Can the US Keep the PACE?
A Natural Experiment in Accelerating the Growth of Solar Electricity

Authors: Nadia Ameli[1*], Mauro Pisu[2], Daniel M. Kammen[3,4]

Affiliations:
[1*] Institute for Sustainable Resources, University College London (n.ameli@ucl.ac.uk)
[2] Economics Department, Organisation for Economic Cooperation and Development
[3] Energy and Resources Group, University of California, Berkeley
[4] Renewable and Appropriate Energy Laboratory, University of California, Berkeley

Abstract

Growing global awareness of climate change has ushered in a new era demanding policy, financial and behavioural innovations to accelerate the transition to a clean energy economy. Dramatic price decreases in solar photovoltaics (PV) and public policy have underwritten the expansion of solar power, now accounting for the largest share of renewable energy in California and rising fast in other countries, such as Germany and Italy. Governments' efforts to expand solar generation base and integrate it into municipal, regional, and national energy systems, have spawned several programs that require rigorous policy evaluations to assess their effectiveness, costs and contribution to Paris Agreement's goals. In this study, we exploit a natural experiment in northern California to test the capacity of Property Assessed Clean Energy (PACE) to promote PV investment. PACE has been highly cost effective by more than doubling residential PV installations.

Introduction

Boosting renewable energy sources is key to reducing greenhouse gas emissions and to accelerating job growth investment in high-growth companies, and in promoting social equity (1). The Paris Agreement, adopted by the US with other 194 countries in November 2015 to limit the increase in global average temperature to well below 2°C above pre-industrial levels, will require a massive increase in renewable energy (RE) generation. Solar energy is one of the most promising renewable energy sources because of its widespread availability. Technology advances have drastically reduced the costs of photovoltaic (PV) panels in the last 10 years (2). In the first quarter of 2015, PV module costs dropped to \$0.72/watt from \$5/watt in 2000 (3). In the US, the solar energy market is growing fast. In 2014, newly installed solar PV capacity reached 6.2 GW, a 30% increase over the previous year, led by the residential, utility and non-residential sectors, which grew by 51%, 38% and 11% respectively (3). California's solar energy market experienced the fastest growth among all US states with additional 3.5 GW of grid-connected PV capacity; solar energy is the largest renewable energy source in California accounting for over 7.6% of total electricity generation (5, 6). Businesses are also increasingly recognising the huge opportunities the nascent solar energy market offers. In early 2015, Tesla launched its battery storage system for residential and business PV installations and is working closely with SolarCity (the largest rooftop solar installer in the US) to reduce further the costs of solar energy (4). Despite these impressive progresses, solar energy is still far away from its full potential as in 2014 solar PV accounted for only 0.4% of US electricity generation.

Governments' efforts to expand solar generation and integrate it into national and regional energy systems have spawned a variety of programs. Recent research has started to investigate the effectiveness of governmental policies on the generation of electricity from renewable sources. However rigorous policy evaluations of specific programs are still rare. Studies have mainly focused on broad energy policies on nation-wide basis, including among others feed-in tariffs (FiT) (7, 8, 9, 10, 11), renewable portfolio standards (RPS) (12, 13, 14, 15, 16), tenders and tax incentives (17). This growing body of empirical evidence have concentrated mostly on FiT and RPS policies as they have vastly used (18). Overall, the evidence in support on RPS policies is mixed, as their effectiveness depend on different policy designs and types of implementation (13), whereas there is stronger evidence supporting the hypothesis that FiT polices are effective.

Regarding RPS, Carley (14) finds little evidence that RPS policies increase RE generation. This "policy failure" may be attributable to poor design and a lack of enforcement mechanism for non-compliers, an hypothesis later corroborated by Delmas and Montes-Sancho (15). Also, Yin and Powers (16) suggests a positive relationship between RPS and the share of electricity capacity based on RE but only conditional on level of policy stringency. Polzin et al. (7) also suggest that RPS can accelerate the diffusion process of RE technologies by reducing technological and regulatory risk associated with investments in RE projects. Aspects of RPS policy are further analysed by Shrimal and Kniefel (12) who demonstrate that those with a sale requirement are more effective than those with a capacity requirement. Nevertheless, both kinds of policy are identified as having negative relationship with overall RE capacity, perhaps as a result of too easy targets that weaken the incentive to invest beyond minimum requirements.

More consensus surrounds the effectiveness of FiT. In particular, Jenner et al. (9) suggest that FiT policies have driven solar photovoltaic capacity development in Europe since 1992 via their impact on the expected return on investment. These results are confirmed by Bolkesjø et al. (10), who conclude that FiT has significantly affected the development of PV and onshore wind farms in five European countries in the period 1990-2012. Zang (11) finds that the length of a FiT contract has more impact on wind capacity additions than the tariff level, suggesting investors favours long-term market security. A number of studies also underline the superiority of FiT compared to other schemes to foster deployment and technological diversity, and lower risks for private actors associated with RE technologies (8, 7, 19).

