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Abstract

Electric utilities, local and state governments utilize a variety of subsidies to promote energy efficiency and renewable energy. We study the California Solar Initiative and find that upfront rebates have a large effect on residential solar installations. We exploit variation in rebate rates across electric utilities over time and control for time-varying factors that affect PV adoption. Our preferred estimates suggest increasing average rebates from \$5,600 to \$6,070 would increase installations by 13 percent. Overall, we predict 58 percent fewer installations would have occurred without subsidies. Over 20 years, we estimate these additional installations reduce carbon dioxide emissions between 2.98 and 3.7 million metric tons and local air pollutants (NOx) by 1,100 to 1,900 metric tons, about as much as is produced by a small to mid-sized natural gas power plant. However, the program is costly. Of the \$437 million in rebates awarded, \$98 million were rents to installations that would have taken place absent rebates. Back of the envelope calculations suggest deadweight loss as high as \$169 million or between \$46 and \$69 dollars per metric ton of carbon dioxide or \$91,000 and \$142,000 per ton of NOx.

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1 Introduction

Many state and local governments have become involved in efforts to reduce local air pollution and emissions of greenhouse gases. Electric utilities have also adopted policies to promote residential energy efficiency and renewable energy production. For both groups, a common approach is the use of subsidies for "green technologies." In this paper, we study a popular program that awards rebates for residential photovoltaic (PV) solar electricity installations in California. Currently, over 130 programs in 27 states and the District of Columbia award rebates for residential PV systems.[1] If the effects of these programs are large, residential solar subsidies may play an important role in efforts to reduce carbon emissions. However, while a number of green technology subsidy programs have received attention in the empirical literature, the extent to which solar subsidies create new adopters, lower emissions, raise or lower welfare is still largely unknown. Given that these policies are costly to ratepayers, governments or both, the extent to which they achieve their desired environmental goals is an important policy question.

We study the California Solar Initiative (CSI), a large subsidy program which targets residential and commercial consumers of PV and related solar technologies. We focus on the Expected Performance Based Buydown (EPBB) program which awards rebates, in dollars per Watt, based on expected PV system generation capacity. Using installation data from 2007 to 2012, we estimate the effect of upfront rebates on adoptions. Three investor owned utilities (IOUs) participate in this program: Pacific Gas and Electric (PG&E), Southern California Edison (SCE) and San Diego Gas and Electric (SDG&E). Program rebates are substantial and amount to between 5 and 25 percent of system cost. One feature of the CSI is that rebate rates decline over time depending on each utility's total installed capacity. This creates variation in rebates across utilities over time that we exploit in our empirical analysis. Because rebate levels depend on the history of past installations and unobserved factors that affect adoption may be correlated over time, our estimation strategy controls for utility-specific time-varying factors related to PV adoption.

Overall, we find that CSI rebates have a large effect on residential PV adoption. Across a number of specifications we find that a $0.10 per Watt or 7 percent increase in the mean rebate rate on average increases the number of installations per day between 11 and 15 percent. In our preferred specification, increasing average rebates from $5,600 to $6,070 would increase installations

[1] For a current count of residential solar rebate programs see http://www.dsireusa.org/solar/.

by 13 percent. Furthermore, while consumers do appear to anticipate changes in the rebate rate by increasing adoptions in the weeks immediately prior to a rebate change, the overall effect we estimate does not depend solely on this short-run behavior. The estimated effect of the rebate does not change substantially across the geographic areas we study or across IOUs. We also provide evidence that the level effect of rebates on adoptions is greater later in the sample despite smaller rebates.

To investigate the overall impacts of the CSI we use our estimates to predict the number of installations, solar electricity capacity and emissions reductions created by the program. Of the approximately 99,000 installations that occurred over this period, we find that 57,000 or 58 percent of installations were due to rebates. This suggests that the CSI had a substantial effect on adoptions. The estimated increase in solar generation capacity, approximately 260 MW, is small at less than 1 percent of typical electricity load in the state.[2] We predict the additional solar generation under the CSI lowers CO_2 emissions by 2.98 to 3.15 million metric tons (MMT) and cuts emissions of nitrogen oxides (NOx) by 1,100 to 1,900 tons over 20 years.

Back of the envelope calculations suggest the CSI results in large benefits to consumers and installers. Total rebates paid from 2007 to 2012 are $437 million. Private surplus, defined as the sum of producer and consumer surplus, increases by approximately $268 million including $98 million in rents to inframarginal installations that would have occurred absent rebates. These effects may explain the popularity of the program. However, overall the program appears costly. Social surplus, which we define as private surplus net of subsidy payments, decreases under the CSI by approximately $169 million.[3,4] Comparing this cost to estimated carbon emission reductions implies average abatement costs between $46 and $69 per metric ton (MT) CO_2, substantially more than recent estimates for the social cost of carbon. For NOx, we find average abatements costs are very high, between $91,000 and $142,000 per MT.

Understanding the relationship between PV subsidies and adoptions is important for several reasons. Upfront rebates of the type awarded under the CSI are widely used. Many utilities, states

[2]Daytime loads in California typically range between 25,000 and 30,000 MW but can peak as high as 60,000 MW.

[3]Our calculations assume price taking firms and linear demand. This allows us to estimate welfare effects of the CSI using only subsidy levels and the change in the number of installations due to CSI rebates.

[4]The change in private surplus in this context is equivalent to the deadweight loss of the subsidy where private marginal costs exceed private marginal benefits.

and local governments have programs similar to California's.[5] In addition to upfront rebates, tax rebates and production based subsidies may provide similar incentives. The US federal government has awarded a tax rebate of up to 30 percent for qualified solar installations since 2005. Internationally, several nations including Germany and Spain, offer production based subsidies. Recent work by Burr (2012) suggests consumers may respond similarly to these different incentives. Understanding how consumers respond to incentives highlights the costs and benefits of promoting PV adoption and may help policy makers design more effective policies. Finally, understanding the effects of solar subsidies provides insight into similar programs for other green energy technologies.

This paper is part of a small but growing literature to understand the impact of subsidies for solar PV. Bollinger and Gillingham (2012) explore the role of CSI rebates in their study of peer effects in PV adoption. They use 33 zip codes along the PG&E and SCE boundary to show that higher CSI rebates are associated with higher adoption rates.[6] In contrast to our approach, Bollinger and Gillingham (2012) use indicator variables instead of the actual rebate levels, and so they do not fully quantify the relationship between rebate rates and the number of adoptions. More recently, Burr (2012) explores consumer responses to different incentive designs in the context of the CSI. Using a dynamic structural model for consumer utility she finds that adoptions would be 85 percent lower in the absence of current CSI subsidies. She finds the CSI would be welfare neutral for a social cost of carbon of approximately $100 per MT. Burr assumes that variation in rebate rates is exogenous, an assumption we explore in our work.

In addition, a number of authors have explored the effect of subsidies on adoption of other durable green goods. Boomhower and Davis (2013) examine the issue of free riders in the context of a Mexican subsidy program to incentivize adoption of efficient air conditioners. They find that while the program did encourage adoption, a large percentage of households would have purchased air conditioners in the absence of subsidies. Chandra, Gulati, and Kandlikar (2010) investigate the effect of tax rebates on hybrid vehicle adoption and find that a large share of hybrid vehicle adoptions, approximately 74 percent, would have occurred without incentives. These results are consistent with our finding that 42 percent of households which adopted PV under the CSI would

[5]Examples of other statewide PV incentive programs include Oregon's Solar Electric Incentive Program, New York state's PV Incentive Program and Massachusetts' Commonwealth Solar II Rebate Program. Details on these and similar state administered PV cash subsidy programs are available at DSIRE, the Database of State Incentives for Renewables & Efficiency, sponsored by the US Department of Energy, http://www.dsireusa.org

[6]Specifically, they focus on periods when the rebate on one side of the boundary is higher than the other. However, they only consider two rebate changes.

have adopted without rebates.

Several authors have investigated the effects of a variety of demand side incentives for hybrid vehicle adoption. Gallagher and Muehlegger (2011) study consumer responses to different types of incentives, and find that the type of incentive matters as much as its magnitude. They find the effect of sales tax waivers on adoption to be ten times that of income tax credits, in part due to their relative immediacy and simplicity. Beresteanu and Li (2011) study the effects of federal tax incentives on hybrid vehicle sales. They find that 20 percent of hybrid vehicle sales in their sample are the result of tax credits. Sallee (2011) investigates the incidence of tax credits for the Toyota Prius, and finds that consumers fully capture these incentives. Finally, Mian and Sufi (2012) study subsidies for adoption of fuel efficient vehicles in the "Cash for Clunkers" program. Both Sallee (2011) and Mian and Sufi (2012) provide evidence that consumers adjust the timing of automobile purchases in response to incentives, behavior similar to the short-run effects we observe in the CSI.

This paper also contributes to a larger literature on the costs and benefits of solar. Borenstein (2008) estimates benefits of PV due to generation coinciding with peak demand, and reduced congestion of transmission and distribution systems. Baker et al. (2013) focus on the importance of different time horizons and associated goals in determining the cost effectiveness of solar PV. Van Benthem, Gillingham, and Sweeney (2008) investigate whether PV subsidies are justified through decreases in balance-of-system (BOS) costs via learning-by-doing, and Dastrup et al. (2012) investigate the extent to which PV installations are capitalized into house values. Recent work by Gowrisankaran, Reynolds, and Samano (2013) focuses on the social cost of intermittent solar production in large-scale electricity generation. We focus on the effectiveness of a specific policy to promote solar electricity in California and estimate costs and benefits of this program.

Finally, there is growing interest in the "greenness of cities" (Glaeser and Kahn, 2010) in general, and in programs promoting energy efficiency in residential and commercial buildings. Recent evidence suggests residential and commercial buildings certified as sustainable or energy efficient by "green labeling" programs sell or lease for higher prices relative to comparable uncertified buildings (Deng, Li, and Quigley, 2012; Eichholtz, Kok, and Quigley, 2013; Kahn and Kok, 2013). The effects of these programs appear correlated with local environmental preferences and climate (Kahn and Kok, 2013). Millard-Ball (2012) studies the impacts of "city climate plans" on outcomes including bicycle and pedestrian facilities, green buildings and solar adoption. While cities with climate plans are more likely to invest in green technologies, this appears to be the result of underlying environmental preferences in these areas rather than the plans themselves. These results highlight the spatial aspects of demand for energy efficient building technologies which may parallel trends in solar adoption.

The remainder of this paper is organized as follows. Section 2 describes the California Solar Initiative and market for residential PV systems in California. Section 3 describes our data and Section 4 presents our empirical strategy. Sections 5 and 6 summarize our main empirical results and calculations for the overall effects of the CSI. Finally, Section 7 concludes.

2 Policy background

The California Public Utilities Commission (CPUC) created the California Solar Initiative (CSI) at the start of 2007 to manage the state PV rebate program and to help meet the solar goals set by the California greenhouse gas law, AB32. The CSI is a $2 billion program targeting both commercial and residential customers and includes incentives aimed at low income households in single and multi-family residences. The CSI is funded by a ratepayer surcharge assessed by utilities.[7] This surcharge contributes an average of $217 million annually to the CSI.[8] Three IOUs participate in the initiative—Pacific Gas and Electric (PG&E), Southern California Edison (SCE) and San Diego Gas and Electric (SDG&E). Rebates are available for solar PV technologies as well as solar hot water heaters. In addition, the CSI offers grants for research, development and deployment of solar technologies. We focus on incentives for residential solar PV installations which represents approximately $500 million of the overall program budget.[9] For these customers the CSI program offers two options, an upfront rebate based on predicted system electricity production, and a monthly payment based on actual production. Because relatively few customers select the monthly option, we focus on the upfront payment called the Expected Performance Based Buydown (EPBB).[10]

[7] The surcharge is collected as part of an existing distribution surcharge. Unfortunately, this makes it difficult to observe the actual CSI fee.

