Assessing the PACE of California residential solar deployment

Impacts of Property Assessed Clean Energy programs on residential solar photovoltaic deployment in California, 2010-2015

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March 2018

This work was supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy – Building Technologies Office under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

Assessing the PACE of California residential solar deployment: Impacts of Property Assessed Clean Energy programs on residential solar photovoltaic deployment in California, 2010-2015

Prepared for the
Office of Energy Efficiency and Renewable Energy – Building Technologies Office
U.S. Department of Energy

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March 2018

The work described in this study was funded by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy – Building Technologies Office
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The authors thank David Lee and Steve Dunn, U.S. Department of Energy (DOE), for their support of this work and the following reviewers: Galen Barbose (Berkeley Lab), Colin Bishopp (Renew Financial), Mark Bolinger (Berkeley Lab), Mark Colby (Ygrene), Jason Coughlin (National Renewable Energy Laboratory), Steve Dunn (DOE), Kyle Fricker (DOE), Greg Frost (Renovate America), Jack Hoskins (DOE), Jonathan Kevles (Renew Financial), Commissioner Andrew McAllister (California Energy Commission), Garrett Nilsen (DOE), Lynn Rasic (Renovate America), Anna Spurlock (Berkeley Lab), Justin Strachan (Ygrene), Lisa Schwartz (Berkeley Lab), and Ben Taube (Ygrene). For assistance with data provision, the authors thank Galen Barbose (Berkeley Lab), Jonathan Bower (Renew Financial), Craig Carlock (Sonoma County), Naim Darghouth (Berkeley Lab), Greg Frost (Renovate America), Jonathan Kevles (Renew Financial), Mike Lemyre (Ygrene), Nikki McQuaid (Ygrene), Colgan Powell (Sonoma County), Chani Vines (Renovate America), and Eric Waidmann (Placer County).

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Executive Summary

This report presents the results of our study on the impacts of residential Property Assessed Clean Energy (R-PACE) programs on deployment of residential solar photovoltaic (PV) systems in California. While previous studies demonstrated that early, regional R-PACE programs increased PV deployment, this new analysis is the first to demonstrate these impacts from the large, statewide R-PACE programs dominating the market today that use private capital to fund the upfront costs of these systems.

We estimate the impacts using econometric techniques on two samples:

- One sample includes large cities only, for which we can include annual demographic and economic data as control variables.
- The other sample includes all California cities but lacks these annual data.

Analysis of both samples controls for several factors other than R-PACE that would be expected to drive PV deployment. All analyses also include fixed effects that control for latent location-invariant and time-invariant factors that would impact PV deployment.

We infer that on average, cities with R-PACE programs were associated with greater PV deployment in our study period (2010-2015). In the large cities sample, PV deployment in the presence of these programs was higher by 1.1 watts per owner-occupied household per month, or 12%. Across all cities, PV deployment in the presence of R-PACE was higher by 0.6 watts per owner-occupied household per month, or 7%. The large cities results are statistically significant at conventional levels; the all-cities results are not.

R-PACE program effects were strongest in 2010-2011 in both samples, but also are positive and statistically significant or nearly so in 2013 and 2014 (in both samples) and in 2015 (in the large cities sample). Our results in the early years mirror those of prior research. Our study is the first to estimate impacts in the later years of our sample.

Our estimates imply that the majority of PV deployment financed by R-PACE programs would likely not have occurred in the absence of the programs. These results suggest that R-PACE programs have increased PV deployment in California even in relatively recent years, as R-PACE programs have grown in market share and as alternate approaches for financing solar PV have developed.

1. Introduction

In this report we estimate the impact of California's residential Property Assessed Clean Energy (R-PACE) programs on the deployment of residential solar photovoltaic (PV) systems in the state. R-PACE is a financing mechanism that uses a voluntary property tax assessment, paid off over time, to facilitate energy improvements and, in some jurisdictions, water and other resilience measures.

Our approach is similar to two previous analyses of early R-PACE programs, by Kirkpatrick and Bennear (2014) and Ameli et al. (2017). However, the prior papers analyzed only a handful of local and regional R-PACE programs that existed from 2007 through 2012. Our study is statewide in scope and covers the years 2010 through 2015. During these years R-PACE programs grew dramatically, evolving into a statewide presence with the backing of billions of dollars in private capital. Both the scale of deployment and the broader financing market for solar PV also changed dramatically in this time. Our analysis offers evidence that R-PACE has been a driver for residential solar PV deployment – not only in the very early years of the program, but also in the years 2013-2015.

1.1 Significance of California R-PACE programs[1]

California's R-PACE programs merit study because they have in many respects been uniquely successful among energy efficiency and solar PV financing programs. In 2014, R-PACE programs in California collectively extended nearly half of all programmatic[2] capital issued to residential customers nationwide (Deason et al. 2016).[3] Moreover, R-PACE is a relatively new option and volumes have risen quickly. Capital extended by R-PACE programs more than doubled each year from 2012 through 2015 as the programs expanded throughout the state.[4] California's R-PACE programs therefore are a promising device for achieving scale in the difficult-to-access market for residential energy retrofits. R-PACE volumes are relatively small compared to the dominant, non-programmatic methods of financing residential PV systems in California: third party ownership models and loans from solar providers. (See section 4.1 for more on these financing approaches.)

Beyond their scale, R-PACE programs are distinctive in several respects from other financing programs:

[1] For up-to-date details on R-PACE programs and attendant issues, see Bellis et al. (2017).
[2] By programmatic capital, we mean capital extended through a structure featuring significant involvement of government or utility actors. We consider R-PACE programs to be programmatic since both state legislation and local government action are required to establish and join programs, and since public agencies (counties or joint powers authorities) co-administer the programs even where private administrators and private capital are employed.
[3] In that year, R-PACE programs extended $248 million in capital for energy efficiency. The total amount of capital extended to residential customers nationwide by energy efficiency financing programs covered in the report was $537 million.
[4] Based on data gathered by PACENation at http://pacenation.us/pace-market-data/, accessed 2/29/18. Volumes rose again in 2016, though they were not double 2015 volumes; 2017 data were not yet final, though volumes through November suggest that 2017 volumes will be below 2015 and 2016.

- Through April 1, 2018, California laws and regulations for R-PACE programs allowed them to extend financing based in large part on attributes of homes rather than borrowers.[5] Specifically, underwriting for R-PACE was based on a property's pre-PACE loan-to-value ratios, the property owner's bankruptcy, mortgage, and property tax repayment history, and the presence or absence of involuntary liens on the property rather than the owner's credit score and debt-to-income ratio. This potentially allows R-PACE programs to extend capital to homes that traditional underwriting may not serve or that may only come with unfavorable terms.
- R-PACE financing for projects is repaid via property tax bills, securing the repayment obligation to the property and thereby lowering interest rates and enabling repayment terms that can be as long as the economic life of the measures financed – the combination of which results in lower monthly payments than some, but not all, unsecured lending options.
- R-PACE financing is tied to the property, not the homeowner, and may be transferable to a new owner upon sale of the property. In practice, R-PACE liens are more often than not paid off in full during a home's sale. For example, among HERO program homes that sold between 2012 and 2015, 45% of assessments transferred with the property sale and 55% were paid off at the time of sale (Goodman and Zhu 2016). The transferability of the assessments addresses in principle a common issue in residential energy efficiency retrofits and solar installations, where current owners may not finance even cash flow-positive investments because the benefits may go to future owners.[6]
- Most California R-PACE programs are capitalized by private funds raised by private companies, who co-administer the programs with local governments or joint powers authorities. Generally, these programs receive no direct investment of public funds and are not otherwise subsidized, either through public funds or funds collected from utility customers for energy efficiency (and solar PV) programs, above and beyond programs available to those participating or not participating in R-PACE programs. Private R-PACE administrators have been successful at selling in secondary capital markets those securities backed by R-PACE assessment payments in order to replenish program capital, allowing the programs to scale rapidly and lowering the cost of capital extended to PACE participants.[7]

[5] The HERO and CaliforniaFIRST programs (and possibly others) began to consider borrower income in their underwriting in 2017, and a new California law (Assembly Bill 1284, passed in 2017) requires all R-PACE programs to conduct income-based underwriting as of April 2018. However, none of the R-PACE programs considered income in their underwriting processes in the years covered by our study.