This paper contributes to this literature by evaluating the Property Assessed Clean Energy (PACE) program. While previous studies have mainly focused on other supporting policies, mostly FiTs and RPS, through econometric or engineering models, this study performs a rigorous evaluation of the PACE program relying on a natural experiment that exploits the geographic discontinuity in the implementation of the program.

PACE is an innovative energy scheme used in certain areas of the US to support renewable energy deployment. The installation of clean energy technology through PACE is financed by local governments, by issuing bonds whose proceeds are used to finance loans to homeowners for PV installations. Residential property owners pay back the loan through an increment on their property tax bill over a 20-year period. If the property is sold before the end of the repayment period, the new owner takes over the remaining debt. The innovative aspect of the PACE program is that it recycles funds at the municipal level, builds equity in increasingly valuable clean energy projects (by easing financial constraints), pays for itself and is transferred with the title on a property.

Our study is related to the work by Kirkpatrick and Bennear (20) who, using econometric techniques, have found a positive effect of the PACE program on PV installations. However, it differs significantly from Kirkpatrick and Bennear (20) as it employs a rigorous policy evaluation approach, which allow us to identify the causal effect of the PACE program on PV installations.

This paper also considers a longer period (up to 2012) and a larger set of cities (with populations below 20 000) than Kirkpatrick and Bennear (20). Exploiting the spatial discontinuity in the implementation of the program, the regression discontinuity (RD) approach enables to select units into treated areas (exposed to a policy) and control areas (not exposed to a policy). This allows the investigator to control for unobserved confounding factors, which if uncontrolled will result in biased estimates. Making causal inference in policy evaluation exercises is challenging as it requires constructing a credible counterfactual, i.e. what the outcome of interest (PV installations) would have been in the absence of the policy intervention (PACE program). The RD approach permits to do just that. Among policy evaluation methods, RD approach has become the preferred alternative to fully randomized experiments, which are considered the gold standard for policy evaluations (23) but are impossible to implement in many settings. To the best of our knowledge, RD design has not been used to test the impact of any energy program implemented at state level in the USA; only Boomhower and Davis (21) employed RD to study participation in an energy-efficiency scheme in Mexico. The RD approach holds a broad potential to evaluate other environmental programs (21, 22) and its application in the energy field would arise the quality of policy evaluation.

The results of this study show that the PACE program has been effective in boosting residential PV installations. As PACE costs nothing to taxpayers, we conclude it is a cost-effective way to increase PV installations and, if deployed more widely, could help meet US' renewable electricity generation targets. Also, the long repayment period and the transferability of the payments allow property owners to invest in deeper energy savings and renewable projects compared with existing alternative financing options (24, 25), without hurting residential mobility.

Materials and Methods

PACE has faced regulatory opposition that has considerably slowed its spread across the US and elsewhere. The Government Sponsored Enterprises (GSEs) Fannie Mae & Freddie Mac, involved in financing and regulating the housing market, have opposed the senior lien status of PACE credits over existing mortgages backed by the GSEs (FHFA 2010). Because of this, many states that initially set up residential PACE programs have suspended or withdrawn them. Until recently, only few counties in California, among which Sonoma County, and few others in Colorado, Florida, New York, Missouri and Connecticut have continued to run this scheme (26) (see supplementary materials).

The geographic specificity in the implementation of residential PACE programs provides a unique natural experiment to evaluate its effectiveness. As the PACE program is implemented at the municipality level, its causal effect on solar installations can be estimated exploiting the cities' spatial proximity to county borders determining the program eligibility. By restricting the sample to those cities that are near to each other but located in different counties, we are able to isolate the effect of the program. Indeed, cities that are close to each other, are more likely to share the same geographical, social and economic characteristics that may affect the take-up rate and the impact of the PACE program (Table S1) (27-29). Many of these characteristics are unobserved and in a standard econometric approach are likely to result in biased estimates.

Because of data availability we focus on Sonoma County, which implemented the first residential countywide PACE program in the nation. We evaluate the effect of this program comparing residential solar installations in Sonoma County and in its neighboring counties (Lake, Marin, Mendocino, Napa and Solano) before and after the program started. We thus combine the RD approach with the difference in difference methodology so as to causally identify the effect of the program. We begin comparing solar installations in all cities in Sonoma and its neighboring counties; then we select cities close to Sonoma's border with neighboring countries using narrow distance ranges, from 15 to 40 km to fully exploit the geographic discontinuity of the program, allowing us to better control for confounding factors.

The data we use come from the administrative records of California Solar Initiative (CSI), overseen by the California Public Utilities Commission. The CSI is a solar incentive program available to customers of the state’s utility companies (Pacific Gas and Electric Company, Southern California Edison and San Diego Gas and Electric). The related database reports solar photovoltaic installations at city-level from 2007 to 2016, which received the CSI incentive. The CSI has a \$2.4 billion budget to stimulate the deployment of approximately 1940 MW of new solar capacity between 2007 and 2016 via solar rebates for residential, commercial, and utility-scale systems. Although the raw dataset contains information up to 2016, our analysis stops in 2012 as afterwards utility companies stopped to accept new applications for the CSI incentive and the database does not report any longer all new solar projects. The database at our disposal tracks solar PV projects only in cities where new investments occurred, therefore cities not included in the dataset had not new solar power installed. We use the US Census data (30) to fill the database with missing cities (due to no new solar installations) thus avoiding sample selection bias. When including the six counties (Lake, Marin, Mendocino, Napa, Solano and Sonoma) the dataset contains more than 770 observations at city-level over the period 2007-2012. These counties are an important test because they are all served by the same utility, Pacific Gas & Electric (PG&E), and have received a very similar flow of information about climate change, energy options, and the economics of different electricity delivery and pricing schemes.

To determine the solar power capacity installed each year, we used the solar projects realised at city-level. However, the CSI database reports solar projects in terms of number of modules mounted instead of watts installed. To express the number of modules installed into watts, we use the standard formula:

$$\text{System size} = \text{quantity of modules} * \text{PTC rating}$$

where the quantity of modules indicates the number of solar modules installed and PTC rating stands for the rating of Performance Test Conditions, which is a universally recognized standard for assessing real-world solar panel performance. Once the solar system size in watts is computed, the solar capacity installed at city-level is obtained by aggregating solar projects by zip codes belonging to the same city. To compare solar installations across cities, the solar capacity installed per city is expressed as the total installed power capacity over city population.

This study assesses PACE’s effectiveness on new solar installations using a regression discontinuity and difference-in-difference approaches, exploiting the geographical discontinuity of the program. Under the RD design, a geographic or administrative boundary allows the investigator to select units into treated and control areas. Indeed, the unique characteristic of this design is the method by which research units are assigned to program or comparison groups as the units’ placement depend solely on the basis of county border (31). Given that PACE was implemented only in Sonoma County, the county boundary determines whether households are eligible for the PACE financing program, thus allowing us to draw arbitrarily the treated (cities eligible for the program) and control groups (cities not eligible for the program).

There are two basic assumptions that have to be met under this approach. First, the spatial border should introduce a sharp discontinuity in the variable of interest. Second, all other covariates should evolve “smoothly” at the spatial discontinuity (23). In this study the county borders introduce a sharp discontinuity in the program eligibility but not in the other covariates (table S1). As long as the other aspects change smoothly, while the eligibility for PACE program changes discontinuously, the causal effect of the policy on solar installations can be identified.

Parameter estimates are based on the Poisson pseudo-maximum-likelihood estimation. This estimation method is especially well suited for the problem at hand as it corrects for over dispersion and excess zeros, due to cities with zero new solar installations (32, 33). Previous application of this model includes for instance bilateral trade analysis, where often no all countries trade all products with all partners (34-36). A large number of zeros in the dependent variable introduces a non-linearity in the empirical model, which will bias the result of simple linear models. Ignoring the zeros (by for instance taking a log transformation of the data) will instead result in the well-known sample selection bias. The Poisson pseudo-maximum-likelihood estimation enables to deal with these problems by estimating the following model:

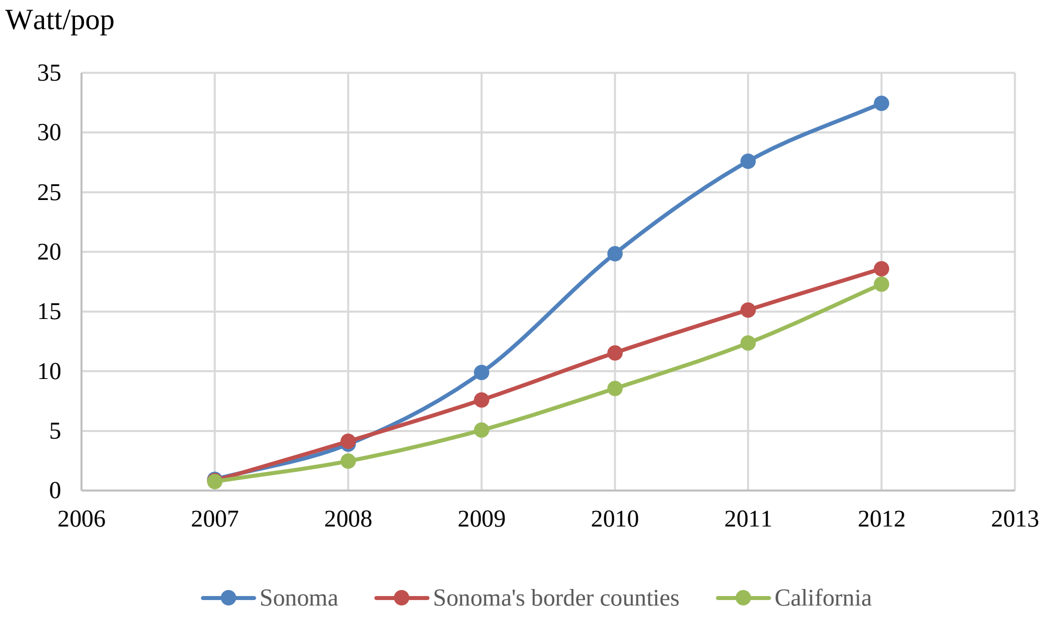
$$y_{ijt} = exp\left\{\alpha_0 + \ \alpha_1 \ PCA_{ijt} + \alpha_2 \ CSI_{jt} + \gamma_1 \ Z_{jt} + \gamma_2 Z_{jt} * year + C_j + T_t + \mathcal{E}_{ijt}\right\}$$

where y_{ijt} is the new solar installations of city i in county j and year t; PCA is the first principle component of ownership rate, home value and median households' income and it is used as indicator for the household wealth (30). The first principal component is a variable summarising most of the information of the underlying variables as it explains most of their variances. In this exercise the first principal component explains about 70% of the variance of the three variables; CSI is the solar incentive in county j at time t, Z_{jt} is the binary policy variable for the presence of a PACE program in county j at time t. We also interact the policy variable with a time trend ($Z_{jt} * year$) to estimate how the treatment effect varies over time. Without the interaction term, γ_1 is the treatment effect; with the interaction term, the treatment effect at a certain point in time is computed as $\gamma_1 + \gamma_2 * year$. The full specification also includes county and year fixed effects (C_j and T_t), to control for unobserved county- and year-specific effects. Finally, $\mathcal{E}_{ijt}$ is an heteroskedastic error term. As shown by Silva and Tenreyro (32), taking the logarithmic transformation of the above regression model and estimating it by linear ordinary least square method will yield biased coefficients; this is because the logarithmic transformation of the dependent variable will change the properties of the error term and the new error term ($\ln\varepsilon_{ijt}$) will be correlated with the regressors. This problem is likely to be more severe the higher is the proportion of zeros in y_{ijt}. This is a non-negligible issue in our dataset as about 40% of the observations of y_{ijt} are zero. To overcome this problem, we employ the Poisson pseudo-maximum-likelihood estimation method, which has gained wide favour in the empirical international trade literature (45). In the table of results, the reported standard errors are clustered at the county level to control for autocorrelation of the error term within counties due to aggregate variables (37).

Results and Discussion

We start by comparing the residential installed PV capacity expressed in watt per capita in California, Sonoma and Sonoma's border counties in 2007 and 2012 (Figures 1 and 2). In 2007, the residential installed PV wattage per capita was similar in Sonoma and Sonoma's border counties being, 0.94 and 0.82, respectively. These values were not the highest registered in California, as the top counties for PV wattage per capita were Santa Cruz (1.83), Glenn (1.58), Yolo (1.47) and Nevada (1.36), while the average for California was 0.84 (Figure 1, Table S2). Since 2009 Sonoma experienced a larger increase in solar installations than its border counties and the whole California. By the end of 2012 the installed PV wattage per person was 32.45 in Sonoma against 18.59 in Sonoma's border counties and 17.29 in California on average (Figure 1, Figure 2, Table S2).

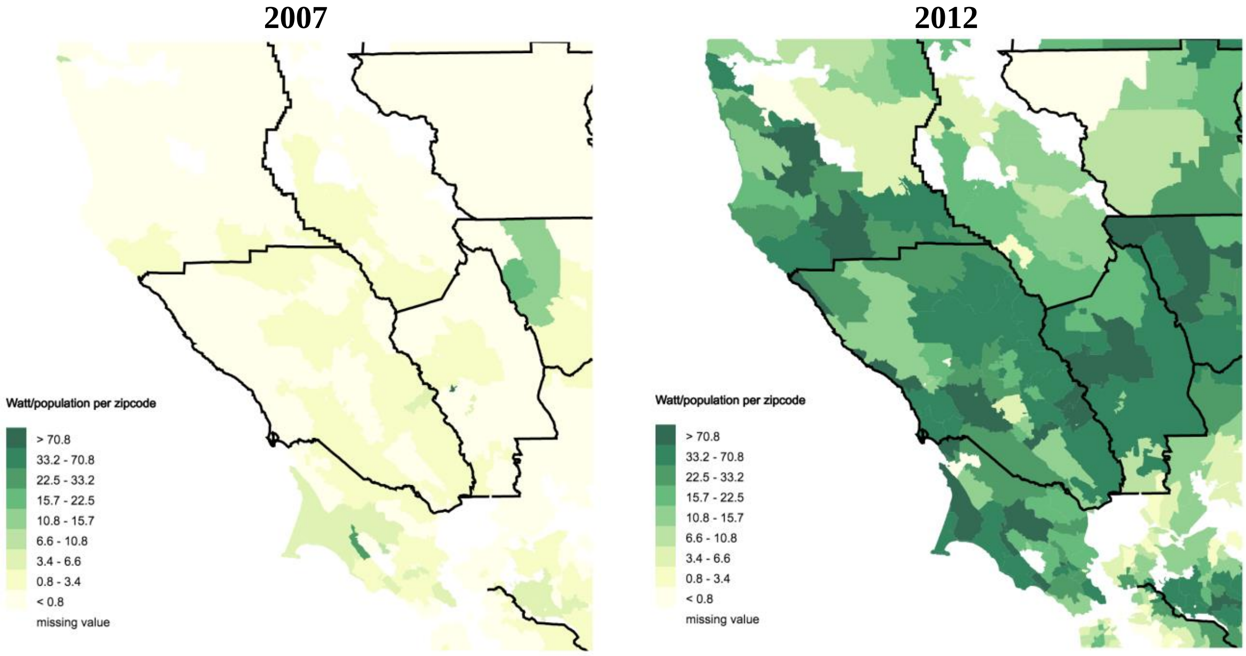
Figure 1 Residential cumulative installed PV wattage per capita in Sonoma, Sonoma border's counties and California (Watt/population)



Source: Authors calculation based on CSI database.

Note: California trend does not include installed solar PV power in Sonoma. Sonoma’s border counties include Lake, Marin, Mendocino, Napa and Solano.

Figure 2 Map of residential installed PV capacity in Sonoma and Sonoma border's counties (zipcode level)



Source: Authors calculation based on CSI database.

We then pass to regression analysis using the sample of municipalities in Sonoma and its five neighboring counties. In addition to the effect of the PACE program over time on new solar installations (computed as new wattage per capita), the regression specification captures the effect of the CSI (California Solar Initiative) incentive – to control for incentives for solar installations besides PACE – and household wealth – captured by the principal component of three variables, namely housing ownership rate, median household income and home value. We also include county and time dummies. We report the results of the basic specification (difference-in-difference analysis) in Table 1. The first two columns show the effect of the PACE program with no interaction with the time trend. The PACE program is positive and significant at more than 1% level. Column 3 reports the results of the specification with the interaction term.

The results show a positive and significant effect of the PACE program on new PV installations. In the first regression specification – without time dummies (Table 1, column 1) – the effect of the PACE program on new PV installations is economically and statistically significant ($p<0.01$). The point estimate indicates that the program more than triple new solar installations in Sonoma compared to neighboring counties. However, the lack of time dummies likely inflates the effect of the PACE as solar installations had been rising over time in Sonoma (and neighboring regions) even before the policy change and might have continued to do so even without the start of the PACE program. The policy variable might in the end just capture part of the secular rise in PV installations unrelated to the policy itself. Adding time dummies (Table 1, column 2) lowers the effect of the PACE program, which however remains positive, economically sizeable and highly significant ($p<0.01$). According to this specification, the PACE program increased new solar installations by 74% ($p<0.01$). Additional regression results (Table 1, column 3 and Figure 3) show that the effect of the policy became stronger over time (from 59% in 2008 to 90% in 2012).

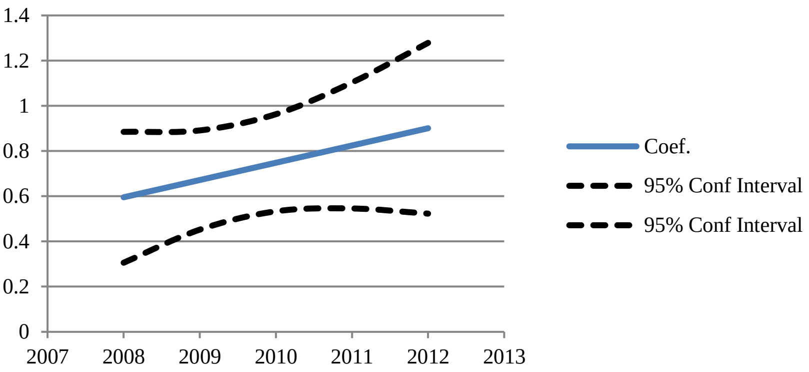
For specifications using the interaction between the PACE program and the time trend, we graph the estimated marginal effect of the PACE program and its 95% confidence interval obtained through the delta method. The marginal effect of the PACE program is positive and significant at 5% level and increases over time (Figure 3).

Table 1. Estimated effects on new solar installations in Sonoma and Sonoma's border counties

Independent variable: new PV wattage per capita			
VARIABLES	1	2	3
PACE program	2.261*** (0.118)	0.741*** (0.107)	0.443* (0.258)
CSI	0.0428 (0.0279)	0.296 (0.411)	0.296 (0.412)
Household wealth	0.666*** (0.205)	0.667*** (0.206)	0.667*** (0.206)
PACE over time			0.0764 (0.0661)
Time dummies	NO	YES	YES
County dummies	YES	YES	YES
Constant	0.191 (0.134)	-1.045 (3.749)	-1.101 (3.723)
Observations	774	774	744
R-squared	0.097	0.149	0.150

Notes: The new PV wattage is computed as the new yearly wattage per capita. Estimates obtained through the Poisson pseudo-maximum-likelihood method. Standard errors are clustered by counties and reported in parentheses. Coefficients of dependent variables, superscripts ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

Figure 3. The marginal effects of the PACE program over time

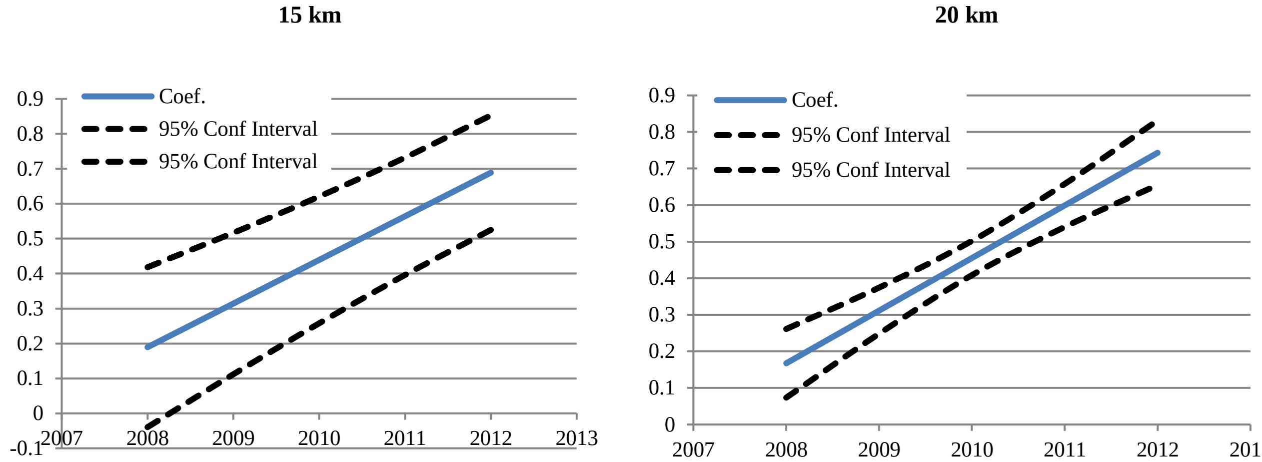


Note: the marginal effects are based on the specification in column 3 of Table 1

Finally, we restrict the sample to those municipalities in Sonoma's bordering countries that are within short distances from Sonoma (15, 20, 30 and 40 km). This provides a stricter test of the effect of the PACE program as bordering counties are likely to share unobserved characteristics common with Sonoma. These additional regressions confirm the previous findings. The marginal effects of the PACE program on new solar installations obtained using the different distance ranges are stable and reveal an increase in solar installations attributable to the PACE program (Figure 4). Using different distance ranges mainly affect the value of the point estimates, with greater coefficients obtained using a larger distance, while the statistical significance remains high (above 99% confidence level) (Table S3, Figure 4). Overall, the set of results suggest that on average the

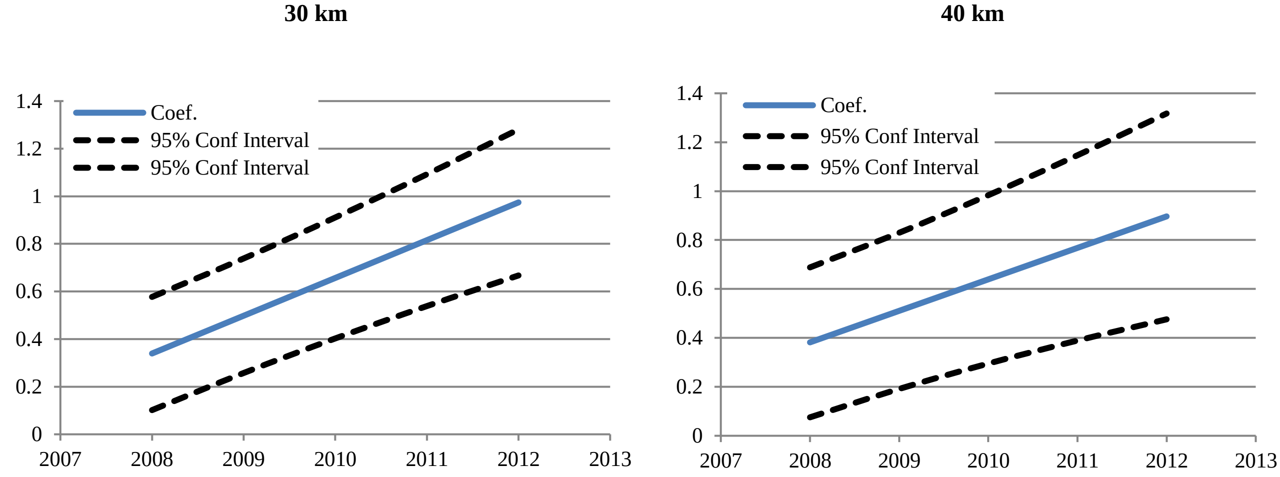
PACE program more than doubled solar installations in Sonoma County compared to its neighboring counties (Tables S3, Figure 4). A robustness check conducted interacting the policy variable with time dummies yields similar results (Table S4). In this specification, the policy variable was interacted with time dummies for year 2008 and the biennium 2009-10 and 2011-12, allowing us to describe more finely the temporal variation of the impact of the PACE program. Overall the results are consistent with those reported in Table S3. In the first year of implementation the PACE program increased new solar installations by 45%; the yearly impact rises to 82% in the 2009-2010 period before slightly decreasing to 76% in the 2011-2012 period. After four years, the impact of the PACE program of new solar installations is still sizeable and statistically significant.

Figure 4. Marginal effects of the PACE program on new solar installations computed for different distance bandwidths



Note: the marginal effects are based on the specification in column 2 of Table S3 based on 15 Km.

Note: the marginal effects are based on the specification in column 2 of Table S3 based on 20 Km.



Note: the marginal effects are based on the specification in column 2 of Table S3 based on 30 Km.

Note: the marginal effects are based on the specification in column 2 of Table S3 based on 40 Km.

The PACE program can also benefit the residential real estate market

Policies to boost renewable energy installations for residential use can also have positive effect on residential market. By lowering energy bills and meeting a rising demand by the public for residential clean energy sources, they can increase homes' value. To explore this issue, we compare the difference in the average house-price growth rate between Sonoma and its neighboring countries before and after the introduction of the PACE program (a difference in difference approach). The time periods selected are 2003-2007 and 2008-2012.

Between 2008 and 2012 house prices dropped precipitously in all counties considered. Compared with the trend in the 2003-2007 period, Sonoma's house-price growth rates decreased much less (-45 percentage points) than in other neighboring countries (-69 percentage points on average) or in the whole California (38) (Table 2). These preliminary findings suggest that solar installations supported Sonoma's residential market and are qualitatively consistent with the results of Dastrup et al. (39) who find that solar panels add 3 to 4% to housing price in the San Diego and Sacramento areas.

Table 2. Median Single-Family Housing Prices (detached homes only)

Year	CA	Lake	Marin	Mendocino	Napa	Solano	Sonoma
2003	$371,522	$205,433	$737,127	$280,871	$461,339	$311,658	$425,320
2004	$451,068	$260,729	$859,287	$337,322	$540,532	$378,507	$505,238
2005	$525,960	$301,097	$976,316	$387,015	$652,959	$459,475	$622,577
2006	$560,641	$311,877	$963,123	$425,067	$679,279	$475,755	$621,709
2007	$554,450	$277,824	$1,028,988	$438,099	$657,528	$424,803	$575,177
2008	$360,790	$209,603	$961,129	$348,766	$460,819	$287,629	$406,982
2009	$276,700	$157,053	$772,914	$261,541	$363,484	$205,017	$348,780
2010	$305,631	$131,773	$805,172	$256,730	$359,304	$211,327	$362,137
2011	$287,523	$109,705	$754,929	$216,355	$339,287	$191,453	$332,557
2012	$321,389	$123,293	$780,121	$225,866	$371,717	$201,843	$356,154
2013	$407,528	$150,558	$928,317	$270,928	$484,990	$271,455	$438,382
2014	$448,655	$172,775	$1,026,182	$298,828	$568,048	$318,762	$490,022
(April) 2015	$451,485	$193,155	$1,074,785	$311,023	$531,068	$336,760	$508,880
2008-2012 %	-0.109	-0.412	-0.188	-0.352	-0.193	-0.298	-0.125
2003-2007 %	0.492	0.352	0.396	0.560	0.425	0.363	0.352
2008-2015 %	0.251	-0.078	0.118	-0.108	0.152	0.171	0.250
Difference 2008-12 - 2003-07	-0.601	-0.764	-0.584	-0.912	-0.619	-0.661	-0.477

Source: Authors calculations based on California Association of Realtors (2015)

Conclusions

Parties to the landmark 2015 Paris Agreement on climate change committed to limit global average temperature increases to ‘well below’ 2 degrees above pre-industrial levels, and to making efforts to remain below 1.5 degrees (COP21 decision 1/CP.20). As recognised by the text of the Agreement, achieving such ambitious targets will require substantial investment in renewable technologies. Solar energy is one of the most promising renewable energy sources because of its widespread availability and technology advances have drastically reduced the costs of PV panels. Although solar energy is maturing rapidly in the US, its expansion still depends on the government support programs (40). Rigorous policy evaluation of such programs is necessary to assess their effectiveness and costs and avoid wasting tax-payer money.

In this paper, we exploit a natural experiment in northern California to assess the effectiveness of the PACE program to promote solar PV investment. Our analysis demonstrates that the PACE program more than doubled solar installations in Sonoma County compared to its neighboring counties, where the program was not implemented. In particular, in the first year of implementation solar installations increased by 45%, while the yearly impact raises to 82% in the 2009-2010 period, before slightly decreasing to 76% in the 2011-2012. The results are robust to using narrow distance ranges (from 15 to 40 km), with smaller effects obtained using shorter distance, which however remain statistically and economically significant. Overall, this analysis support the hypothesis that the PACE program has been highly effective in boosting residential PV installations in northern California.

This study is an example of a rigorous policy evaluation based on an experimental framework. This approach is still quite rare in the energy and environment policy field compared to other areas of social science probably because of scientists' lack of familiarity with this technique and specific issues linked to energy policy evaluations (such as missing baselines, long time lag between intervention and response, high outcome variability, lack of sufficiently detailed geographical data) (15). From a methodological point of view, this paper advances our understanding about how to assess energy and environmental policies, by providing evidence on what types of interventions work and under what conditions. We believe the methodology used in this analysis is broadly applicable to other programs/policies and should become part of the toolbox of empirical studies in the energy and environment field to lead to better policy evaluation (41).

From a policy perspective, this study demonstrates that policies lowering financing barriers could increase the take-up of low-carbon technologies and will potentially enable renewable deployment on a large scale. The PACE case study suggests the importance and the need of financing programs which address the initial financial constraints risks and cash flow barriers of solar technologies to increase their take-up.

These results are encouraging, but should be interpreted with some caution, as they are based on six counties in northern California. Additional states, such as Colorado, Florida, New York, Missouri and Connecticut have also implemented PACE schemes. A more comprehensive assessment of the PACE program should be conducted, also considering the experience of these states. The results of this study could be specific to California if for instance "green communities" like California have more stringent environment regulations or are simply more eager to adopt renewable energy technologies than other states. Moreover, since several states have started to implement the PACE program in the commercial sector, future work should explore the effect the PACE program beyond the residential sector.

Further effort should also be devoted to developing a better understanding of the interactions between the PACE program and the real estate market. This paper has explored this question by investigating the difference in the average house-price growth rate between Sonoma and its neighboring countries before and after the introduction of the PACE program. The preliminary findings suggest that solar installations supported the residential market. However, no causal interpretation can be attached to these findings. More in depth studies, following Dastrup et al. (39), are needed to shed light on the effect of renewable energy and the real estate market.

Moreover, a comparison of the PACE program with alternative policy options to promote solar PV, is needed to advance the understanding of RES support schemes and policy evaluations. This is another direction where our efforts will be devoted next.

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Supplementary Materials

Supplementary text

Table S1 – S4

Data and materials availability:

The CSI database is available at https://www.californiasolarstatistics.ca.gov/

Data used for the data visualization and controls used in the econometric model are available at https://www.census.gov/geo/maps-data/data/gazetteer.html

The codes for data visualization maps are available at https://github.com/micheleorsi/datavisualization/tree/master/installation-watt