[8] This and other surcharges are detailed in a CPUC (2006) ruling clarifying responsibilities of the IOUs in complying with California Senate Bill SB1.

[9] In CSI documents this program is sometimes referred to as the "general market program."

[10] Fewer than 1 percent of residential installations in our sample opted for the monthly PBI payment.

Under the EPBB system, rebate rates begin at \$2.50 per Watt and decrease based on each IOU's total installed solar capacity. The schedule, reproduced in Table 1, was set at the program outset and allocates the statewide solar capacity to utility-specific quantities within each rebate "step." For example, for statewide PV capacity greater than 50 MW and less than 70 MW, CSI rebates are awarded at step 2 or \$2.50 per Watt. However, determining whether a particular residential installation in an IOU qualifies for the step 2 incentive requires that the program administrator allocate the total capacity within the step to the different utilities and their residential and commercial customers. Table 1 shows that PG&E residential installations that occur when the utility's total residential PV capacity is less than 10.1 MW receive \$2.50 per Watt. Similarly for SCE and SDG&E, the relevant thresholds are 10.6 and 2.4 MW. The remaining capacity within the step is allocated to commercial installations under each of the participating IOUs. Looking ahead to the empirical exercises, we exploit the fact that rebate levels change at different times for each IOU depending on that utility's installed residential capacity.

Overall, CSI statistics suggest that the program had a large effect. As of February 2013, CSI reports 1,432 MW of capacity installed or pending under the program consisting of nearly 142,000 projects. Approximately 546 MW are listed as residential with the remaining 886 MW classified as commercial. Since 2007, over \$1.5 billion in incentives have been awarded including over \$400 million for residential installations.

In addition to the CSI, two other features of the solar market during this period are worth noting. First, during our sample the federal government offered a tax credit of up to 30 percent of system cost for homeowners who installed PV. The credit was initially capped at \$2,000. However, the cap was removed after December 31, 2008 as part of the American Recovery and Reinvestment Act. Since the mean installation cost in our sample is approximately \$40,000, removal of the cap greatly increased the size of the federal incentive. Second, the end of our sample saw a dramatic increase in residential PV systems that were owned by third-parties.[11] In these cases, the PV equipment is owned by a firm who then either leases the system back to the homeowner or who sells the residence electricity via a power purchase agreement. This business model may be attractive to capital or credit constrained households and may increase the pool of potential solar adopters. Because these changes may affect PV adoption rates over time, our empirical model below captures these and

[11] Based on our calculations in 2007 approximately 7 percent of CSI installations were owned by third parties. However, by 2011 approximately 53 percent were third-party owned.

other time-varying factors using time fixed-effects.[12]

3 Data

Our analysis exploits installation data from the California Solar Initiative (CSI). CSI reports installation date, rebate amount, utility and zip code as well as installation characteristics for all solar PV systems that received an incentive under the program.[13] We focus on the period from the beginning of the program on January 1, 2007 through October 31, 2012. We use only installations that received the upfront EPBB payment and exclude installations that opted for the monthly PBI incentive. Because the CSI data include all projects for which an application for a rebate was submitted regardless of whether the project was completed, we drop all observations for cancelled or delisted projects. We use only those installations classified as residential by CSI. The CSI data lists dates of several important project milestones. We use the date of the "first reservation request review" as the installation date for each project.[14] Finally, CSI lists the actual rebate rates as well as the total incentive amount awarded to each project. However, many of the actual rebates listed are constructed as weighted averages of two steps.[15] To minimize the potential for bias if strategic customers are able to obtain higher effective rates when weighted average rates are used, our calculations use the CSI reported incentive step and rebate rate corresponding to the reservation request date for each project instead of the reported weighted average.[16] The correlation coefficient between our measure of the rebate rate and the rate reported for each project is 0.99.

Table 2 presents summary statistics for the total rebate awarded, system cost and size by utility. The CSI rating is the electricity generation capacity adjusted for installation specific parameters such as inverter efficiency, panel orientation, and the solar energy resource of the installation lo-

[12] These factors may also change the effect of rebates on adoption. We explore this possibility by estimating the effect of rebates in different time periods. These results are shown in Table 6 below.

[13] We use the "Working Data Set" file posted on November 14, 2012. We drop the last two weeks to account for any lag in updating the CSI database with new installations.

[14] The reservation request is the contract between the system owner and the CSI. Upon review, a successful applicant is awarded the current rebate rate which will be used to calculate the total incentive at the completion of the project.

[15] Presumably this is due to some feature of the timing of application and installation of the various projects that may have occurred around a rebate change date.

[16] We observe the dates at which rebate levels for the IOUs changed from CSI press releases, annual reports and the "Go Solar California" monthly newsletter. While rebate change dates were not pre-announced, consumers and installers were provided information about the remaining capacity at each rebate level (step) via a web-based "CSI Trigger Tracker" application.

cation. Looking across IOUs, average system prices range from approximately \$35,900 to \$37,400 and rebate levels range from \$3,600 to \$5,300. Average CSI ratings are fairly consistent at between 4.46 to 4.77 kW. The data also suggest large subsidies are awarded for a few very large residential installations. Across the three IOUs, maximum rebates range from \$106,000 to \$138,000 for systems costing between \$397,000 and over \$1 million.

In several empirical specifications below we focus on a subsample defined by a 20-mile corridor around the boundary between PG&E and SCE. In this sample, shown in the bottom panel of Table 2, rebates and system sizes are somewhat larger relative to the full sample. The number of installations per day for PG&E and SCE average from 16.4 to 23.4 in the full sample and from 0.56 to 0.85 in the 20-mile corridor. In the full sample of zip codes approximately 22 percent of daily observations have no installations compared with 63 percent of observations in the 20-mile corridor.

Next, we consider where the locations of installations under the CSI. Figure 1 shows the total number of residential PV installations under the CSI by zip code compared with zip code level population density. Installations more or less follow population patterns with a greater number of installations in California's developed urban areas. However, solar installations appear clustered outside major cities. For example, there are relatively few installations in the most densely populated parts of the San Francisco and Los Angeles metro areas. Instead, solar counts are highest in a ring of zip codes outside each city. This likely reflects our focus on residential installations, which are more likely to occur on single family homes. This pattern illustrates *where* the CSI may contribute to the "greenness" of a cities' housing stock, outside of the urban core. Since Glaeser and Kahn (2010) find that in general, CO_2 emissions from electricity consumption are larger for suburban than for urban households, this pattern of adoption may magnify the effect of solar rebates on emissions.[17]

To illustrate the overall trends in rebates and installations, Figures 2(a), 2(b) and 2(c) summarize average rebate rates, system prices and installations for PG&E, SCE and SDG&E from 2007 through 2012. Rebate levels begin at \$2.50 per Watt in 2007 and decrease to \$0.20 per Watt for PG&E and SDG&E, and \$0.25 per Watt for SCE by 2012. Notice that the rebate steps change at different times for each utility. This is the main source of variation we exploit in our empirical

[17] In California, Glaeser and Kahn (2010) find this is true in San Francisco and Sacramento, but not Los Angeles.

analysis. Average system costs per Watt decrease over the period from approximately $10 per Watt to $6 per Watt. Average daily installations increase from nearly zero, initially, to almost 50 per day in 2012 for PG&E and SCE. Daily installations are substantially lower for SDG&E, peaking at approximately 15 per day.[18] Given that prices have steadily decreased over time while installation rates have risen, one may wonder about the impact of CSI rebates on adoptions.

Figures 4(a), 4(b) and 4(c) provide evidence that consumers do respond to changes in rebate levels. The number of installations per day is plotted for each utility from 2007 through 2012. For exposition we plot only weekdays, though a surprising number of installations are recorded on weekends.[19] The vertical lines denote dates when the rebate rate was lowered. In general, we see large increases in the number of installations in the weeks leading up to a drop in the rebate rate. The periods between rebate changes also show a general upward trend consistent with greater numbers of installations over time. Looking forward to the empirical exercises, the overall increase in installation rates combined with decreasing rebate levels suggests that controlling for changes in time-varying factors that affect PV adoption will be important in identifying the effect of rebates on installations.

Finally, our empirical approach below proposes using the boundary between the PG&E and SCE territories to help create exogenous variation in CSI rebate rates. We focus on PG&E and SCE because SDG&E represents a substantially smaller share of adoptions. We use GIS data obtained from Ventyx to locate the boundary and to identify zip codes that lie within a 20-mile corridor around the boundary. Figure 3 shows the PG&E and SCE service territories as well as the region around the territory boundary. These two IOUs serve regions that cover the vast majority of the state stretching from southern California to near the Oregon border. The boundary between PG&E and SCE, drawn in black, begins in Santa Barbara and stretches nearly 900 miles north to the Nevada border. Zip codes whose centroids fall within the 20-mile corridor are shaded in gray. Because less populous zip codes tend to be larger in size, the 20-mile corridor excludes some rural regions of the boundary as some zips code centroids do not fall within 10 miles of either side of the territory boundary.[20]

[18]This difference may largely be due to the relative sizes of these utilities. While SCE and PG&E serve 14 and 15 million electricity consumers respectively, SDG&E serves only 1.4 million. In per capita terms, 2012 installations are significantly higher in SDG&E than in either SCE or PG&E.

[19]Our estimates for the effect of rebates on adoption in Section 5 include installations on weekdays and weekends. Parameter estimates are similar to those reported when weekends are excluded.

[20]These zip codes are left unshaded in Figure 3.

4 Empirical strategy

Because rebate levels are determined by prior installations and because unobserved factors that affect adoptions within each utility territory may be correlated over time, our identification strategy seeks to isolate exogenous variation in rebate rates while holding constant unobserved factors that affect PV adoption.[21] Our approach is twofold. First, we use time effects to account for mean and utility specific time varying unobservables that may affect PV adoption. Second, we exploit the geographic discontinuity created by the boundary between the PG&E and SCE service territories. This boundary was created in the early 1900's when the area between the two utilities was largely rural, such that the location is plausibly orthogonal to factors affecting PV adoption today. We focus on a narrow 20 mile corridor around this territory boundary. This approach is similar to Ito (forthcoming) who investigates consumer responses to marginal and average electricity prices using the territory boundary between SCE and SDG&E in Southern California. Because changes in the rebate rate are determined by total installed PV capacity in either IOU's territory, installations in the boundary region should minimally affect the rebate rate. Further, by looking in a small neighborhood around the boundary we hope to hold constant unobserved factors affecting adoption. A key identifying assumption is that unobservables that affect adoption for households in the boundary region are not correlated with unobservables at the utility level more broadly.

To get a sense for the similarity of households within each region, Table 3 summarizes zip code mean demographic and housing characteristics for all zip codes within the PG&E and SCE territories as well as within 40-mile and 20-mile wide corridors at the territory boundary. These observable characteristics are reasonably good predictors of PV installations.[22] We present means weighted by population within each zip code. Beginning with the full sample, we see that percent white, household income, percent family occupied, and number of rooms are all significantly different between PG&E and SCE territories.[23] When the sample is limited to the 40-mile corri-

[21] For example, environmental preferences may vary over time. Bollinger and Gillingham (2012) show that hybrid vehicle registrations, a proxy for environmental preferences, are positively correlated with PV adoption. Millard-Ball (2012) shows that observable and unobservable local characteristics likely play a role in PV adoption decisions. Our identification strategy assumes solar preferences at any given point in time are similar on each side of the utility boundary.

[22] A regression of total PG&E and SCE installations from 2007 through 2012 by zip code on the variables in Table 3 explains approximately 46 percent of the variation in adoptions. The observable characteristics are jointly significant $F(7, 1087) = 135.94$ and each variable is independently statistically significant ($p < 0.01$) with the exception of percent of units which are owner occupied.

[23] Number of rooms can be thought of as a proxy for house size.

dor around the boundary, the differences in observable characteristics between utilities in general decrease. Income and number of rooms are no longer statistically significantly different. Finally, moving to the preferred 20-mile corridor sample, we see that the differences decrease further. In no case are the differences in means between utilities significant at the 5 percent level and only in the cases of percent white and percent family occupied are they significant at the 10 percent level. This suggests that focusing on a small neighborhood around the utility boundary does result in observations with similar observable characteristics.[24] Furthermore, to the extent that unobservables that affect solar installations are correlated with these observable factors, these results suggest that the 20-mile corridor sample may also have the property of holding these factors constant across utilities.[25]

Since PV installations even at the zip code level are relatively rare events, we sum installations on each side of the boundary to produce daily installation totals for each IOU.[26] We model the number of installations per day as:

$$I_{u,t} = \beta_0 + \beta_1 rebate_{u,t} + \epsilon_u + \epsilon_t + \epsilon_{u,t} \tag{1}$$

Where $I_{u,t}$ is a count variable for the daily installation rate for utility u at time t. We focus on the effect of changes in the rebate on adoption rather than estimating demand directly from consumer system prices for two reasons. First, prices reported to the CSI may be unreliable because of incentives for third-party installers to over-report costs.[27] Second rebate levels, rather than consumer prices net of rebates, may be more salient for policy makers.[28] Since the rebate rate determines the net cost to the consumer of adopting solar, in our preferred specification $rebate_{u,t}$ enters in levels. We model unobserved factors that affect PV installations at the utility level as

[24] As discussed below, our dependent variable aggregates installations across zip codes by utility within the boundary area. Therefore, including observable characteristics directly or using zip code fixed effects is not possible.

[25] While these results also suggest a more narrow corridor may be desirable, we do not observe the precise installation location. Therefore, the fineness of the discontinuity is limited by the width of each zip code, which can be several miles.

[26] As a robustness check, Appendix Table 1 presents results using zip code daily level data. These results are quite similar to those presented below using utility daily level data.

[27] Installers may receive a federal tax credit under the Investment Tax Credit program based the fair-market value of leased systems. This may lead to misreporting of prices as alledged by the US Treasury. http://www.renewableenergyworld.com/rea/news/article/2012/10/treasury-dept-fingers-solarcity-in-exploration-of-the-dark-underbelly-of-solar-leasing.

[28] Of course, the effect of rebates on consumer prices requires an understanding of subsidy pass-through, which may vary from market to market. Here by focusing on the equilibrium effect of rebates, we implicitly lump pass-through into an overall effect of changing rebate levels on adoption.

mean effects ϵ_u. Time varying factors common to both utilities, such as changes in the federal tax code and PV component prices, are modeled as mean effects ϵ_t.[29] Finally, because unobserved time varying factors such as marketing programs, third-party installers, changes in familiarity with PV technology and peer effects may also vary by utility, our preferred specification also includes interactions $\epsilon_u \times \epsilon_t$.

We estimate the parameters of Equation 1 using negative binomial regression. Given the count nature of the data and potential for a large fraction of zero values, overdispersion seems likely and the negative binomial model seems a reasonable choice. We test for overdispersion using the regression based test proposed by Cameron and Trivedi (2005). We reject the null hypothesis of no overdispersion with $t = 11.90$ ($g(\mu) = \mu$) and $t = 12.20$ ($g(\mu) = \mu^2$). In light of these results, we present the negative binomial as our preferred specification but also provide results of *OLS* and *Poisson* specifications for comparison.

5 The effect of rebates on solar panel adoption

We begin by focusing on installations near the PG&E and SCE boundary. Table 4 presents estimates of the effect of the rebate rate on PV installations under different specifications of Equation 1 in the 20-mile corridor sample. Columns 1, 2 and 3 assume common year effects for PG&E and SCE. Columns 4, 5 and 6 include utility by year interactions. We report standard errors clustered at the utility level to allow for the possibility of serial correlation. Column 6 is our preferred model.[30] Focusing on the negative binomial results, the coefficient on rebate rate in column 3 is estimated as 0.211 and is not statistically significant when common time effects are assumed. Including utility by year interactions in column 6, the point estimate on the rebate rate is 1.346 and is statistically significant ($p < 0.05$).[31] At the mean rebate level of $1.46 per Watt, this estimate implies that an

[29]Prices for installed PV systems depend on the fraction of the rebate passed through to consumers and therefore are likely correlated with rebate rates. Because we are primarily interested in the reduced form relationship between rebates and installations, we opt for fixed-effects that capture mean changes in prices and abstract from the specific relationship between installed prices and adoption. The reader is referred to Burr (2012) for an investigation of the relationship between system prices and adoption.

[30]A likelihood ratio test rejects the hypothesis that α=0 with a chi-squared statistic of 580.90, further suggesting the negative binomial model is preferred to Poisson regression.

[31]If instead we model time varying unobservables using utility by quarter of sample effects, the coefficient on rebate level is 1.32 with $p = 0.051$. If quadratic or cubic utility-specific time trends are used, the coefficient on rebate level is 1.15 with $p = 0.01$.

increase of $0.10 in the rebate rate corresponds to a 14.4 percent increase in the daily installation rate.[32] To get a sense for the size of the incentive change, a $0.10 increase in the rebate rate equals an increase in the total rebate awarded from $6,193 to $6,728 for the mean installation in this sample rated at 5.35 kW. Comparing across estimation strategies, the *OLS* and *Poisson* models produce mean effects of similar magnitudes. An increase in the rebate of $0.10 per Watt is associated with mean effects of 11.8 percent and 14.3 percent in the more flexible specification and 1.6 percent and 1.7 percent when assuming common time-effects.

The differences in estimates across columns 1-3 and 4-6 of Table 4 suggest that controlling for utility specific time varying factors is important. While our geographic discontinuity approach "holds constant" local unobserved factors affecting PV adoption, it would not control for utility specific trends. For example, if utilities or regional installers had marketing programs that publicized the CSI program or the benefits of solar, we may expect different adoption trends across IOUs.[33] Alternatively, changes to electricity prices or rate structures could drive differences in adoption behavior across IOUs over time.[34] Because there are a number of possible utility specific time varying factors that may affect PV adoption, our preferred specification includes utility by time effects. However, this raises another potential issue. With utility by year effects, identification of the relationship between rebates and adoption relies on within-year variation in rebates.

Given the installation behavior observed in Figures 4(a) and 4(b), one may worry that our results reflect short-term responses to changes in the rebate rate, *i.e.* shifting some installations ahead by a few weeks to take advantage of higher rebates, rather than a longer-run response to rebate levels. To investigate this issue, we reestimate Equation 1 excluding groups of observations near each change in the rebate level.[35] These results are shown in Table 5. Column 1 shows our previous estimate. Column 2 drops observations 2 weeks prior to and 2 weeks after each change in rebate level. Columns 3, 4 and 5 drop observations 4, 8 and 12 weeks before and after each change

[32] From Table 2, the average daily installation rate is approximately 0.70

[33] Conversations with a senior utility employee suggest that marketing strategies did vary substantially by utility and over time.

[34] If instead of utility specific year effects we add average annual electricity prices to the model with common time effects (column 3 of Table 4), the estimated coefficient on CSI rebates increases from 0.221 to 0.426 and is significant ($p < 0.10$). While average prices are likely a poor measure of the actual prices paid by solar adopters, this result suggests electricity prices may explain some of the difference between the results in columns 1-3 and those in columns 4-6.

[35] This approach is similar to the "Donut-RD" approach outlined by Barreca, Lindo, and Waddell (2011) for dealing with heaping in a regression discontinuity framework.

in rebate. We see that dropping weeks immediately before and after each rebate change results in somewhat larger estimates of the effect of the rebates of approximately 14.6 percent and 15.0 percent for a \$0.10 change in the rebate level. Excluding observations 8 weeks and 12 weeks before and after each change suggests slightly smaller estimates of 10.9 percent and 11.6 percent. These results seem consistent with the type of anticipatory behavior we observed in Figures 4(a) and 4(b). Overall, the relationship between rebates and adoptions seems fairly robust to the short-run effects around rebate changes.

One may worry that our use of utility daily level data may ask more of our identification strategy than is necessary. In particular, aggregation ignores potential spatial variation in solar preferences, such as those found by Millard-Ball (2012) and Kahn and Kok (2013). This creates the possibility of measurement error or that our results are driven by a few zip codes. As a robustness check, we estimate several specifications similar to Table 4 column 6 using zip code level data. These results are shown in Appendix Table 1. The estimated effects of rebates on installations are quite similar to the results above, even accounting for zip code level mean effects. An increase of \$0.10 per Watt corresponds to an increase in the daily adoption rate between 13.0 and 13.3 percent across models that include utility by year fixed effects, demographic and house characteristics, and zip code effects. Since these results are similar to our main results and because aggregation simplifies our calculations of overall program effects below, we proceed using utility-day as our unit of analysis.

Next we investigate whether the relationship between rebate rates and installations varies during our sample period. There are several reasons we might expect the relationship to vary over time. Consumers may respond differently to changes in the rebate rate when the level is relatively high or relatively low. For example, the population of potential adopters may be larger when the overall size of the incentive is greater. On the other hand, if environmental preferences grow over time or if there are peer effects, the population of potential adopters could be larger later in the sample despite the overall decline in rebate rates. In addition, larger potential federal tax credits after 2008 and the entry of third-party owned systems later in the sample may also change the effect of rebates on a adoption. To investigate these possibilities we divide our sample into three periods from 2007 through 2008, 2009 through 2010, and 2011 through October 2012. Recall from Figures 2(a) and 2(b) that average rebate rates drop from period to period, while average daily installation rates increase. To allow for changes in behavior over time, we interact rebate rates with an indicator variable for each two-year period. Table 6 shows the results of this exercise. The point estimates vary from 1.826 early in the sample to 0.835 in the period from 2011 through 2012. The average percentage increase in adoptions due to a \$0.10 increase in the rebate rate is 20 percent in the early period and decreases to approximately 8.7 percent late in the sample. To understand whether this decline is due to a smaller predicted increase in the number of installations or a greater overall daily installation rate we also report the estimated increase in installations in levels. Here, we see that while a \$0.10 increase in rebates in 2007 and 2008 translates to approximately 0.07 more installations per day. In the later periods, the effect is approximately 0.11 suggesting that the decline in the installation semi-elasticity is due to higher daily installation rates later in the sample. Overall, these results suggest a relatively larger number of potential solar adopters at the end of the period despite lower rebate levels.

Turning to our choice of the 20-mile corridor as our preferred sample, Table 7 presents estimates of the relationship between rebates and daily installation for several different samples. Column 1 includes all zip codes within the PG&E and SCE territories. Column 2 includes zip codes within a 40-mile corridor along the boundary and column 3 is the 20-mile sample. Column 4 uses only those zip codes transected by the boundary. In each case, the total number of installations per day is calculated as the sum of installations by utility for zip codes that meet the criteria above. Intuitively, allowing more of the installations to occur away from the boundary increases the likelihood that rebate levels are responding to unobserved trends in PV adoption and are therefore endogenous. On the other hand, exploring a larger geographic area can highlight whether the effects estimated in Table 4 are unique to the boundary region or generalize to the larger population of PG&E and SCE ratepayers.

Looking across the different samples, the point estimates are surprisingly similar. This suggests that in percentage terms, the average effect of increasing rebates is similar regardless of sample. We interpret this result as evidence that, conditional on controlling for utility specific time varying factors, the geographic discontinuity approach provides little additional benefit in accounting for unobserved factors that affect adoption. This has two implications. First, there may be remaining unobserved factors that do matter, meaning that changes in the rebate rate are endogenous. For example, environmental preferences that vary over time but are correlated across each utility's territory. In this case, our estimates of the effect of changes in the rebate can be viewed as lower bounds of the true effect. Second, with the caveat that there may be some remaining bias, the similarity of our estimates across the different samples suggests that the our results may generalize more broadly to all of PG&E and SCE.

To investigate the overall impact of the CSI we would like to use data on all installations from each of the three participating IOUs. Column 5 shows the estimated relationship between rebates and installation rates using data from all zip codes and all three utilities. We see that the point estimate is somewhat smaller at 1.223 suggesting that a $0.10 increase in the mean rebate level implies a 13.0 percent increase in daily installations. Comparing with the 20-mile sample, here a $0.10 increase in the rebate rate equals an increase in the total rebate awarded from $5,600 to $6,070 for the mean installation in this sample rated at 4.60 kW. However, since the percentage effects are quite similar to those in the various PG&E and SCE samples, we use the estimates from all three IOUs in our calculations of the overall program impacts.

Finally, we relax our assumption that rebates have the same effect on adoptions across the three IOUs. We estimate the average effect of rebate rates on daily installations by interacting an indicator variable for each utility with the rebate rate. Table 8 summarize the point estimates and the average effects associated with a $0.10 increase in the rebate rate. We see that the effects are fairly similar across IOUs. For SCE and SDG&E, a $0.10 increase in the rebate rate is associated with a 11.8 percent to 12.2 percent increase in the average daily installation rate. The estimated effect is somewhat larger for PG&E at approximately 15.2 percent. We find the similarity across IOUs reassuring and adopt the more parsimonious specification assuming equal effects across utilities in our calculations of the overall program impacts below.

6 Overall impacts of the California Solar Initiative

Given consumer responses to CSI rebates estimated above, we would like to understand the overall effects of the program along several dimensions. Specifically, we are interested in how many installations the CSI generated, what environmental benefits the program conferred and at what cost. We begin by estimating the total number of installations created. While understanding short-run inter-temporal substitution is important for isolating the effect of rebate changes on adoptions, in the context of evaluating the overall impacts of the CSI this behavior is arguably less important than in the automobile policies studied by Sallee (2011) and Mian and Sufi (2012). Here, because of the large number of rebate changes, adoptions shifted forward in time to take advantage of higher rebates are in a sense borrowed from a later time period and would have still occurred under the program, albeit several weeks later. Therefore, we ignore these effects when calculating the overall impacts of the CSI. To predict the total number of installations under the CSI program we use the parameter estimates from the sample including all three IOUs, *i.e.* column 5 of Table 7. We then compare the predicted number of installations with a counterfactual prediction assuming no rebates. In each case, we generate the predicted number of installations (*i.e.* $\hat{I}_{u,t} = exp(X_{u,t}\beta)$) assuming either the actual CSI rebate or zero rebate then sum over all utilities and all prior periods to calculate the total number of installations to date. Figure 5 shows the results of this exercise where cumulative installations are plotted over time using actual installations, predicted installations under the CSI rebate levels and predicted installations without rebates. Predicted installations follow the actual CSI installations quite closely, beginning with zero in 2007 and growing to approximately 99,000 total installations by October 2012. The counterfactual case assuming no rebates illustrates the large effect of the CSI on installations. Here, the overall growth in installations is much more modest, reaching a maximum of approximately 41,000 installations by October 2012. This suggests that the effect of CSI was quite large, resulting in over 57,000 additional installations or approximately 58 percent of total installations.

These results suggest substantial increases in private surplus due to a greater number of adoptions and subsidy payments for installations that would have occurred without rebates. For inframarginal installations, the CSI generates pure rents that given the size of the rebates awarded may be substantial. However, estimating the welfare effects of the CSI is difficult without knowing the nature of competition in the installation market and the underlying marginal cost and demand curves. To learn something about costs and benefits from the CSI we make the following assumptions. We define private surplus as the sum of consumer and producer surplus. Social surplus is defined as private surplus net of subsidy payments. We estimate the change in private surplus under the CSI by assuming the predicted number of installations with and without rebates fall on the same demand curve.[36] We assume linear demand between these points. In addition, we assume that installers are price takers and marginal costs are linear. While these assumptions are admittedly restrictive, to a first approximation, they allow us to estimate the changes in private and

[36]Recall that predicted installations are based on our empirical model using a full set of utility by time effects. Here we assume these effects capture changing preferences for solar, peer effects, marketing, mean electricity prices and other potential demand shifters.

social surplus under the CSI using only subsidy levels and changes in the number of installations due to rebates. This approach seems reasonable given the limitations of our data, however, several qualifications are warranted. First, the true surplus changes depend on the shapes of demand and marginal costs, which are unlikely to be linear. Second, if there is market power in the installation market, CSI subsidies may act to reduce deadweight loss from market power. In this case, our calculations would overstate the social cost of the CSI.[37] Finally, our assumptions above also imply the incidence of the subsidy can fall on consumers, installers or can be shared between the two. For example, with constant marginal costs the subsidy is fully passed on to consumers and the change in installers' producer surplus under the CSI is zero. With upward sloping marginal costs the change in private surplus is shared between consumers and installers. We remain agnostic as to the distribution of private gains under the CSI program.

Figure 6 illustrates the welfare effects of CSI subsidies under the assumptions above. The left-hand side shows the constant marginal cost case. CSI subsidies increase the number of installations from Q_o to Q_s. Total rebate payments are represented by the sum of areas A, B and C. Consumer surplus increases by $A + B$ and the change in producer surplus is zero such that the total increase in private surplus is $A + B$. Rents to inframarginal installations are equal to Area A.[38] To understand the overall impacts of the CSI, we define the change in social surplus as the change in private surplus net of rebate payments, here shown as Area C. This term can be thought of as an overall measure of the social cost of the program.[39] The case of upward sloped marginal costs is shown at the right of Figure 6. Here again total adoptions increase from Q_o to Q_s with CSI subsidies. Total rebate payments are represented by the area $a + b + c + d + e + f + g$ which is equal to area $A + B + C$. With rebates, consumer surplus increases by $a + b + g$ including rents of $a + g$ to inframarginal installations. Producer surplus increases by $d + e + f$ including rents $e + f$ to inframarginal installations. Overall, private surplus increases by $a + b + d + e + f + g$ and social surplus decreases by area c. Under the assumptions above, the changes in private and social surplus are equivalent regardless of whether marginal costs are constant or increasing. Therefore,

[37] Even assuming constant markups, estimating changes in social and private surplus with market power would require additional assumptions about the shapes of marginal cost and demand.

[38] As noted by Boomhower and Davis (2013), these transfers are pure rents only if raising rebate dollars is costless. Below we consider the possibility that funding the CSI creates additional deadweight loss.

[39] If other social costs such as environmental externalities are ignored, the change in social surplus is deadweight loss. Of course, the CSI program may reduce externalities and other social costs. We address the potential benefits of the CSI below.

we remain agnostic to the incidence of the subsidy and instead focus on the overall changes in social and private surplus.[40]

A final issue relates to the possibility that the financing of CSI rebates creates additional distortions in the residential electricity market. The CSI program is funded by a surcharge on electricity consumption for the three participating IOUs. Higher prices and lower electricity consumption under the surcharge, which result in deadweight losses, would impact the overall welfare effects of the program. Unfortunately, we lack detailed data on electricity consumption and because the CSI surcharge is bundled as part of a distribution surcharge, the CSI fee is unobserved. To get a sense for the magnitude of deadweight loss, we estimate the surcharge amount by dividing total rebate payments by estimated residential electricity consumption for the three IOUs. We assume the surcharge is fully passed through to ratepayers and calculate the implied change in electricity consumption using an elasticity of 0.39 (Reiss and White, 2005). This suggests a deadweight loss of approximately \$3.4 million. Since this effect appears small and because we lack precise estimates, we ignore the cost of raising CSI funds in the welfare calculations below.

We calculate the change in private surplus due to CSI rebates for each day in our sample and aggregate over the entire period from 2007 to 2012.[41] These calculations are summarized in Table 9. Overall, approximately \$437 million in rebates are awarded. Private surplus increases by approximately \$268 million including \$98 million in rents to inframarginal installations.[42] To calculate the change in social surplus under the CSI we subtract total subsidy payments from the change in private surplus. Social surplus decreases by \$169 million reflecting the overall cost of reallocating subsidy dollars from ratepayers to solar installations.

Because we have not gone to the same lengths to investigate whether rebate rates in SDG&E can be treated as exogenous, we repeat these calculations excluding installations from SDG&E. The number of installations with and without rebates are predicted using the parameter estimates from column 1 in Table 7. The overall effects are summarized on the righthand side of Table 9. We see that excluding SDG&E leads to qualitatively similar results. The CSI rebates generate approx-

[40] Estimating pass through of CSI rebates is beyond the scope of this work.

[41] We estimate the total rebate amount awarded and the change in effective price on each day by multiplying the CSI rebate rate by average system size in the month when the installation occurred.

[42] That inframarginal installations represent 42 percent of adoptions yet receive only \$98 million or 22 percent of subsidies reflects the fact that these installations represent a larger share of adoptions later in the sample when rebate levels are lower.

imately 61 percent of installations during this period. Total subsidy payments are approximately \$392 million and lead to an increase in private surplus of approximately \$235 million including \$78 million in rents for inframarginal installations. The total decrease in social surplus is approximately \$157 million.

One of the main justifications for incentivizing solar is that additional PV capacity lowers emissions associated with electricity generation. We use the predictions above to estimate reductions in CO_2 and NOx emissions due to the CSI. To do this we assume that none of the additional installations under the CSI would have occurred otherwise at some point in the future. That is to say, the rebates create new adopters and don't simply result in the temporal shifting of future adoptions to the present. This assumption is conservative in the sense that it creates the largest possible benefit for the CSI. For simplicity, we assume PV systems have a 20-year system life and ignore discounting.[43] We assume a PV capacity factor of 0.18 and use two scenarios for the emissions of electricity generation displaced by solar installations.[44] In the first scenario we use average CO_2 and NOx emissions rates for electricity generation. In the second scenario, we note that the solar generation profile is more likely to coincide with periods of peak electricity demand (Borenstein, 2008). We also use two sources for average and marginal emissions rates. Graff Zivin, Kotchen, and Mansur (2013) derive emission rates for the Western interconnection (WECC) using the US EPA's continuous emissions monitoring data for fossil-fuel electricity generating plants. To approximate the peak period, we average the Graff Zivin, Kotchen, and Mansur (2013) estimates over the period from 10am to 4pm.[45] Second, because WECC as a whole may be dirtier than California, we use California average emissions rates from eGRID (2009). We approximate peak emissions using annual "non-baseload" emissions rates.

Results of these calculations are summarized at the bottom of Table 9. Total solar capacity increases by approximately 260 MW. At the average emissions rate, total emissions savings are approximately 2.98 MMT CO_2 using the WECC rate and 2.45 MMT CO_2 using the California

[43]The assumption of zero discounting is conservative given that it weighs equally system costs, incentives and benefits that accrue over many years of operation and treats equally carbon emissions reductions today and at the end of the system's life. Overall these assumptions are intentionally "generous" to the program in that they result in lower average abatement costs.

[44]We follow PG&E in assuming an 18 percent capacity factor for PV systems http://www.pge.com/about/environment/calculator/assumptions.shtm.

[45]Specifically, for CO_2 we use average and peak rates of 0.36 and 0.38 MT per MWh (WECC) and 0.30 and 0.45 MT per MWh (California). For NOx we use average and peak rates of 0.50 and 0.42 lb. per MWh (WECC) and 0.42 and 0.32 lb. per MWh (California).

average. Assuming solar displaces primarily peak generation, the estimated CO_2 emissions savings range from 3.15 MMT to 3.70 MMT. As before, the righthand side of Table 9 summarizes results when installations in SDG&E are excluded. In this case, estimated emissions reductions are between 2.26 and 3.41 MMT CO_2. To get a sense for the size of these emissions reductions, the 260 MW of solar electricity capacity times the assumed capacity factor translates into approximately 50 MW in effective capacity. The emissions rates we use here closely represent natural gas generators in California. Since gas fired plants in California range in size from several MW to several hundred MW, with median size of about 20 MW, these emissions reductions are comparable to removing a small to mid-sized gas plant. Arguably, these savings are modest but still non-trivial.

In terms of costs, a common measure of cost-effectiveness is program cost, here subsidy payments, per unit of abatement. Table 9 shows that average program costs range from \$139 per MT to \$147 per MT CO_2 assuming WECC emissions and \$118 per MT to \$178 per MT CO_2 using California values. However, this calculation ignores the benefits of rebates to consumers and installers. Instead we use average abatement cost, defined as the total change in social surplus divided by the total change in CO_2 emissions, as our measure of the economic cost of carbon reductions under the CSI. Average abatement costs in Table 9 range from approximately \$54 per MT to \$57 per MT (WECC) and \$46 per MT to \$69 per MT (California). In comparison, the Interagency Working Group on Social Cost of Carbon, United States Government (2013) estimates the social cost of CO_2 under a variety of assumptions. Their mean values for 2010 range from \$11 to \$52 per MT depending on the social discount rate. This suggests that the costs of CO_2 abatement under the CSI may exceed the benefits of lower emissions.[46]

For NOx, the total estimated emissions savings over 20 years range from 1,195 to 1,866 MT for all three IOUs depending on our assumption about the emissions rate of generation displaced by solar. When installations in SDG&E are excluded, emissions savings range from 1,100 to 1,718 MT. Across the scenarios, average abatement costs range from \$91,000 and \$142,000 per ton of NOx. These costs are quite high. During the California electricity crisis, permit prices under Southern California's NOx trading program peaked at \$62,500 per ton. After the crisis, permit prices ranged between \$2,000 and \$3,000 per ton (Fowlie, Holland, and Mansur, 2012). This suggests NOx abatement

[46]Interestingly, even if the displaced electricity had the emissions rates of peak ERCOT or Eastern interconnection estimates (Graff Zivin, Kotchen, and Mansur, 2013), average abatement costs would still be approximately \$49 and \$37 per MT, respectively.

costs under the CSI are substantially higher than abatement costs for other technologies. Similarly, abatement costs exceed NOx damages, around $200 per ton, according to recent estimates by Muller and Mendelsohn (2009).[47] Of course, these high abatement costs in part reflect the relatively clean electricity displaced by solar installations in California. Residential PV would have a larger effect on NOx emissions in places like the US Midwest where peak NOx emissions rates can be 5 to 10 times larger. Holding constant electricity generation and using an emissions rate 10 times larger than our California peak estimate still suggests costs on the order of $10,000 per ton.[48]

Some qualification of the results above is warranted. First, the calculations above can be thought of as a near-term analysis that holds fixed factors such as load, generation and the configuration of the electricity grid. Second, additional solar generation capacity may create other benefits such as reduced grid congestion, improvements in air quality and lower marginal generation costs. Here we abstract from these other potential benefits and instead focus on CO_2 and NOx costs to allow the reader to compare the CSI with other programs to reduce emissions.[49] Third, we ignore the possibility of peer effects such as those documented by Bollinger and Gillingham (2012) which may amplify or diminish the effect of rebates. Fourth and perhaps most important, some proponents of solar subsidies argue that incentives are justified due to learning economies. Our counterfactual above assumes learning is negligible and therefore would underestimate the overall effect of the CSI on adoptions if learning effects are large.

While estimating the effect of learning is beyond the scope of this paper, we provide the following evidence that our assumption of little learning is justified. First, learning implies a reduction in marginal costs as the industry streamlines production and installation processes. In terms of materials, over 50 percent of the final installed cost of a system is due to modules and other components for which prices have fallen considerably over the past decade.[50] However, the market for these components is global, and learning likely depends primarily on total experience. California PV adoptions, particularly installations attributable to the CSI program, account for only a small percentage of the global PV market. As of 2012, approximately 100 GW of PV capacity had been

[47]We use the median across California counties as reported in Appendix B of Muller and Mendelsohn (2009).

[48]This calculation is optimistic as these locations may also have less solar generation potential than California.

[49]For a more thorough discussion of these issues we refer the reader to Borenstein (2008) and Baker et al. (2013).

[50]The Solar Energy Industries Association reports a 60 percent decrease in average solar panel prices between 2011 and 2012, http://www.seia.org/research-resources/solar-industry-data

installed worldwide,[51] of which about 0.5 GW had been installed in our study area with only 0.3 GW attributable to the CSI. Given that the CSI accounted for less than half a percent of the worldwide PV market, any learning effects of the CSI on lowering component costs are likely small. Moreover, recent studies by Nemet (2006) and Papineau (2006) find little evidence for learning in module costs.

Learning could also bring down labor and overhead costs associated with installation which account for approximately 25 percent of installed system cost.[52] Baker et al. (2013) summarize recent estimates of learning-by-doing in the PV market and find learning rates of approximately 20 percent. This implies that a doubling of cumulative installed capacity, a proxy for experience, results in a 20 percent decrease in costs. Given our finding that the CSI roughly doubled adoptions during our study period, a 20 percent learning rate implies a 20 percent decrease in labor and overhead costs through learning. Since these costs contribute roughly 25 percent to final system prices, this translates to a 5 percent decrease in system price due to learning. In short, the incremental effect due to the CSI on prices appears small relative to the approximately 33 percent decrease in installed prices we observe over our study period.

7 Conclusions

The goal of this paper is to understand the effect of upfront subsidies on residential solar PV adoption. Because subsides are a common tool used by policy makers, quantifying consumer responses has implications for policies to promote solar and a variety of other green technologies. We explore this question in the context of the California Solar Initiative (CSI), a large and popular cash subsidy program aimed at increasing PV adoption. We focus on residential rebates under the CSI between 2007 and 2012. Across a variety of specifications we find that a $0.10 per Watt or approximately $400 to $500 increase in the rebate is associated with an 11 to 15 percent increase in the average installation rate. Our preferred estimates suggest that without rebates 57,000 or 58 percent fewer

[51] According to the firm GlobalData, 98 GW of PV capacity were installed worldwide as of 2012, http://www.pv-magazine.com/news/details/beitrag/330-gw-of-global-pv-capacity-predicted-by-2020_100010123/#axzz2OKMJuYHI

[52] An NREL presentation by Woodhouse et al in 2011 reports an average price of $5.71 per Watt for residential PV systems, of which $0.60 is for electrical labor, $2.15 for modules, $0.42 for inverters, $0.46 for BOS materials, $1.40 for installer overhead, labor and profit, and the remainder for permitting taxes and miscellaneous. Assuming 10 percent profit for simplicity, this implies installer labor and overhead account for $0.83. Together, all labor and overhead costs account for $1.43 or 25 percent of total installed cost. See http://www.nrel.gov/docs/fy11osti/52311.pdf

installations would have occurred during this period.

To understand the overall impacts of the program we estimate changes in emissions and private surplus under the CSI in a series of back of the envelope calculations. We find that benefits to consumers and installers appear large. Of the approximately $437 million in rebates paid during this period, private surplus gains to installers and adopters are approximately $268 million. Because subsidies for green technologies are often motivated by energy or environmental goals, we estimate the overall increase in PV capacity and reduction in CO_2 emissions under the program. We find that solar capacity increases by approximately 260 MW relative to a counterfactual assuming no rebates. Emissions of CO_2 are between 2.98 million MT and 3.15 million MT lower due to the program. Similarly, we predict NOx emissions over 20 years fall between 1,100 and 1,900 MT. However, these emissions reductions are costly. Comparing the estimated change in social surplus to emissions reductions suggests average abatement costs between $46 per MT to $69 per MT CO_2 and $91,000 and $142,000 per MT of NOx.

In terms of program design, a key feature of the CSI is the declining schedule of rebates over time. This appears to have been motivated by the expectation that PV system prices would fall, potentially leading to a larger market for solar systems later in program. Our results in Table 6 provide some evidence consistent with this idea, namely that changes in rebates later in the sample appear to have a larger effect on average daily installation rates in levels. Whether this is the effect of lower prices, third party installers, federal tax credits, stronger environmental preferences or more familiarity with solar technology remains an open question. Nevertheless, this design feature may have reduced the overall cost of the program by allowing CSI to pay lower rebates later in the program.

To explore this issue we compare total rebate payments under the CSI with a constant rebate designed to produce the same total number of installations. Using our three period model, the rebate required to achieve the same total number of installations is approximately $0.71 per Watt. At this level, the overall expenditure on rebates would have been $329 million compared with $437 under the actual program. In hindsight, the CSI may have achieved similar results with a constant rebate for over $100 million less. That said, the declining rebate schedule did have the advantage of reducing year-to-year variation in rebate payments, which may have simplified planning and administration. Because fewer installations took place during the early (late) years when rebate rates were high (low), annual rebates awarded ranged between \$60 and \$100 million compared with \$2 to \$175 in our constant rebate case. Of course, another potential advantage of the CSI declining rebate schedule over constant rebates is that more adoptions were encouraged early in the program. This feature may have helped support early installers through an initial period of high system prices and low demand.

The popularity of the CSI program could in part be due to the large increases in private surplus we estimate. It appears that both consumers and installers gained substantially under the program. In particular, benefits were large for inframarginal installations that would have occurred absent rebates. This feature appears to be a common characteristic of subsidy programs for green technologies. Chandra, Gulati, and Kandlikar (2010) and Boomhower and Davis (2013) similarly find that a large number of consumers of hybrid vehicles and energy efficient appliances would have purchased these goods absent rebates.

Overall, we find that the CSI program had a large affect on adoption of residential PV systems in California. To the extent that increased production of renewable energy is a goal for policy makers, PV subsidies could play a role in reaching this goal. That said, our calculations suggest emissions reductions from new solar installations are modest and the costs of increasing adoption are large.

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8 Figures

Figure 1: Total CSI residential PV installations and population density by zip code.

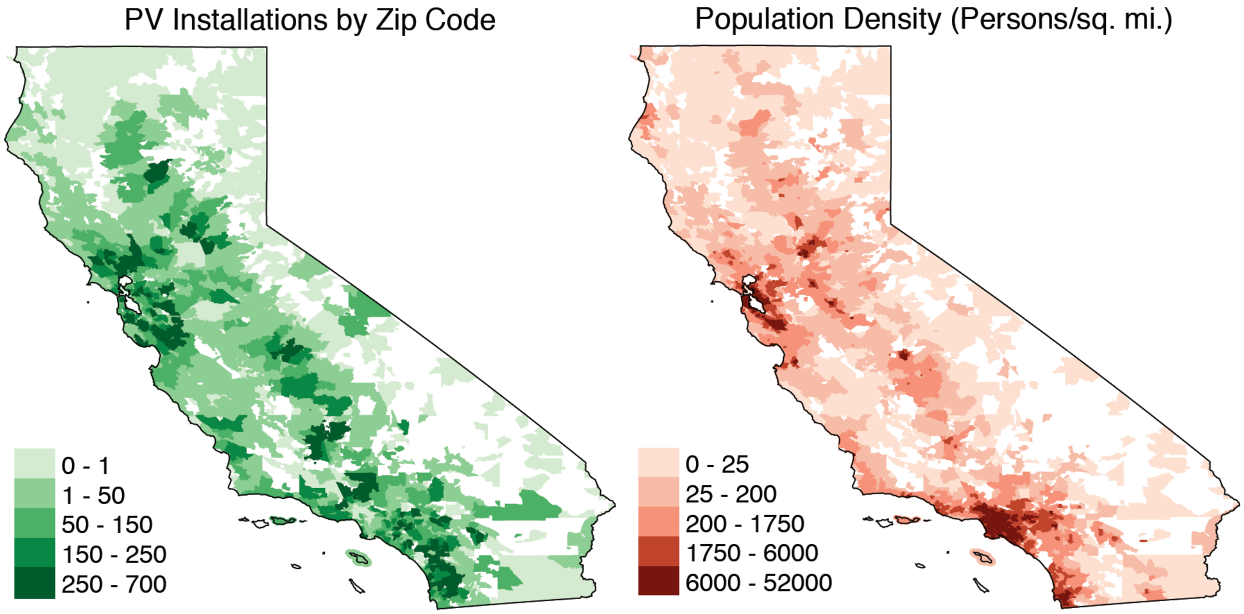
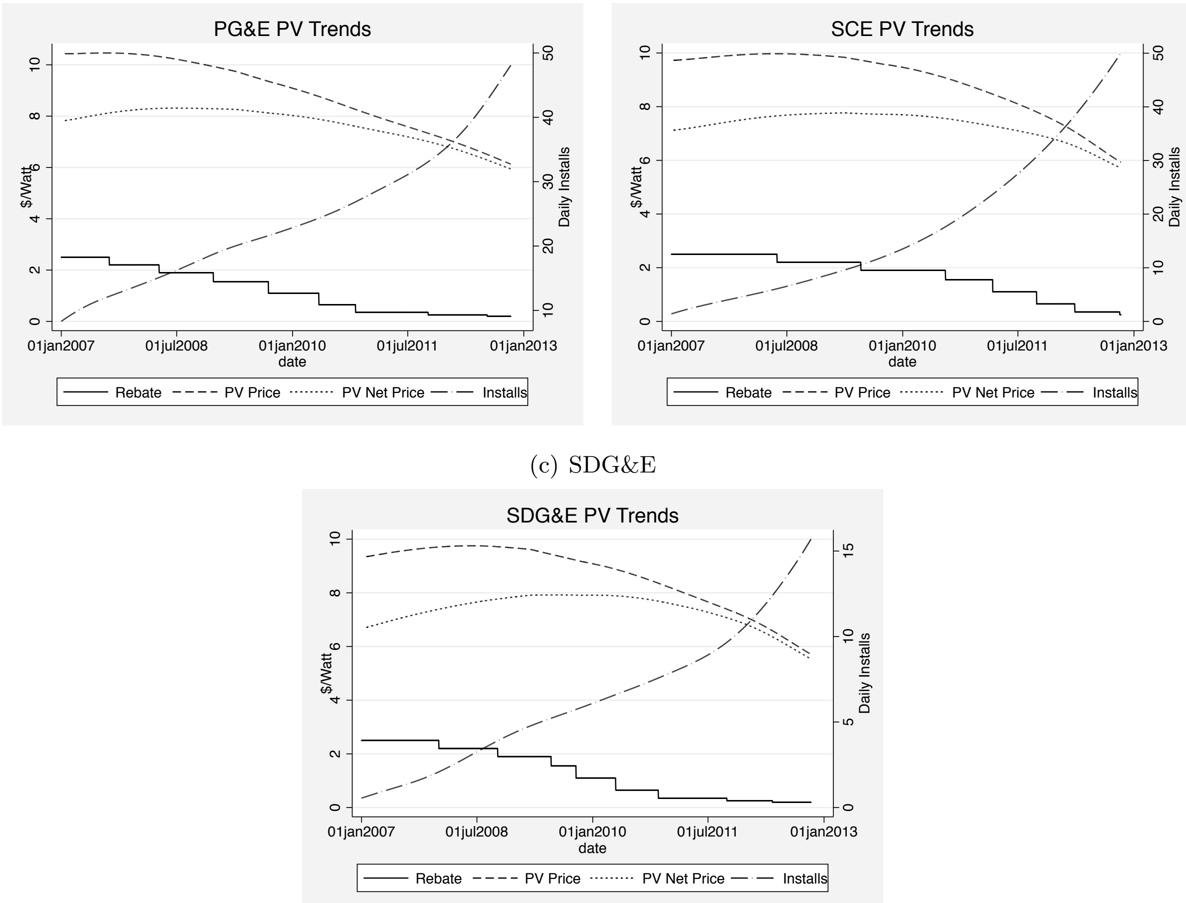


Figure 2: Average rebates, system prices and installations for Pacific Gas and Electric (PG&E), Southern California Edison (SCE) and San Diego Gas and Electric (SDG&E).



(a) PG&E

(b) SCE

(c) SDG&E

Figure 3: Map of PG&E, SCE and SDG&E territories and the PG&E-SCE boundary region. Zip codes included in the 20-mile buffer sample are darkly shaded in the righthand figure.

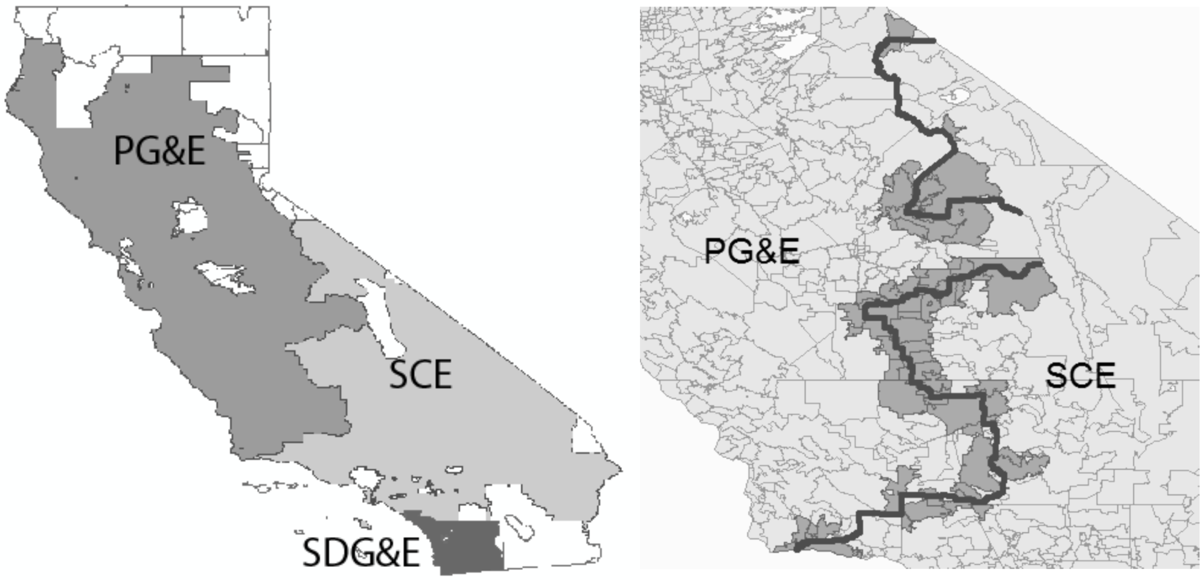
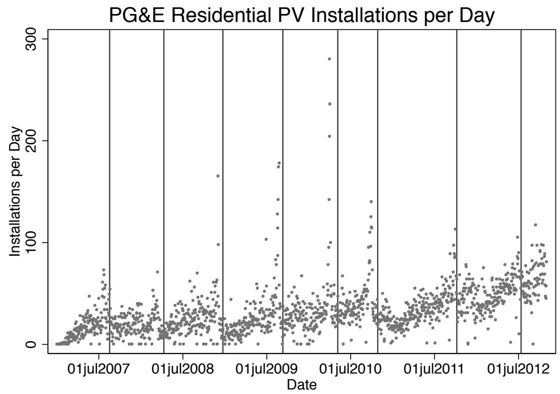
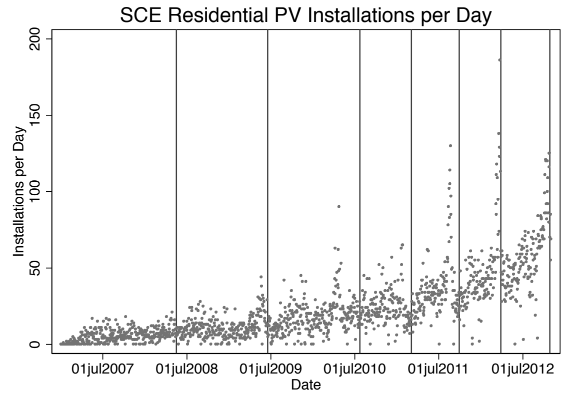


Figure 4: Total installations per day for Pacific Gas and Electric (PG&E), Southern California Edison (SCE) and San Diego Gas and Electric (SDG&E).

(a) PG&E



(b) SCE



(c) SDG&E

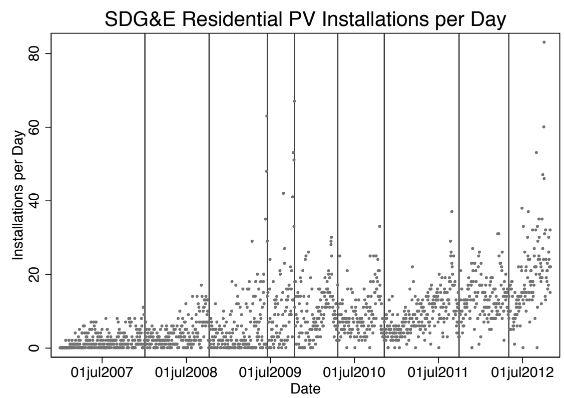


Figure 5: Predicted total PV installations and counterfactual installations assuming no CSI program rebates.

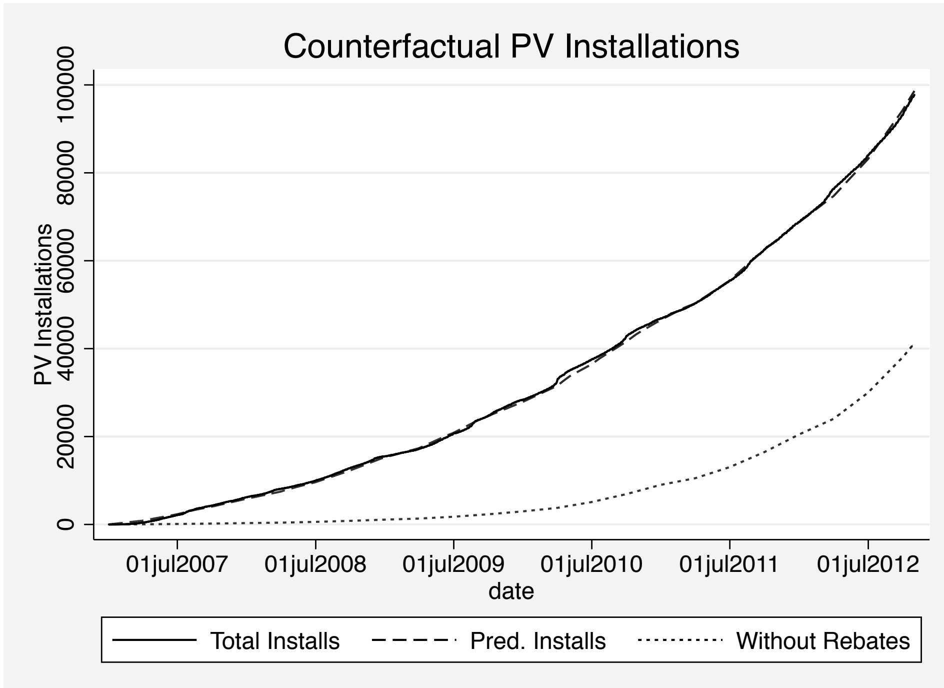
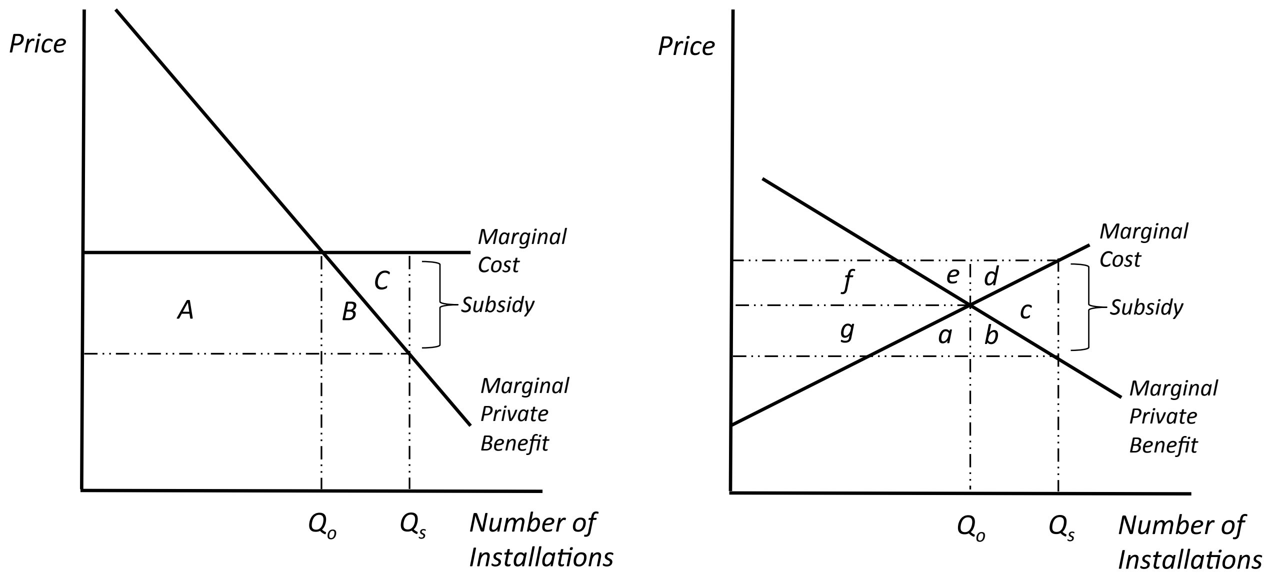


Figure 6: Welfare effects of CSI program rebates in terms of changes in private and social surplus.



9 Tables

Table 1: CSI rebate rate schedule for EPBB program by utility.

Step	Rebate Rate ($/W)	Total Capacity (MW)	PG&E Capacity (MW)	SCE Capacity (MW)	SDG&E Capacity (MW)
1	n/a	50	0.0	0.1	0.0
2	$2.50	70	10.1	10.6	2.4
3	$2.20	100	14.4	15.2	3.4
4	$1.90	130	18.7	19.7	4.4
5	$1.55	160	23.1	24.3	5.4
6	$1.10	190	27.4	28.8	6.5
7	$0.65	215	31.0	32.6	7.3
8	$0.35	250	36.1	38.0	8.5
9	$0.25	285	41.1	43.3	9.7
10	$0.20	350	50.5	53.1	11.9

Notes: Adapted from CSI Statewide Trigger Tracker at http://www.csi-trigger.com/

Table 2: Summary statistics for the full sample and the 20-mile corridor.

	Mean	Std. Dev.	Max.	Min.
	Full Sample			
PG&E				
total rebate ($)	4,002	4,950	137,895	53
rebate rate ($/W)	1.21	0.82	2.50	0.20
total system cost ($)	36,474	24,925	1,028,017	0
CSI rating (kW)	4.46	2.82	71.55	0.27
installation rate (num./day)	23.40	24.57	280.00	0.00
total installations	49,866			
SCE				
total rebate ($)	5,291	5,069	137,216	252
rebate rate ($/W)	1.72	0.72	2.50	0.25
total system cost ($)	37,377	21,109	483,784	0
CSI rating (kW)	4.77	2.67	54.88	0.72
installation rate (num./day)	16.39	21.11	186.00	0.00
total installations	34,925			
SDG&E				
total rebate ($)	3,612	4,382	106,240	201
rebate rate ($/W)	1.28	0.89	2.50	0.20
total system cost ($)	35,864	20,256	396,560	1,400
CSI rating (kW)	4.72	2.74	48.29	0.80
installation rate (num./day)	6.07	7.92	83.00	0.00
total installations	12,939			
	20-mile corridor			
PG&E				
total rebate ($)	4,572	4,925	40,710	349
rebate rate ($/W)	1.21	0.82	2.50	0.20
total system cost ($)	42,990	23,211	191,787	4,898
CSI rating (kW)	5.68	2.94	28.51	1.02
installation rate (num./day)	0.56	1.03	8.00	0.00
total installations	1,192			
SCE				
total rebate ($)	6,175	5,537	63,954	383
rebate rate ($/W)	1.72	0.72	2.50	0.25
total system cost ($)	39,224	21,844	226,781	3,000
CSI rating (kW)	5.19	2.79	34.14	0.97
installation rate (num./day)	0.85	1.40	11.00	0.00
total installations	1,804			

Table 3: Observable household characteristics by geographic region.

Differences in Zip Code Means of Observable Demographics and House Characteristics Across Utilities

		Population	% White	HH Income	% Family	% Own. Occ.	Rooms	Year Built
full sample								
	PG&E	35,271	0.63	54,384	0.71	0.59	5.08	1970.4
	SCE	45,607	0.57	49,112	0.76	0.57	4.86	1968.8
	Difference	-10,336***	0.07***	5,273***	-0.05***	0.02	0.21***	1.56
40 mi. buffer								
	PG&E	34,789	0.61	38,060	0.78	0.57	4.99	1973.5
	SCE	28,750	0.66	40,671	0.73	0.55	4.81	1956.4
	Difference	6,039*	-0.06*	-2,611	0.05***	0.03	0.18	17.10
20 mi. buffer								
	PG&E	31,496	0.61	36,509	0.77	0.55	4.85	1973.5
	SCE	33,382	0.66	39,437	0.75	0.57	4.94	1972.8
	Difference	-1,886	-0.05*	-2,927	0.02*	-0.02	-0.09	0.70

Notes: Reported observables are populated weighted means of zip code average values. Test statistics for differences in means are from a populated weighted regression where standard errors are clustered at the zipcode level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels respectively.

Table 4: Effect of California Solar Initiative (CSI) rebate rates on the daily PV installation rate near the PG&E and SCE boundary.

Models for Average Daily Installation Rates in 20 Mile Region						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	OLS	**Poisson**	**Neg. Binomial**	**OLS**	**Poisson**	**Neg. Binomial**
Rebate rate ($/W)	0.116	0.170***	0.211	0.829	1.337**	1.346**
	(0.1520)	(0.0540)	(0.1740)	(0.4210)	(0.6060)	(0.6550)
Confidence interval (95%)	[-1.817,2.049]	[0.065,0.275]	[-0.131,0.552]	[-4.518,6.176]	[0.149,2.525]	[0.061,2.630]
% change in install rate	1.6%	1.7%	2.1%	11.8%	14.3%	14.4%
Year Effects	Yes	Yes	Yes	No	No	No
Quarter Effects	Yes	Yes	Yes	Yes	Yes	Yes
Utility Effects	Yes	Yes	Yes	No	No	No
Year*Utility Effects	No	No	No	Yes	Yes	Yes
Observations	4262	4262	4262	4262	4262	4262

Notes: Dependent variables are the total daily PV installation rates in number per day by utility for zipcodes within 20 mile buffer. Percentage change in installation rate calculated for a $0.10 increase in the rebate rate at the mean values of independent variables. Standard errors clustered at the utility level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Table 5: Robustness to excluding periods near rebate step changes for installations in the 20 mile region near the PG&E and SCE boundary.

Robustness to Excluding Observations Near Rebate Change Dates

	(1) Base	(2) 2 wk.	(3) 4 wk.	(4) 8 wk.	(5) 12 wk.
Rebate rate ($/W)	1.346**	1.361**	1.401**	1.034***	1.095**
	(0.6550)	(0.6270)	(0.6320)	(0.3160)	(0.4280)
Confidence interval (95%)	[0.061,2.630]	[0.133,2.589]	[0.163,2.640]	[0.415,1.652]	[0.257,1.933]
% change in install rate	14.4%	14.6%	15.0%	10.9%	11.6%
Year Effects	No	No	No	No	No
Quarter Effects	Yes	Yes	Yes	Yes	Yes
Utility Effects	No	No	No	No	No
Year*Utility Effects	Yes	Yes	Yes	Yes	Yes
Observations	4262	3865	3459	2647	1835

Notes: Dependent variables are the total daily PV installation rates in number per day by utility for zipcodes within 20 mile buffer. Base model includes all observations. "2 week," "4 week," "8 week," and "12 week" models drop observations within 2, 4, 8, and 12 weeks of each change in rebate level. Percentage change in installation rate calculated for a $0.10 increase in the rebate rate at the mean values of independent variables. Standard errors clustered at the utility level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Table 6: Effect of California Solar Initiative (CSI) rebate rates on the daily PV installation rate near the PG&E and SCE boundary during different sample periods.

Average Daily Installation Rates in 20 Mile Region by Period

	2007-2008	**2009-2010**	**2011-2012**
Rebate rate ($/W)	1.826***	1.720***	0.835***
	(0.4230)	(0.3460)	(0.2370)
Confidence interval (95%)	[0.997,2.655]	[1.043,2.398]	[0.370,1.300]
% change in install rate	20.0%	18.8%	8.7%
Level Change in install rate	0.067	0.112	0.106
Year Effects	No	No	No
Quarter Effects	Yes	Yes	Yes
Utility Effects	No	No	No
Year*Utility Effects	Yes	Yes	Yes
Observations	4262	4262	4262

Notes: Dependent variables are the total daily PV installation rates in number per day by utility for zipcodes within 20 mile buffer. Percentage change in installation rate calculated for a $0.10 increase in the rebate rate. Standard errors clustered at the utility level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Table 7: Robustness of main results across different geographic samples.

Robustness to Different Geographic Samples	(1) All PG&E and SCE Zip Codes	(2) 40 mi.	(3) 20 mi.	(4) Split Zip Codes	(5) All IOUs
Rebate rate ($/W)	1.321***	1.306***	1.346**	1.283*	1.223***
	(0.2070)	(0.3850)	(0.6550)	(0.7600)	(0.1430)
Confidence interval (95%)	[0.914,1.727]	[0.551,2.060]	[0.061,2.630]	[-0.206,2.771]	[0.942,1.504]
% change in install rate	14.1%	14.0%	14.4%	13.7%	13.0%
Quarter = 2	0.571***	0.610***	0.649***	0.611***	0.517***
	(0.0120)	(0.0620)	(0.0880)	(0.1240)	(0.0530)
Quarter = 3	0.890***	0.881***	1.003***	0.990***	0.814***
	-0.08	-0.109	-0.131	-0.139	-0.087
Quarter = 4	1.013***	0.950***	1.078***	1.010***	0.976***
	(0.0210)	(0.1020)	(0.1690)	(0.1770)	(0.0320)
Year = 2008	0.998***	0.665***	0.593***	0.620***	1.148***
	-0.04	-0.084	-0.142	-0.164	-0.05
Year = 2009	1.761***	1.209***	1.095***	1.243***	2.684***
	(0.1010)	(0.1870)	(0.3190)	(0.3700)	(0.1390)
Year = 2010	2.677***	1.993***	1.885***	2.002***	3.852***
	-0.162	-0.305	-0.513	-0.593	-0.252
Year = 2011	4.012***	3.138***	3.201***	3.376***	4.480***
	-0.311	-0.573	-0.973	-1.122	-0.314
Year = 2012	5.461***	4.582***	4.687***	4.820***	5.154***
	-0.431	-0.813	-1.383	-1.602	-0.33
Utility = PG&E	1.456***	0.372***	-0.367***	-0.148	2.326***
	-0.024	-0.048	-0.083	-0.095	-0.013
Utility = SCE					0.882***
					-0.004
Year = 2008 & Utility = PG&E	-0.064	0.384***	0.531***	0.545***	-0.262***
	-0.046	-0.082	-0.138	-0.161	-0.014
Year = 2008 & Utility = SCE					-0.174***
					-0.02
Year 2009 & Utility = PG&E	0.016	0.751***	0.942***	0.804**	-1.007***
	-0.104	-0.188	-0.313	-0.359	-0.004
Year = 2009 & Utility = SCE					-0.975***
					-0.067
Year = 2010 & Utility = PG&E	0.388**	1.439***	1.544***	1.477**	-0.950***
	-0.174	-0.325	-0.556	-0.644	-0.017
Year = 2010 & Utility = SCE					-1.257***
					-0.136
Year = 2011 & Utility = PG&E	-0.425***	1.087***	0.900**	0.777*	-1.101***
	-0.119	-0.225	-0.374	-0.44	-0.014
Year = 2011 & Utility = SCE					-0.618***
					-0.097
Year = 2012 & Utility = PG&E	-1.247***	0.328***	-0.054	-0.161***	-1.160***
	-0.023	-0.033	-0.045	-0.05	-0.012
Year = 2012 & Utility = SCE					0.095***
					-0.027
Constant	-2.830***	-4.761***	-5.199***	-5.591***	-3.419***
	-0.544	-1.043	-1.754	-2.029	-0.394
Observations	4262	4262	4262	4262	6393

Notes: Dependent variables are the total daily PV installation rates in number per day by utility for zipcodes within each area. The results in column 1 aggregate installations over PG&E's and SCE's territories. "40 mi." includes only installations within 20 miles on each side of the PG&E/SCE territory boundary, "20 mi." includes installations within 10 miles of the boundary and "split zip codes"include installations in in zip codes divided by the utility boundary. All IOUs includes observations for all zip codes within PG&E, SCE and SDG&E territories. Percentage change in installation rate calculated for a $0.10 increase in the rebate rate at the mean values of independent variables. Standard errors clustered at the utility level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Table 8: Effect of rebates on average daily installation rates by utility.

Effect of Rebates on Average Daily Installation Rates by Utility

	PG&E	**SCE**	**SDG&E**
Rebate rate ($/W)	1.417***	1.118***	1.150***
	(0.0530)	(0.0790)	(0.0370)
Confidence interval (95%)	[1.314,1.521]	[0.964,1.272]	[1.077,1.223]
% change in install rate	15.2%	11.8%	12.2%
Year Effects	No	No	No
Quarter Effects	Yes	Yes	Yes
Utility Effects	No	No	No
Year*Utility Effects	Yes	Yes	Yes
Observations	6393	6393	6393

Notes: Dependent variables are the total daily PV installation rates in number per day by utility for all zipcodes within PG&E, SCE and SDG&E territories. Percentage change in installation rate calculated for a $0.10 increase in the rebate rate. Standard errors clustered at the utility level. ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels.

Table 9: Installations, capacity, carbon emissions and social surplus under the California Solar Initiative.

Overall Impacts of the California Solar Initiative

	CSI Overall (All IOUs)		PG&E and SCE Only	
Total Installations	98,621		85,950	
Intallations Without Rebates	41,236		33,171	
Percentage Due to CSI	58%		61%	
Total Capacity (kW)	452,822		393,258	
Capacity Without Rebates	192,547		153,680	
Percentage Due to CSI	57%		61%	
Total Subsidy Payments ($M)	$ 437		$ 392	
Change in Private Surplus	$ 268		$ 235	
Rents to Inframarginal Install.	$ 98		$ 78	
Change in Social Surplus	$ (169)		$ (157)	
	Avg. Grid	Peak Grid	Avg. Grid	Peak Grid
WECC Emissions Rates				
CO_2 Abatement (MMT CO_2)	2.98	3.15	2.74	2.90
Program Cost per Ton ($/MT)	$ 146.72	$ 138.79	$ 142.98	$ 135.25
Average Abatement Cost ($/MT)	$ 56.74	$ 53.67	$ 57.26	$ 54.17
NO_x Abatement (MT NO_x)	1,866.20	1,569.02	1,717.81	1,444.26
Program Cost per Ton ($/MT)	$ 234,165.18	$ 278,517.62	$ 228,197.66	$ 271,419.84
Average Abatement Cost ($/MT)	$ 90,558.16	$ 107,710.48	$ 91,395.49	$ 108,706.41
CA Emissions Rates				
CO_2 Abatement (MMT CO_2)	2.45	3.70	2.26	3.41
Program Cost per Ton ($/MT)	$ 178.20	$ 118.10	$ 173.66	$ 115.09
Average Abatement Cost ($/MT)	$ 68.91	$ 45.67	$ 69.55	$ 46.09
NO_x Abatement (MT NO_x)	1,560.72	1,195.49	1,436.62	1,100.43
Program Cost per Ton ($/MT)	$ 279,998.26	$ 365,541.41	$ 272,862.69	$ 356,225.68
Average Abatement Cost ($/MT)	$ 108,283.08	$ 141,364.98	$ 109,284.29	$ 142,672.02

Notes: Carbon abatement calculations under WECC emissions use average and peak emissions rates from Graff Zivin et. al. (2013). California emissions rates use average and peak emissions from eGrid (2009).

Appendix

As a robustness check on our main specification, we repeat our analysis using zip code daily installation data in place of our utility level aggregate data. These results are shown in Appendix Table 1. Column 1 uses only quarter and utility by year time effects. Because solar preferences may depend on local demographic factors, column 2 adds zip code level demographics. Column 3 adds observable characteristics of the local housing stock. Finally, column 4 replaces zip code controls with mean effects. Across all four specifications the estimated relationship between CSI rebates and PV installations is quite similar to our main results. A $0.10 per Watt increase in the rebate rate is associated with a 13.0 to 13.3 percent increase in the average daily adoption rate. In column 2 we see that population, percentage of households that are white, household income, and the percentage of houses that are family occupied are all positively correlated with PV adoption. Adding house characteristics in column 3, we seen that all the parameters remain positive except year built which is negative. Few of the point estimates are statistically significant which may be the result of strong correlation across the controls. Finally, controlling for zip code mean effects, the main effect of rebates on installations is consistent with our main results.

Appendix tables

Table 1: Effect of California Solar Initiative (CSI) rebate rates on the daily zip code-level PV installation rate near the PG&E and SCE boundary.

Zip Code Level Installation Rates in 20 Mile Region				
	(1)	(2)	(3)	(4)
	Neg. Binomial	**Neg. Binomial**	**Neg. Binomial**	**Neg. Binomial**
Rebate rate ($/W)	1.238*	1.253***	1.245***	1.220***
	(0.7000)	(0.2880)	(0.2890)	(0.2870)
Confidence interval (95%)	[-0.134,2.611]	[0.688,1.818]	[0.678,1.811]	[0.657,1.784]
% change in install rate	13.2%	13.3%	13.3%	13.0%
Population (1000s)		0.055***	0.053***	
		(0.0060)	(0.0060)	
% White		1.759*	2.119	
		(1.0400)	(1.3080)	
HH Income ($1000s)		0.036***	0.018	
		(0.0120)	(0.0150)	
% Family		1.881*	1.699	
		(1.0070)	(1.6720)	
% Own. Occ.			2.022	
			(1.8650)	
Rooms			0.047	
			(0.3680)	
Year Built			-0.032**	
			(0.0160)	
Year Effects	No	No	No	No
Quarter Effects	Yes	Yes	Yes	Yes
Utility Effects	No	No	No	No
Year*Utility Effects	Yes	Yes	Yes	Yes
Zip Effects	No	No	No	Yes
Observations	128526	128526	128526	128526

Notes: Dependent variables are the total daily PV installation rates in number per day by zipcode, by utility for zipcodes within 20 mile buffer. