	July	July	July

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

Standard errors in parentheses and clustered at county-class level.

Table 6: Results - Capacity

	(1)	(2)	(3)	(4)	(5)	(6)
April 2012	-0.437^{***}	-0.437^{***}	-0.419^{***}			
	(0.049)	(0.049)	(0.051)			
May 2012	-0.391^{***}	-0.391^{***}	-0.371^{***}			
	(0.034)	(0.034)	(0.035)			
June 2012	-0.276^{***}	-0.276^{***}	-0.252^{***}			
	(0.027)	(0.029)	(0.027)			
July 2012	-0.502^{***}	-0.502^{***}	-0.486^{***}	-0.502^{***}	-0.502^{***}	-0.484^{***}
	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
August 2012	-0.485^{***}	-0.486^{***}	-0.468^{***}	-0.485^{***}	-0.486^{***}	-0.467^{***}
	(0.015)	(0.017)	(0.015)	(0.015)	(0.017)	(0.015)
September 2012	-0.493^{***}	-0.494^{***}	-0.477^{***}	-0.493^{***}	-0.494^{***}	-0.475^{***}
	(0.014)	(0.016)	(0.014)	(0.014)	(0.016)	(0.014)
October 2012	-0.534^{***}	-0.534^{***}	-0.518^{***}	-0.534^{***}	-0.534^{***}	-0.517^{***}
	(0.012)	(0.014)	(0.012)	(0.012)	(0.014)	(0.012)
November 2012	-0.581^{***}	-0.581^{***}	-0.567^{***}	-0.581^{***}	-0.581^{***}	-0.566^{***}
	(0.012)	(0.014)	(0.012)	(0.012)	(0.014)	(0.012)
December 2012	-0.604^{***}	-0.604^{***}	-0.591^{***}	-0.604^{***}	-0.604^{***}	-0.590^{***}
	(0.016)	(0.019)	(0.017)	(0.016)	(0.019)	(0.017)
January 2013	-0.595^{***}	-0.595^{***}	-0.577^{***}	-0.595^{***}	-0.595^{***}	-0.577^{***}
	(0.017)	(0.022)	(0.018)	(0.017)	(0.022)	(0.018)
February 2013	-0.624^{***}	-0.624^{***}	-0.608^{***}	-0.624^{***}	-0.624^{***}	-0.608^{***}
	(0.018)	(0.023)	(0.019)	(0.018)	(0.023)	(0.019)
March 2013	-0.627^{***}	-0.626^{***}	-0.610^{***}	-0.627^{***}	-0.626^{***}	-0.610^{***}
	(0.013)	(0.016)	(0.013)	(0.013)	(0.016)	(0.013)
April 2013	-0.637^{***}	-0.637^{***}	-0.621^{***}	-0.637^{***}	-0.637^{***}	-0.621^{***}
	(0.012)	(0.014)	(0.012)	(0.012)	(0.014)	(0.012)
May 2013	-0.629^{***}	-0.629^{***}	-0.612^{***}	-0.629^{***}	-0.629^{***}	-0.612^{***}
	(0.012)	(0.015)	(0.011)	(0.012)	(0.015)	(0.011)
June 2013	-0.672^{***}	-0.672^{***}	-0.657^{***}	-0.672^{***}	-0.672^{***}	-0.657^{***}
	(0.011)	(0.014)	(0.012)	(0.011)	(0.014)	(0.012)
July 2013	-0.658^{***}	-0.659^{***}	-0.643^{***}	-0.658^{***}	-0.659^{***}	-0.643^{***}
	(0.012)	(0.015)	(0.012)	(0.012)	(0.015)	(0.012)
August 2013	-0.671^{***}	-0.671^{***}	-0.656^{***}	-0.671^{***}	-0.671^{***}	-0.656^{***}
	(0.013)	(0.016)	(0.013)	(0.013)	(0.016)	(0.013)
September 2013	-0.696^{***}	-0.696^{***}	-0.682^{***}	-0.696^{***}	-0.696^{***}	-0.682^{***}
	(0.012)	(0.015)	(0.012)	(0.012)	(0.014)	(0.013)
September 2013	-0.696^{***}	-0.696^{***}	-0.682^{***}			
	(0.012)	(0.014)	(0.013)			
November 2013	-0.749^{***}	-0.750^{***}	-0.738^{***}	-0.749^{***}	-0.750^{***}	-0.738^{***}
	(0.013)	(0.016)	(0.014)	(0.013)	(0.016)	(0.014)
December 2013	-0.739^{***}	-0.739^{***}	-0.727^{***}	-0.739^{***}	-0.739^{***}	-0.727^{***}
	(0.022)	(0.025)	(0.023)	(0.022)	(0.025)	(0.023)
Large Class	0.149^{***}	-0.585^{***}	-0.580^{***}	0.149^{***}	-0.589^{***}	-0.584^{***}
	(0.024)	(0.003)	(0.002)	(0.024)	(0.003)	(0.002)
Average End-use Price	0.046^{***}	-0.027^{**}	0.044^{***}	0.045^{***}	-0.025^{*}	0.043^{***}
	(0.016)	(0.013)	(0.016)	(0.016)	(0.013)	(0.016)
Constant	1.015^{**}	5.373^{***}	0.900^{***}	1.035^{**}	5.122^{***}	0.390^{**}
	(0.421)	(1.728)	(0.329)	(0.430)	(1.667)	(0.155)
Observations	47,880	47,880	47,880	45,486	45,486	45,486
Time Fixed Effects	+	+	+	+	+	+
County-Year Fixed Effects	+	-	+	+	-	+
County-Class Fixed Effects	-	+	+	-	+	+
Treatment Start in	April	April	April	July	July	July

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

Standard errors in parentheses and clustered at county-class level.

Appendix B Results - Bunching adjusted

Table 7: Results Bunching Adjusted - Capacity

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment Effect	-0.315^{***}	-0.315^{***}	-0.279^{***}	-0.332^{***}	-0.332^{***}	-0.295^{***}
	(0.010)	(0.018)	(0.009)	(0.010)	(0.019)	(0.009)
Large Class	0.149^{***}	-0.566^{***}	-0.567^{***}	0.149^{***}	-0.583^{***}	-0.583^{***}
	(0.024)	(0.003)	(0.002)	(0.024)	(0.003)	(0.001)
Average End-use Price	0.045^{***}	-0.024^{*}	0.045^{***}	0.044^{***}	-0.021	0.044^{***}
	(0.016)	(0.013)	(0.016)	(0.016)	(0.013)	(0.016)
Constant	1.018^{**}	5.054^{***}	0.876^{***}	1.039^{**}	4.854^{***}	0.386^{**}
	(0.423)	(1.661)	(0.325)	(0.432)	(1.613)	(0.154)
Observations	47,880	47,880	47,880	45,486	45,486	45,486
Time Fixed Effects	+	+	+	+	+	+
County-Year Fixed Effects	+	-	+	+	-	+
County-Class Fixed Effects	-	+	+	-	+	+
Treatment Start in	April	April	April	July	July	July

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

Standard errors in parentheses and clustered at county-class level.

Table 8: Results Bunching Adjusted - Capacity

	(1)	(2)	(3)	(4)	(5)	(6)
April 2012	-0.276^{***}	-0.276^{***}	-0.246^{***}			
	(0.060)	(0.060)	(0.063)			
May 2012	-0.239^{***}	-0.240^{***}	-0.208^{***}			
	(0.041)	(0.041)	(0.043)			
June 2012	-0.069^{**}	-0.069^{*}	-0.031			
	(0.033)	(0.036)	(0.033)			
July 2012	-0.300^{***}	-0.301^{***}	-0.272^{***}	-0.300^{***}	-0.301^{***}	-0.270^{***}
	(0.020)	(0.022)	(0.021)	(0.021)	(0.022)	(0.021)
August 2012	-0.234^{***}	-0.234^{***}	-0.202^{***}	-0.234^{***}	-0.234^{***}	-0.200^{***}
	(0.021)	(0.025)	(0.022)	(0.022)	(0.025)	(0.022)
September 2012	-0.200^{***}	-0.201^{***}	-0.167^{***}	-0.200^{***}	-0.201^{***}	-0.165^{***}
	(0.020)	(0.024)	(0.021)	(0.020)	(0.024)	(0.021)
October 2012	-0.233^{***}	-0.233^{***}	-0.201^{***}	-0.233^{***}	-0.233^{***}	-0.199^{***}
	(0.018)	(0.023)	(0.018)	(0.018)	(0.023)	(0.018)
November 2012	-0.308^{***}	-0.308^{***}	-0.279^{***}	-0.308^{***}	-0.308^{***}	-0.278^{***}
	(0.016)	(0.021)	(0.017)	(0.016)	(0.021)	(0.017)
December 2012	-0.375^{***}	-0.376^{***}	-0.349^{***}	-0.375^{***}	-0.376^{***}	-0.348^{***}
	(0.024)	(0.029)	(0.025)	(0.024)	(0.029)	(0.025)
January 2013	-0.280^{***}	-0.280^{***}	-0.236^{***}	-0.280^{***}	-0.280^{***}	-0.235^{***}
	(0.028)	(0.037)	(0.029)	(0.028)	(0.037)	(0.029)
February 2013	-0.348^{***}	-0.348^{***}	-0.308^{***}	-0.348^{***}	-0.348^{***}	-0.308^{***}
	(0.030)	(0.041)	(0.031)	(0.030)	(0.041)	(0.031)
March 2013	-0.290^{***}	-0.289^{***}	-0.246^{***}	-0.290^{***}	-0.289^{***}	-0.246^{***}
	(0.022)	(0.028)	(0.022)	(0.022)	(0.028)	(0.022)
April 2013	-0.318^{***}	-0.318^{***}	-0.275^{***}	-0.318^{***}	-0.318^{***}	-0.275^{***}
	(0.020)	(0.025)	(0.020)	(0.020)	(0.025)	(0.020)
May 2013	-0.327^{***}	-0.328^{***}	-0.286^{***}	-0.327^{***}	-0.328^{***}	-0.286^{***}
	(0.020)	(0.027)	(0.019)	(0.020)	(0.027)	(0.019)
June 2013	-0.406^{***}	-0.406^{***}	-0.369^{***}	-0.406^{***}	-0.406^{***}	-0.369^{***}
	(0.018)	(0.024)	(0.019)	(0.018)	(0.024)	(0.019)
July 2013	-0.396^{***}	-0.396^{***}	-0.358^{***}	-0.396^{***}	-0.396^{***}	-0.358^{***}
	(0.018)	(0.024)	(0.018)	(0.018)	(0.024)	(0.018)
August 2013	-0.415^{***}	-0.415^{***}	-0.379^{***}	-0.415^{***}	-0.415^{***}	-0.379^{***}
	(0.020)	(0.027)	(0.020)	(0.020)	(0.027)	(0.020)
September 2013	-0.435^{***}	-0.435^{***}	-0.400^{***}	-0.435^{***}	-0.435^{***}	-0.400^{***}
	(0.018)	(0.026)	(0.019)	(0.018)	(0.026)	(0.019)
October 2013	-0.471^{***}	-0.472^{***}	-0.438^{***}	-0.471^{***}	-0.472^{***}	-0.438^{***}
	(0.019)	(0.023)	(0.019)	(0.019)	(0.023)	(0.019)
November 2013	-0.549^{***}	-0.549^{***}	-0.521^{***}	-0.549^{***}	-0.549^{***}	-0.521^{***}
	(0.021)	(0.026)	(0.022)	(0.021)	(0.026)	(0.022)
December 2013	-0.616^{***}	-0.616^{***}	-0.592^{***}	-0.616^{***}	-0.616^{***}	-0.592^{***}
	(0.031)	(0.035)	(0.032)	(0.031)	(0.035)	(0.032)
Large Class	0.149^{***}	-0.566^{***}	-0.565^{***}	0.149^{***}	-0.583^{***}	-0.582^{***}
	(0.024)	(0.003)	(0.001)	(0.024)	(0.003)	(0.001)
Average End-use Price	0.045^{***}	-0.024^{*}	0.044^{***}	0.044^{***}	-0.022	0.043^{***}
	(0.016)	(0.013)	(0.016)	(0.016)	(0.013)	(0.016)
Constant	1.018^{**}	5.064^{***}	0.886^{***}	1.039^{**}	4.862^{***}	0.392^{**}
	(0.421)	(1.664)	(0.327)	(0.430)	(1.616)	(0.156)
Observations	47,880	47,880	47,880	45,486	45,486	45,486
Time Fixed Effects	+	+	+	+	+	+
County-Year Fixed Effects	+	-	+	+	-	+
County-Class Fixed Effects	-	+	+	-	+	+
Treatment Start in	April	April	April	July	July	July

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

Standard errors in parentheses and clustered at county-class level.