[6] Specifically, this would arise where current owners do not retain the property long enough for the investments to pay back via lower energy costs and where the lack of market information on one home's energy usage relative to another home's usage results in energy improvements not being sufficiently capitalized into the home's sale price to make up the difference. The extent of insufficient capitalization of energy efficiency investments in housing markets is unclear. If the value of energy improvements is fully or partially hidden from the purchaser, we might expect some undercapitalization. Labels and certifications may overcome this issue. See Wells et al. (2017). However, most households in California do not bear any label or certification.

[7] See http://pacenation.us/pace-market-data for volumes of R-PACE securitization over time. See Kramer et al. (2015) for discussion of secondary market transactions for energy efficiency financing programs.

- In part because of the factors considered in underwriting, R-PACE approvals are fast, and many potential customers were pre-approved during the study period.[8] In part because many projects financed by R-PACE are emergency replacements – for example, replacement of a broken air conditioning or water heating unit – quick approval is very important for encouraging customer participation in energy efficiency programs (Zimring et al. 2011).[9]
- Because R-PACE financing is secured by properties, and because property tax assessments have senior status to mortgages in foreclosure proceedings,[10] R-PACE programs have generated concerns among mortgage market and consumer protection stakeholders. Concerns around mortgage market impacts of R-PACE led the Federal Housing Finance Agency (FHFA) to write a statement in 2010 directing Fannie Mae and Freddie Mac not to purchase R-PACE-encumbered mortgages for securitization.[11] Though California R-PACE programs were eventually able to move forward, this statement may have slowed their momentum in California and elsewhere. Concerns around R-PACE and consumer protections have motivated both Federal and California legislative proposals. California has passed three bills – one in 2016 and two in 2017 – creating a regulatory framework for the industry and revamping R-PACE consumer protections.[12] The provisions of these bills may protect consumers from making an ill-advised financial decision and from irresponsible contractors.

1.2 Importance of measuring R-PACE impacts on solar PV deployment

During our study period (2010 to 2015), California R-PACE programs funded $1.8 billion[13] in clean energy improvements. Some 37% of this investment, or $670 million, went towards renewable energy systems – nearly all of which is rooftop PV systems.[14] This study addresses solar PV deployment only.

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[8] R-PACE providers or their agents can gather the data used for underwriting a household and sizing the assessment amount for which the homeowners may qualify before visiting the household to discuss potential projects. (As of January 1, 2018, SB 242 prohibits R-PACE providers from informing contractors of a homeowner's maximum potential assessment amount.)

[9] Some other, conventional financing options at contractors' disposal also allow for quick financing approval. Repayment terms on these unsecured loans rarely extend as long as the economic life of the items financed, and interest rates are often higher as well.

[10] The senior status of the R-PACE lien only applies to the amounts in arrears at the time of a foreclosure sale. The entire balance of the R-PACE lien is not paid off. Instead, the remaining balance and its associated repayment obligations pass on to the next owner. R-PACE is not unique in this regard; senior status position applies to all special assessment districts in California, and across the country.

[11] See https://www.fhfa.gov/Media/PublicAffairs/Pages/FHFA-Statement-on-Certain-Energy-Retrofit-Loan-Programs.aspx. For discussion of the ramifications of this statement, see https://emp.lbl.gov/publications/pace-and-federal-housing-finance.

[12] Assembly Bill 2693 can be found at https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201520160AB2693. Assembly Bill 1284 can be found at https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180AB1284. Senate Bill 242 can be found at https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180SB242.

[13] http://pacenation.us/pace-market-data/, accessed 2/1/18.

[14] The majority of the investment — about $1 billion — went towards energy efficiency measures. About $70 million went towards water efficiency measures.

We received data on the number of PV systems and total installed capacity financed by R-PACE from some PACE providers, and estimated the balance based on our expert understanding of market share by provider as of the end of 2015. We estimate that PACE programs financed about 131 MW of solar PV during the study window.

However, this is an estimate of the amount of solar PV that R-PACE programs have *financed* – which may not be the same as the amount that R-PACE programs have *driven*.[15] If some R-PACE participants would have installed solar PV even absent R-PACE using alternate financing methods, then R-PACE availability did not drive those installations, lowering the true impact of R-PACE. Conversely, if peer effects[16] are such that a single household PV installation raises the probability for other households to install PV (however financed), then a single R-PACE-financed installation may drive other installations, raising the impact of R-PACE. Research suggests that peer effects are important for PV deployment, though relatively small in magnitude (see, e.g., Bollinger and Gillingham 2012; Graziano and Gillingham 2015).

The vast majority of R-PACE financing dollars go toward energy efficiency and renewable energy measures.[17] Therefore, policymakers are interested in the role of these programs in encouraging deployment of these energy resources above and beyond what would have occurred absent R-PACE programs. Accordingly, the balance of this report estimates the amount of PV that PACE programs may have driven.

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[15] In program evaluation parlance, this is an estimate of gross deployment, not net deployment.

[16] Peer effects in this case refer to the impact of one household's PV adoption on the tendency of other households to adopt PV themselves.

[17] R-PACE programs also finance water efficiency measures, but these play a small role. Some R-PACE programs offer financing for seismic strengthening and (in Florida) storm hardening measures. But in California little R-PACE financing has been extended for these measures.

2. Recent history of R-PACE programs and residential PV deployment in California

2.1 Diffusion of California R-PACE programs

Figure 1 illustrates the growth over time in the share of California households in incorporated cities with an R-PACE program. R-PACE was available in relatively few cities in the early years of our dataset; many more cities had joined R-PACE programs by the end of 2014.

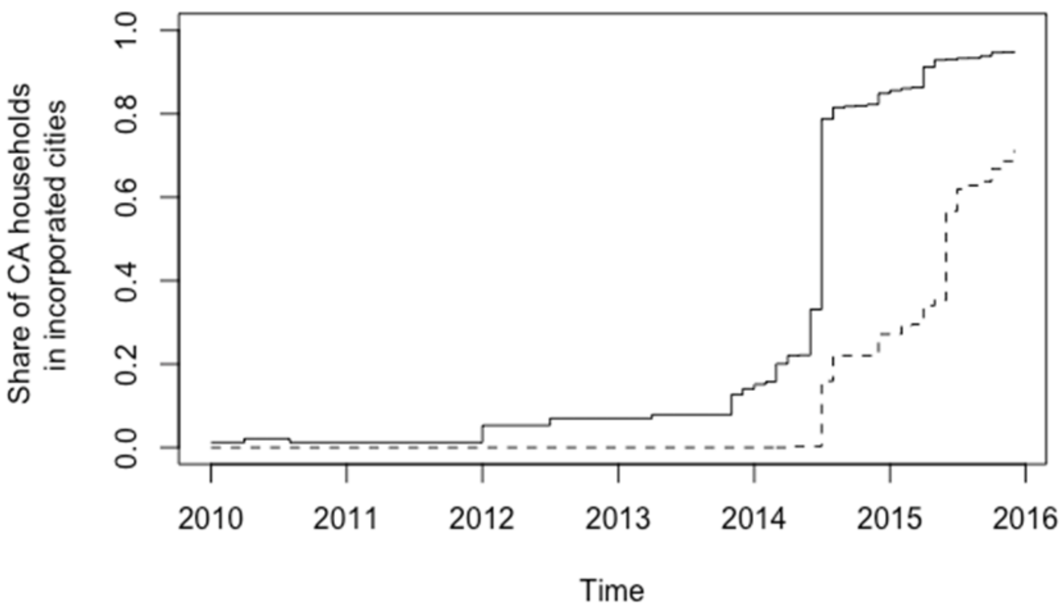

Figure 1. Growth in the share of California households in incorporated cities[18] with an R-PACE program, 2010-2015. Solid line indicates share of households served by at least one program; dashed line indicates share of households served by multiple programs.

In the beginning of 2010, the first year of our study, three R-PACE programs were operating in California: the Palm Desert Energy Independence Program, the Sonoma County Energy Independence Program (SCEIP), and the Yucaipa Energy Independence Program. However, the Palm Desert and Yucaipa programs no longer exist today; they were closed or rolled into privately-administered programs that are still in operation as those programs expanded. Because of these atypical program

[18] The dataset that we assembled for analysis in this report includes incorporated cities only. R-PACE programs are also available in many unincorporated county areas. However, we found it impossible to generate other control variables used in the study reliably for unincorporated county areas, which are often geographically expansive and therefore tend to cross utility service territory boundaries. Moreover, while demographic information is available at the county level, it is not available for unincorporated county areas specifically. A graph of R-PACE expansion that includes unincorporated county areas would look very similar to this one.

developments, we have eliminated the cities these two programs served (Palm Desert and Yucaipa) from our analysis.

SCEIP still exists today and has operated continually from the beginning of our study window.[19] From its inception, SCEIP served all nine incorporated cities in Sonoma County as well as unincorporated County areas.

Placer County opened its mPOWER program in March 2010 in the County's six incorporated cities plus unincorporated areas. However, the County paused the program on July 10, 2010, in response to the FHFA statement. The program resumed operations in March 2013, later adding a handful of cities and unincorporated areas in neighboring counties.

Additional programs began in subsequent years. The Western Riverside Council of Governments (WRCOG, a joint powers authority whose membership originally consisted of cities in western Riverside county), in partnership with Renovate America (a private company that administers and sources capital for R-PACE programs), launched the WRCOG HERO Program at the very end of 2011 in 17 cities in western Riverside County. The SANBAG HERO Program launched in late 2013 in neighboring San Bernardino County in partnership with the San Bernardino Association of Governments (another joint powers authority). The HERO programs diffused across the state in subsequent years.

In partnership with the Golden State Financing Authority joint powers authority, Ygrene Energy Fund (a private company that administers and sources capital for R-PACE programs) launched an R-PACE program in the City of Sacramento in mid-2012. Ygrene expanded to eastern Riverside county cities in late 2013, to additional cities in Sacramento County and neighboring counties in 2014, then across the state in subsequent years.

The California FIRST program, administered by the California Statewide Communities Development Authority (joint powers authority) and Renew Financial (private R-PACE administrator), had entered into agreements with many California municipalities in 2010 prior to the FHFA statement. When the program launched in mid-2014, it did so in a large number of municipalities simultaneously – by far the largest expansion of R-PACE availability in any single month. California FIRST continued to diffuse statewide in subsequent years.

Some of the municipalities in which California FIRST launched had previously joined other R-PACE programs. As R-PACE programs have expanded statewide, so has the share of municipalities and households served by multiple providers (see Figure 1).

Several other R-PACE providers entered the market in the last two years, but as they did not offer programs in our study period, we do not discuss them here.

[19] Except for a one-week pause in July 2010 in response to the FHFA statement described above.

2.2 California residential PV deployment, 2010-2015

As Figure 2 shows, residential PV deployment rates have grown rapidly in the years covered by our study. Policy supports for residential PV (i.e., incentives from utilities and at the federal and state levels) and the sharply declining cost of PV installations are major drivers of this growth (Barbose and Darghouth, 2017). Innovations in PV financing have also played a role (Bolinger and Holt, 2015; Hobbs et al., 2013), which we discuss further in section 4.1.

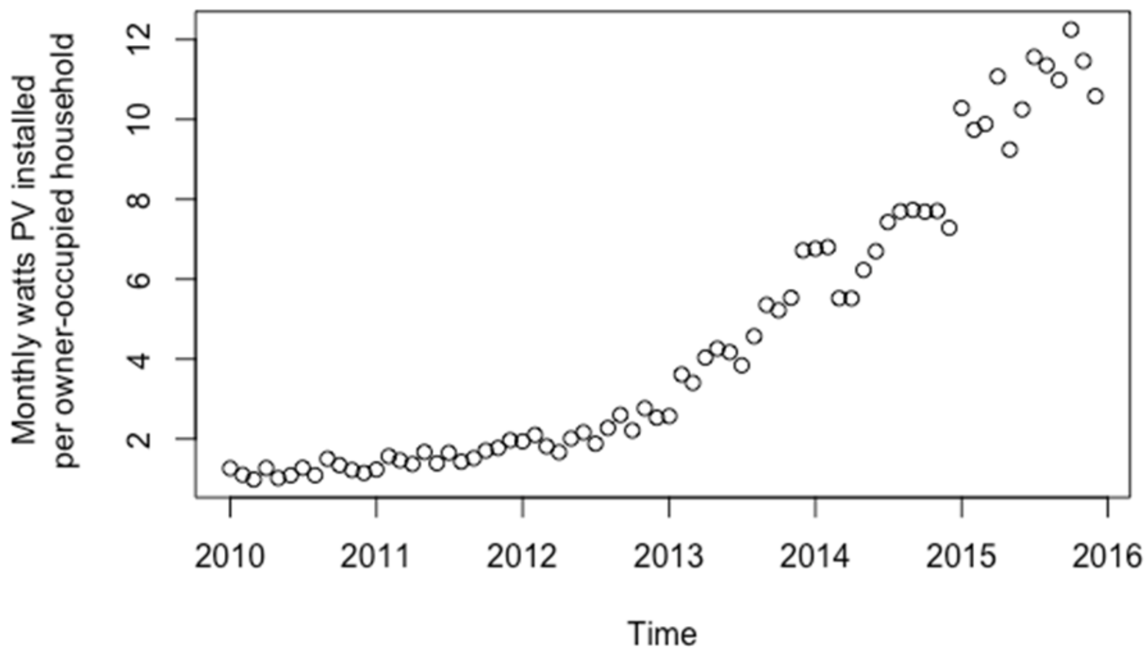

Figure 2. Growth in monthly residential solar installations (watts per owner-occupied household) in California, 2010-2015. This figure includes all California incorporated cities served by a utility for which we have solar PV installation data, as described in section 2.2.

3. Econometric estimation of the impact of R-PACE on residential PV deployment

This section describes the results of our statistical estimates of the relationship between municipal R-PACE participation and PV deployment. The Appendix provides methodological details and full regression results, including statistical significance testing.

3.1 Estimation

We infer the impact of R-PACE on PV installations by exploiting the variation in the timing of municipal R-PACE adoption (Figure 1). We run regression analyses to estimate the impact of the presence of R-PACE in a city on that city's PV deployment, measured in watts of PV capacity per owner-occupied household. Our fixed effects regression approaches allow us to isolate the impact of R-PACE from other unobserved time-invariant differences among cities and from changes in any factors affecting PV installation rates in the state as a whole over time (Figure 2).[20] We also control for several factors that would be expected to drive PV deployment that were changing during the study period in ways that were not parallel across all cities. These factors include electricity prices, utility-level incentives for PV, and, where available, annual changes in city-level demographic data (income, home values, and education levels). We discuss the variables we constructed in more detail in section 3.2.

If other time-varying factors that influence PV deployment affected cities with R-PACE programs differently than other cities during the study period, our analysis does not control for them, and we would be attributing some of the impact of these factors to the presence of R-PACE.[21] We cannot rule these scenarios out, so we cannot be certain that we are estimating a causal effect of R-PACE on PV deployment. However, we feel it is unlikely that any confounding effects are large.[22]

The Appendix provides a detailed description of our econometric estimation methods.

3.2 Data

Berkeley Lab maintains a national dataset of more than 1.1 million PV installations in the United States though 2016 (Barbose and Darghouth, 2017). We use a subset of that dataset specific to California

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[20] As an example, our time fixed effects would control for any impact of renewable energy certificate prices that vary over time – though these prices are probably not a substantial driver for PV adoption.

[21] For example, if cities tend to establish other policies or measures that support PV at the same time that cities join an R-PACE program, we would be erroneously attributing the impact of those measures to R-PACE. Or, R-PACE adoption could follow a surge (for whatever reason) in local interest in PV, such that cities that adopt R-PACE also experienced a correlated time-varying increase in demand for PV. Such an increase in demand must happen concurrently with R-PACE adoption to be problematic for our model. By including city-level fixed effects in our model, we control for any time-*invariant* differences among cities in their demand for PV.

[22] Most cities do not design their own R-PACE programs, but join existing programs, generally after solicitation by an R-PACE provider. As such, R-PACE adoption is not solely driven by local demand but also by external action. Moreover, most policies and programs affecting PV deployment are not established at a local level but are common across utility territories or the state in general.

residential PV, which alone contains over 400,000 PV installations for the period 2010-2015. Our data cover all PV installations in the territories of four investor-owned utilities[23] and four municipal utilities.[24] The dataset contains detailed information on installations including system size, installation date, costs, and location. The dataset also notes the rebate[25] each system received, if any, which we use to construct our variable on incentives discussed in section 3.2 of this report. From this dataset, we calculate the total PV capacity installed in each California city in each month. We then divide this capacity by the total number of owner-occupied households[26] in each city, taken from the American Community Survey (ACS), to arrive at the dependent variable used in our econometric models.

We gathered municipal R-PACE participation dates directly from program administrators. These dates represent the day on which each R-PACE program was first available in each municipality. If this date is in the first half of a month, we treat that program as available in that month; if the date is in the second half of the month, we treat the program as being first available the following month. In any month where at least one R-PACE program is available according to this method, we code R-PACE as present in that municipality-month. We also test the impact of the availability of multiple R-PACE programs in the same municipality-month, using the same definition of availability.

To create our electricity price variable, we divided annual utility revenues by utility residential retail sales for the utility serving each municipality using data collected by the U.S. Energy Information Administration. Where a municipality was served by more than one utility, we weighted these prices by the respective share of the municipality's area served by each. We did not have revenue and sales data for a handful of small utilities, and dropped municipalities served wholly or in part by utilities with missing data. The resulting variable does not match the actual price faced by households in each month in two respects. First, California utilities employ tiered electricity rates[27] depending on household usage, so different customers of the same utility face different prices depending on their level of usage relative to climatically-defined baselines. Second, we used only annual data, which do not reflect seasonal changes in electricity rates nor any mid-year rate changes. Still, this blunt variable has a clear impact in the model.

Solar PV incentives in California were designed to decline over time in a step function as installed PV capacity met pre-existing thresholds. However, our data on system incentives over time did not exhibit a clean step function. Incentives were granted based on the date the system was submitted for

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[23] These include three large California utilities – Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E) – as well as Pacific Power.

[24] These include the City of Palo Alto Utilities, the Imperial Irrigation District, the Los Angeles Department of Water and Power, and the Sacramento Municipal Utility District.

[25] For customers of PG&E, SCE, and SDG&E, the incentives were paid by the California Solar Incentive program based on expected system performance. Each utility's available incentives declined over time depending on the volume of installations in that utility's service territory. For other utilities in the dataset, incentives were set by the utilities themselves.

[26] R-PACE is only available to owner-occupied residential buildings with three or fewer units.

[27] Inclining block rate structures for California investor-owned utilities charge a higher rate for each incremental block of electricity consumption.

incentive processing. This date was often months, and in some cases years, prior to actual system installation. Therefore, no single incentive amount describes the typical incentive received on any given date. To define our incentive variable – intended to approximate the available incentive in a municipality in any given month – we fit a sigmoid curve to the actual incentives received over time by a given utility for the solar projects in our dataset. This variable also is somewhat blunt, but has a clear impact in the model.

Where possible, we also include annual city-level demographic data from the ACS: median home value, mean household income, and percent of the population with at least a bachelor's degree. The annual ACS dataset, however, does not contain data for small cities – generally those with population under 65,000 – and coverage changes somewhat year-to-year as city populations change. We therefore ran our analyses on two samples: first, larger cities only, with annual demographic data included; second, all California cities regardless of size, without annual demographic data. We discuss results from both samples below and in the Appendix.

3.3 Results

Here we summarize the results of our analysis, focusing on estimates of R-PACE program impact on PV deployment. For full regression results and discussion, see the Appendix.

3.3.1 Average impact of R-PACE on PV deployment, 2010-2015

In our sample that includes California cities with population of 65,000 or more, we estimate that R-PACE programs (where available) were associated with an increase in PV deployment of about 1.1 watts per owner-occupied household per month on average across all years of our dataset. In percentage terms, this estimate corresponds to a 12% increase in PV deployment in areas where R-PACE was available, due to the presence of R-PACE. We estimate that, each month, one additional home out of every 5,600 homes with access to an R-PACE program installed a system. This sums to 12,000 systems in large cities from 2010 to 2015. In our linear regression model, which allows for statistical significance testing (see the Appendix for more details), the impact of R-PACE in the large cities dataset is statistically significant at the 95% confidence level.

In our sample that includes all California cities, we estimate a smaller average impact of R-PACE: 0.6 watts per owner-occupied household per month. This result is not statistically significantly different from zero at conventional levels of confidence. The statistical power[28] of models run on this sample is limited because we do not have annual demographic data for small California cities. In percentage terms, this estimate corresponds to a 7% increase in PV deployment in areas where R-PACE was available, due to the presence of R-PACE. Each month in this sample, an additional one out of every 9,900 homes with access to an R-PACE program installed a system. This sums to 9,500 systems from 2010 to 2015.

[28] Statistical power is the likelihood that a statistical model will detect a statistically significant effect, assuming that effect exists.

Table 1 summarizes these results.

Table 1. Estimated R-PACE impacts averaged over entire samples: 2010-2015

Sample	Impact of R-PACE where present (watts per owner-occupied household driven by R-PACE)	Impact of R-PACE where present (% of capacity driven by R-PACE)	Estimate of total systems installed due to R-PACE
Large cities with annual demographic data	1.1	12%	12,000
All cities, no annual demographic data	0.6	7%	9,500

Given the fact that multiple R-PACE programs are now available in many cities, we also ran models that included a variable for the existence of multiple R-PACE programs. In theory, additional R-PACE programs could encourage PV deployment by either engaging customers that the first R-PACE program failed to reach or by driving down the cost of R-PACE financing due to competitive pressures. The point estimates for multi-program impact are promising: the effect of at least one additional PACE program is positive and about 40% as large as the effect of a single program. However, the confidence interval on the multiple-program variable is very large and the result is not nearly statistically significant, so we cannot be at all certain of the actual impact.

The increase in PV deployment due to R-PACE may be the result of increases in both the number of installations and the installation of larger systems. When we run our model on the large cities sample, but with number of installations per owner-occupied household as the dependent variable, we get a positive R-PACE impact on number of installations that is nearly statistically significant at conventional levels and nearly as large as the impact on installed watts detailed above. When we run this model on average installation size, we get a positive point estimate, but this point estimate is smaller and not nearly statistically significant. However, the average R-PACE-financed PV installation in our study window (from data provided by the R-PACE programs) was 5.96 kW, while the average PV installation in our full California dataset in this period was 5.53 kW. So R-PACE-financed systems are larger on average than other systems. R-PACE programs would not be expected to increase the size of systems financed by other means, so the regression results for R-PACE impacts on system size are sensible.

3.3.2 Annual impacts of R-PACE on PV deployment, 2010-2015

When we estimate the impact of R-PACE on PV deployment separately in each calendar year in our dataset, we see a similar pattern in both datasets (cities with population >65,000 and all cities). Figure 3 and Figure 4 show this pattern.

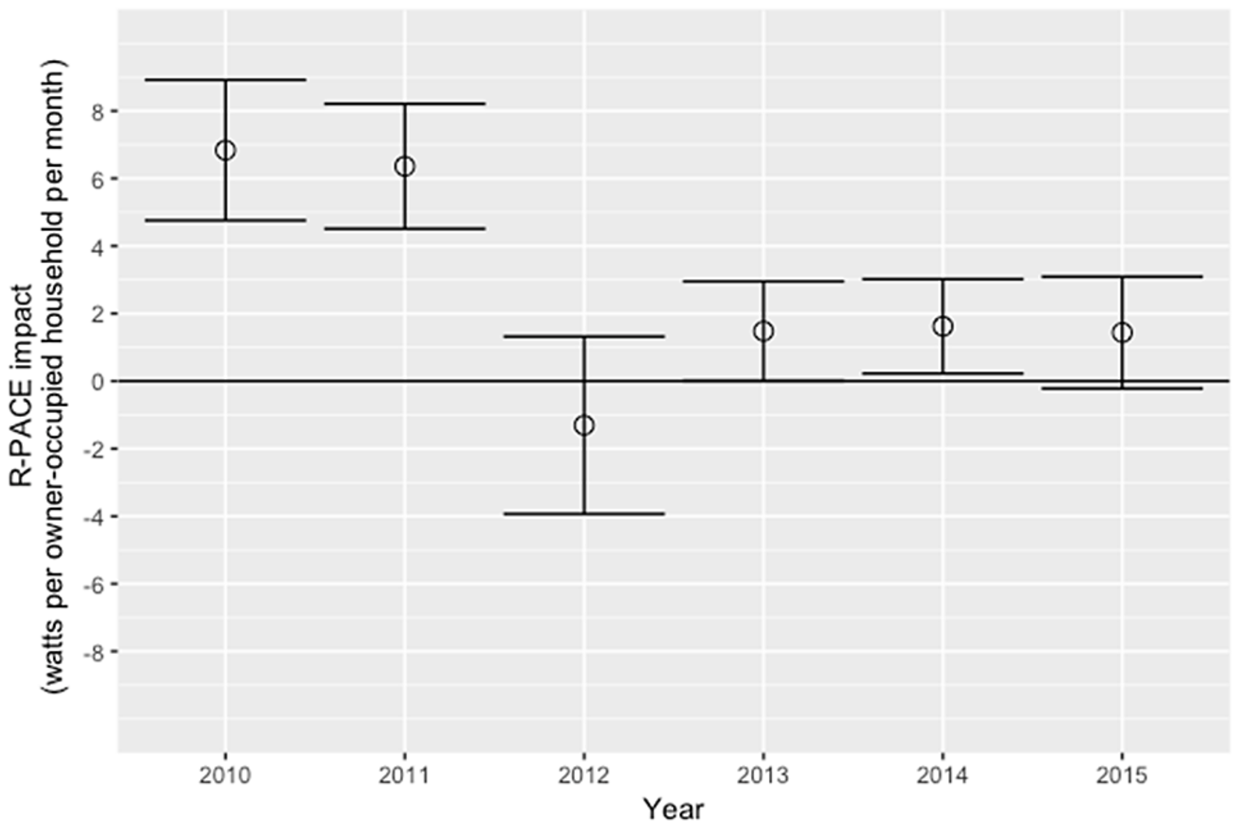

Figure 3. Estimated annual impacts of R-PACE programs on PV deployment in California cities with population >65,000. Results are from the linear regression model, described in the Appendix. Circles denote the point estimates from regression analysis; brackets denote 95% confidence intervals.

In 2010 and 2011, R-PACE impacts on PV deployment are relatively large and clearly statistically significant. These results are mostly consistent with – and of even larger magnitude than – those of Kirkpatrick and Bennear (2014) and Ameli et al. (2017). In 2012, our estimates for R-PACE impacts are negative, but do not approach statistical significance in either sample.[29] In 2013 and 2014, estimated R-PACE impacts are in the vicinity of one watt per owner-occupied household per month, and are generally statistically significant or nearly so. For 2015, results from our two samples diverge: in our large cities sample, impacts are positive and similar to those in 2013 and 2014, while in our all-cities sample our point estimate is negative but small and not close to statistical significance.

[29] 2012 was a nadir year for R-PACE: PACENation data show only $3 million in total R-PACE activity in that year, much less than even 2010 and 2011. So it is not surprising that R-PACE impacts in 2012 are difficult to discern statistically.

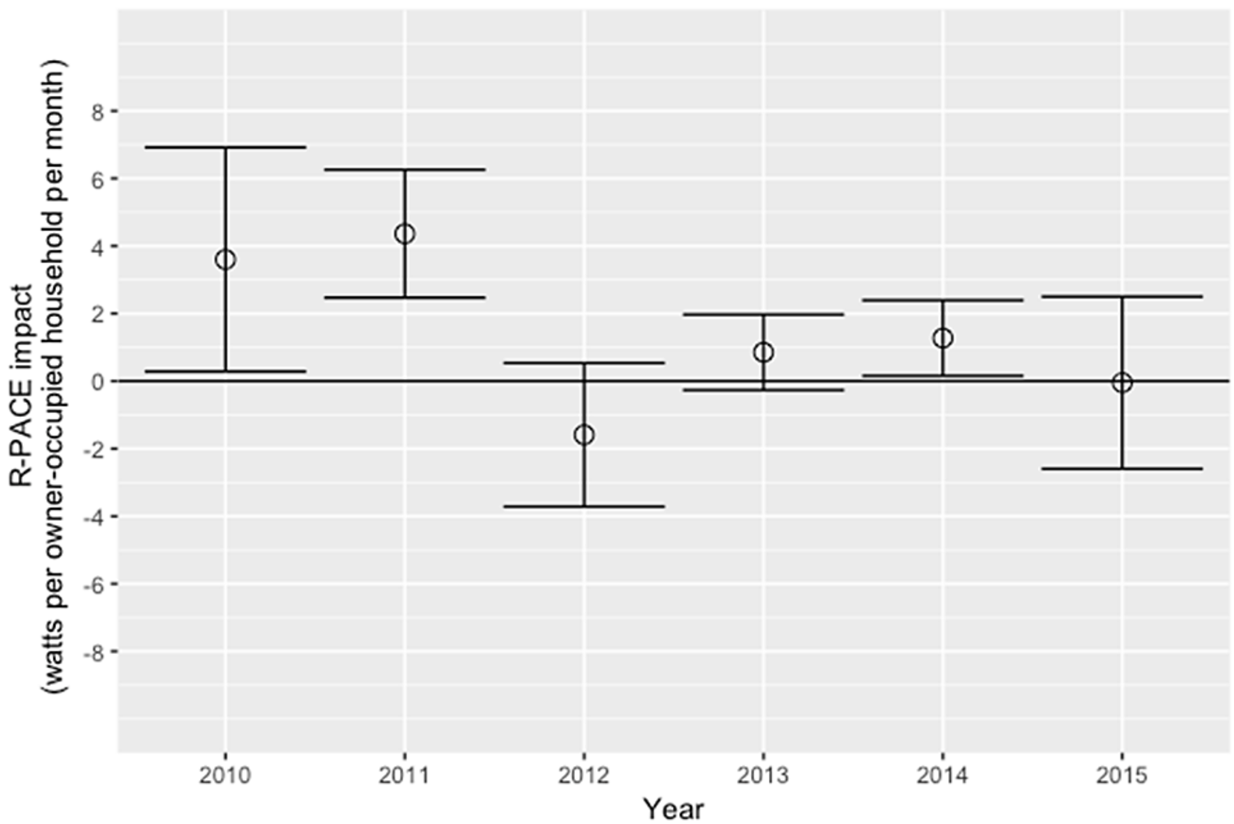

Figure 4. Estimated annual impacts of R-PACE programs on PV deployment in all California cities. Results are from the linear regression model, described in the Appendix. Circles denote the point estimates from regression analysis; brackets denote 95% confidence intervals.

3.3.3 Estimated impact of R-PACE on total PV deployment, 2010-2015

Our econometric estimates compare PV deployment: (1) where and when R-PACE programs were present to (2) where and when R-PACE programs were not present. As such, we are estimating the additional amount of deployment in R-PACE city-months associated with the presence of at least one R-PACE program. By comparing our econometric estimates to the amount of PV financed by R-PACE, we can get a sense for the share of R-PACE-financed PV capacity (MW) that these programs may have driven. If the two numbers are similar, this would suggest that most R-PACE-financed PV would not have been deployed otherwise. If our econometric estimates of R-PACE-driven PV are considerably lower than the total amount of PV that R-PACE has financed, this would suggest that much of the capacity financed by R-PACE may have been deployed even absent the program. If, on the other hand, our estimates were considerably higher than the financed capacity, this would imply that peer effects overwhelmed any deployment that would have occurred absent the program.

Our large-cities sample with complete demographic data implies that R-PACE drove deployment of a total of 73 MW of PV from 2010 through 2015 in large cities in California. Our all-cities sample implies that R-PACE drove somewhat less deployment – a total of 58 MW of PV – in all cities in California, but not including any deployment in unincorporated areas.

In section 1.2 we report our estimate that R-PACE programs financed 131 MW of PV in the study period. This is a statewide estimate, including large and small cities and unincorporated areas, so it cannot be compared directly to our econometric estimates. We therefore adjust this estimate based on the approximate share of R-PACE-eligible houses statewide in large cities, small cities, and unincorporated areas using our detailed monthly data on R-PACE program availability by jurisdiction. This method yields an estimated 73 MW of R-PACE-financed PV in large cities, and 106 MW of R-PACE-financed PV in large and small cities combined.

Comparing these values to our econometric estimates, in our large cities sample R-PACE programs were associated with about 100% of the increase in PV (73 MW) that they financed (73 MW). On the other hand, our all-cities sample suggests that R-PACE programs were associated with an increase in PV deployment (58 MW) about 55% as large as they financed (106 MW). As noted above, our econometric estimates are uncertain, and so are these percentages derived from them. Given the totality of our results, it is most likely that the majority – and perhaps the significant majority – of the PV deployment that R-PACE has financed would not have occurred absent the programs.

4. Discussion

Our results suggest that R-PACE programs have likely been drivers for residential PV deployment. This result is in accord with the findings of Kirkpatrick and Bennear (2014) and Ameli et al. (2017), whose studies focused on the early years of R-PACE and found large and statistically significant impacts of R-PACE programs on deployment. We also find large and statistically significant impacts in these years, and find smaller but still substantial effects in later years that are statistically significant in one of our samples. The evidence for positive R-PACE impacts on deployment in the later years is stronger for larger cities, for which we can control for city-level changes in local demographics and economics during the study period.

In the balance of this section, we explain these results and assess their implications for R-PACE and other financing programs for solar PV. We also discuss their potential applicability to energy efficiency measures, which constitute a larger share of R-PACE investment.

4.1 Evolution of the residential PV financing market and R-PACE impacts over time

The development of solar PV-specific financing products during our study window – both solar leases and solar loans – may help explain changes in R-PACE program impact over time.

The first and still most notable financing development in the U.S. residential PV market is third-party ownership, in which the PV system is not owned by the customer or the utility, but by a solar company. Either through leasing arrangements (in which customers pay fixed monthly payments) or power purchase agreements (in which customers pay a fixed price per kilowatt-hour of electricity generated by the system), solar companies offer systems for no money down.

These financing arrangements seem to have been an important driver of the growth in PV deployment in California (Hobbs et al. 2013). Third-party ownership accounted for only 18% of the residential PV systems in our data that were installed in 2010 (the first year of our dataset). However, third-party ownership grew quickly from there – to 41% in 2011 and 62% in 2012 – then remained between 60% and 70% in the subsequent three years.

Prior to the development of solar leasing, solar-specific financing vehicles for residential customers were rare. Homeowners could finance systems with home equity, if they had equity to draw on. However, home equity loans involve significant transaction costs that might dissuade some borrowers. For those without cash or home equity, financing a residential solar system was a daunting challenge. In this environment in 2010, it is easy to understand how R-PACE would have a large deployment impact.

The growth of third-party ownership as a financing option created another viable dedicated financing path for residential solar installations. This likely reduced the impact of R-PACE, explaining why we observe higher impact per owner-occupied household with access to a R-PACE program in 2010 and

2011 than in subsequent years. That said, R-PACE programs' most probable *total* impact on deployment is larger today than in early years simply because the programs are much more broadly available. Moreover, our data show that R-PACE still likely drove deployment in the latter years of our dataset.

One distinction between R-PACE and third-party ownership is that R-PACE PV customers often own their systems, which creates a different value proposition than leasing.[30] Loans offered by solar providers, which also permit homeowners to own their PV systems, have been growing in market share since 2014. This effect became more pronounced in 2016, outside our study period. These "solar loans" typically offer terms up to 20 years at interest rates competitive with R-PACE.[31] Therefore, R-PACE may offer less distinct value going forward. This is speculation, however, pending sufficient data to evaluate R-PACE impacts in 2016 and 2017, and some differences in the consumer value proposition between R-PACE and solar loans remain.

4.2 Implications for R-PACE and energy efficiency projects

As noted in section 1.2 in this report, 37% of R-PACE dollar volume has gone toward financing renewable energy projects, virtually all of which are solar PV. However, a larger share – 58% – has financed energy efficiency measures.[32] Policymakers also want to know about R-PACE impacts on deployment of energy efficiency measures. California recently identified R-PACE as one of the vehicles that will contribute to its new energy efficiency targets set in Senate Bill 350,[33] and several states are considering an increasing focus on financing as opposed to utility rebates to drive deployment of energy efficiency (Kramer et al., 2015).

Energy efficiency activities are diverse and occur in a wide variety of contexts, from dedicated energy efficiency retrofits to replacing broken equipment with high efficiency models to home renovations that are not principally about energy at all. And, unlike PV – which utilities must connect to the grid – there is no requirement for households to report efficiency improvements to utilities or any other authority.

Thus, while high-quality and relatively complete installation-level data were readily available to support our analysis of R-PACE impacts on PV deployment, no similar dataset exists for energy efficiency. As such, we cannot employ similar methods to infer how R-PACE may drive deployment of energy efficiency.

We therefore consider whether R-PACE is likely to drive a different share of the energy impacts from the energy efficiency investments it finances than for PV. Energy efficiency program impacts are

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30 Some R-PACE customers use R-PACE funds to pay upfront for solar leasing arrangements, so not all R-PACE PV projects are customer-owned. In addition, R-PACE and third-party ownership are not mutually exclusive.

31 Most solar loans are unsecured loans and are offered by major solar providers, often in cooperation with financing providers such as Mosaic. For one example, see http://www.solarcity.com/residential/solar-loan.

32 http://pacenation.us/pace-market-data/. Of the balance, 5% has gone toward water efficiency, with 1% unaccounted for – likely supporting other measures or due to rounding.

33 See https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201520160SB350. PACE is referenced in section 25310(d)(11).

generally stated in terms of energy savings, not measure deployment. For example, a household will likely replace a broken furnace regardless of a program. The issue is: 1) whether access to that program led the household to choose a more efficient furnace than it otherwise would have, and 2) whether the program induced the household to include in the project such measures as insulation and weather-stripping that complement the new furnace, which it would not have installed otherwise.[34]

When considering the share of R-PACE-financed efficiency savings that the programs drive, relative to PV deployment, there are factors that point in both directions. Many efficiency investments are less expensive than PV systems, and homeowners may be better able to afford to pay for them upfront. This likely means that financing of any kind is less important in driving efficiency investments. And many vendors, banks, and credit unions have offered loans for the purchase of energy equipment, so other financing options are available. On the other hand, these unsecured financing alternatives for energy efficiency measures may have higher interest rates or shorter terms than R-PACE. As such, these financing options can seldom offer monthly payments as low as R-PACE. Moreover, even for homeowners with home equity to draw on, energy efficiency improvements often are not expensive enough to justify the costs of taking out home equity[35] (unless financing a number of individual measures, or financing non-energy home improvements). In many cases, home equity loans require a minimum loan amount higher than the efficiency project the homeowner is seeking to finance. So, while financing broadly speaking may be less important for efficiency relative to PV, other efficiency financing options may be less competitive with R-PACE.

In future research, Berkeley Lab will be exploring the impact of R-PACE participation on household energy usage, for both energy efficiency and renewable energy technologies. Our study design will allow us to infer the impact of R-PACE-financed projects on energy usage relative to the case where these households had not implemented the R-PACE-financed projects.[36]

[34] Because R-PACE can finance multiple measures at once, a homeowner will often find it more affordable to include additional measures into a basic furnace replacement project when compared to other financing options that only finance the new furnace.

[35] One exception is households with a home equity line of credit (HELOC) in place. Such households can pull equity out of their homes with essentially no transaction costs, up to the maximum credit line. HELOCs are variable-rate products that often allow interest-only payments, so they introduce financial opportunities and risks that are quite different than R-PACE.

[36] However, we will not be able to assess whether the presence of R-PACE drove the household to implement the project.

5. Conclusions

We estimate that R-PACE has likely increased deployment of residential PV in California. According to our model, R-PACE programs are associated with an increase in PV deployment of 1.1 watts per owner-occupied household each month, or 12%, in our large cities sample. They are associated with an increase in PV deployment of 0.6 watts per owner-occupied household each month, or 7%, in our all-cities sample. The large cities result is statistically significant at conventional levels; the all-cities result is not.

R-PACE program effects were clear and large in 2010 and 2011 (and likely before that, as demonstrated by other studies). As PV financing has evolved, R-PACE impacts on PV deployment have declined on a per-household basis, though they have grown in an absolute sense as the program has expanded across the state. In recent years, for the most part R-PACE program impacts remain positive and statistically significant or nearly so. The majority of PV financed by R-PACE were most likely driven by the programs' presence.

Our analysis has focused on PV deployment only. We have not evaluated the overall costs and benefits of R-PACE programs to participants, the state of California, or society more broadly. Therefore, our analysis does not speak to the overall value of these programs. However, as the programs are intended to encourage solar PV deployment, our results show that these programs have historically achieved one of their main goals. Though our results in more recent years are somewhat mixed, on balance these results suggest that R-PACE programs continued to drive PV deployment throughout the study period (through 2015) even as other financing options for residential PV became available.

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Appendix. Econometric details and full results

A.1 Econometric methods

A.1.1 Linear regression

We first employ a linear regression model with a panel data structure, estimating a fixed effects difference-in-differences model similar to the one employed by Kirkpatrick and Bennear (2014). We estimate the effect of R-PACE program presence and other variables on the monthly deployment of PV, measured in kilowatts per household. We estimate variants of the specification

$$y_{it} = \propto 0 \ \ + \propto X_{it} + \beta P_{it} + \gamma_i + \delta_t + \varepsilon_{it}$$

where y_{it} is the kilowatts of new PV installation in municipality *i* in month t, X_{it} is a vector of other relevant variables that vary across municipalities and months, P_{it} is a dummy variable indicating whether there is at least one R-PACE program available in municipality *i* in month t, γ_i are municipality fixed effects, δ_t are month in sample fixed effects, and ε_{it} is a potentially heteroskedastic and serially correlated error term.

We include variables in X_{it} that reflect differences in the value proposition of PV for homeowners in different municipalities and months: a measure of electricity prices; a measure of incentives offered for solar adoption; and, in some models, three measures of population demographics that may be consequential for R-PACE adoption: median household income, mean home value, and percentage of adults with at least a bachelor's degree. These variables for population demographics are only available on an annual basis for relatively large cities, and not at all for unincorporated county areas. Construction of these variables is covered in the main text of this report.

Results from estimating this model were heavily influenced by small municipalities with few households – a problem also noted by Kirkpatrick and Bennear (2014). To address this issue, we weighted municipalities by the total number of owner-occupied households in each municipality, thereby giving greater weight to outcomes in municipalities with the potential for more PV installations.

We cluster standard errors in both the municipality and time dimensions. While the latter makes little difference, the former results in significantly larger standard errors than when the data are not clustered. As is true of many panel data settings (see Duflo et al. 2004), these results imply that our errors are highly serially correlated, an issue that is addressed by clustering standard errors as described.

We also ran models with lagged R-PACE variables, in case the impact of program adoption is not fully realized for a month or two. Results with lagged variables were very similar to those reported here, indicating that lagging is not necessary. As many of the jurisdictions that adopt R-PACE are joining programs that are already fully operational elsewhere in California, this result is not surprising.

A.1.2 Tobit regression

As noted by Ameli et al. (2017), many municipalities in the data have zero new installed residential PV in some months. The linear model does not account for this feature of the data.

To appropriately account for this, we estimate a Tobit model (Tobin 1958), using the same variables described in the linear regression. As above, our Tobit estimates are weighted by the number of owner-occupied households in each municipality and include municipality and time fixed effects. Because of technical issues,[37] the standard errors from the Tobit model may not be reliable. Therefore, we do not report them and do not attempt statistical inference based on the Tobit results. The Tobit model is otherwise well-suited to our setting.[38]

The results we show from the Tobit regression are the marginal impacts on the expectation of the dependent variable at the owner-occupied household-weighted means of all independent variables in the dataset. Our model accounts for both impacts on the odds of zero results and on the expectation of a result, assuming that result is positive.[39]

A.2 Full econometric results

A.2.1 R-PACE availability pooled across years

Table A-1 and Table A-2 show our results when the R-PACE program availability variable is pooled across all years of the data. The R-PACE coefficient therefore estimates the average impact of R-PACE program availability on monthly PV deployment over all six years of our dataset (2010-2015).

Table A-1 shows linear regression results, while Table A-2 shows Tobit results. We view the Tobit point estimates as preferable, but rely on the linear regression results for statistical significance. Fortunately, the estimated coefficients from the two models are consistently similar, easing interpretation.

In each table:

- Column (1) shows results from the full sample without considering annual city-level demographics.
- Column (2) shows results from only the cities with annual demographic data, but does not include these annual variables.
- Column (3) shows results from only the cities with annual demographic data including those annual variables.

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[37] The fixed effects Tobit model is afflicted by the incidental parameters problem (Neyman and Scott 1948), and is therefore biased and inconsistent in short panels. Greene (2007) shows through simulation that the bias in coefficients and marginal effects from the Tobit model is very minor in even fairly short panels. Our panel has length T = 72, a long panel by any standard. As such, we have confidence in the marginal effects we report. However, Greene shows that standard errors in fixed effects Tobit models are biased downward and therefore anticonservative. This bias appears to persist even as the panel lengthens – though the simulations do not consider a panel nearly as long as ours.
[38] The Tobit model is inconsistent in the presence of heteroskedasticity but consistent in the presence of serial correlation (Robinson 1982). Our data are not strongly heteroskedastic; they are serially correlated.
[39] See Wooldridge (2002), equation 16.16.

Table A - 1. R-PACE impacts pooled over all years, linear regression model

	Dependent variable:		
	Watts PV per owner-occupied household		
	(1)	(2)	(3)
R-PACE program	0.690	1.348*	1.382**
	(0.579)	(0.719)	(0.634)
Electricity cost	1.398***	1.404***	1.442***
	(0.221)	(0.266)	(0.280)
Incentives	5.354***	5.330***	6.415***
	(0.806)	(1.046)	(1.011)
Median household income			−0.055
			(0.060)
Household value			−0.059***
			(0.013)
% bachelor's degree			−14.882
			(9.280)
Observations	29,700	7,344	7,344
R^2	0.601	0.685	0.719
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A - 2. R-PACE impacts pooled over all years, Tobit model.

	Dependent variable:		
	Watts PV per owner-occupied household		
	(1)	(2)	(3)
R-PACE program	0.617	1.315	1.085
Electricity cost	1.442	1.438	1.181
Incentives	5.412	5.283	5.124
Median household income			−0.044
Household value			−0.048
% bachelor's degree			−12.232
Observations	29,700	7,344	7,344
Log-likelihood	-994516559	-649938232	-635596789

Note: We do not present standard errors from the Tobit model given potential problems in interpreting them.

Columns (1) and (3) are our preferred specifications. Column (2) is inferior to column (3) because it does not include the annual demographic data. We show column (2) to better understand the changes in the results moving from column (1) to column (3). Comparing column (2) to column (1) illustrates compositional effects of restricting the sample; comparing column (2) to column (3) illustrates the impact of including the annual demographic variables separated from this compositional effect.

We discuss the coefficient on the R-PACE variables in the main text, with some expanded technical discussion below. As for other variables in the model, higher electricity prices are associated with greater PV uptake and are statistically significant in all models and all samples. This is expected as on-site generation reduces households' need to purchase electricity from the grid, and is therefore more valuable where electricity prices are high. Incentives offered for PV deployment are also positively associated in a statistically significant manner with greater PV deployment in all models and all samples, as expected.

Higher income, higher home values, and greater education levels are all negatively associated with PV deployment. This relationship is only statistically significant for home values. The behavior of this variable is somewhat surprising as we might expect cities with more valuable properties to adopt more PV. However, the size of the effect is extremely small. The behavior of these variables is consistent in all models and samples.

Comparing column (2) to column (3) in the linear model (Table A-1) shows that the annual demographic variables – which collectively describe relative changes in local economic conditions among jurisdictions over time – have little effect on the magnitude of the impact from R-PACE but reduce the uncertainty in its estimate. While we cannot be sure, we can postulate that if annual demographic data were available for all jurisdictions, the statistical significance of our all-cities estimate might go up. On the other hand, the Tobit results (Table A-2) for column (3) show a smaller impact from R-PACE than column (2). This difference is due to changes in the Tobit scale factor, which estimates the odds of a zero observation for the dependent variable at the weighted means. This scale factor is very close to one for all models that do not include annual demographics, but is about 0.8 for models that do include them. Shifts in the Tobit results between columns (2) and (3) in Tables A-2 and A-4 are primarily driven by changes in the scale factor, not in the coefficients directly estimated by the Tobit regression.

A.2.2 Yearly R-PACE impacts

Table A-3 shows results of linear regression analyses where R-PACE impact is estimated separately in each year. Table A-4 shows these results for the Tobit analyses. Rather than a single binary R-PACE variable, we define R-PACE availability separately in each calendar year. Figure 3 and Figure 4 in the main text illustrate the results from linear regression, columns (1) and (3), including confidence intervals. Our discussion of the results in the previous subsection extends to these analyses with the exception of the annual R-PACE variables, which we discuss in the main text of this report. Again, changes in R-PACE impacts between columns (2) and (3) in the Tobit analysis are due to changes in the scale factor.

Table A - 3. Annual R-PACE impacts, linear regression model.

	Dependent variable:		
	Watts PV per owner-occupied household		
	(1)	(2)	(3)
R-PACE2010	3.866**	6.123***	6.665***
	(1.592)	(1.137)	(1.035)
R-PACE2011	4.369***	4.931***	6.236***
	(0.935)	(1.091)	(0.940)
R-PACE2012	−1.310	−1.349	−0.864
	(1.025)	(1.275)	(1.200)
R-PACE2013	0.856	0.951	1.400*
	(0.592)	(0.744)	(0.767)
R-PACE2014	1.149*	1.610**	1.562**
	(0.605)	(0.738)	(0.702)
R-PACE2015	−0.651	2.187	1.397
	(1.453)	(1.382)	(0.851)
Electricity cost	1.449***	1.493***	1.531***
	(0.259)	(0.312)	(0.321)
Incentives	5.528***	5.471***	6.436***
	(0.815)	(1.040)	(0.997)
Median household income			−0.061
			(0.069)
Household value			−0.058***
			(0.013)
% bachelor's degree			−13.578
			(10.162)
Observations	29,700	7,344	7,344
R^2	0.597	0.683	0.718
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A - 4. Annual R-PACE impacts, Tobit model.

	Dependent variable:		
	Watts PV per owner-occupied household		
	(1)	(2)	(3)
R-PACE2010	4.112	6.321	5.859
R-PACE2011	4.564	5.005	5.381
R-PACE2012	−1.649	−1.795	−1.100
R-PACE2013	0.955	1.016	1.249
R-PACE2014	1.107	1.607	1.356
R-PACE2015	−0.327	2.298	1.277
Electricity cost	1.463	1.471	1.274
Incentives	5.508	5.379	5.481
Median household income			−0.046
Household value			−0.051
% bachelor's degree			−13.977
Observations	29,700	7,344	7,344
Log-likelihood	-993622407	-648800705	-634366795

Note: We do not present standard errors from the Tobit model given potential problems in interpreting them.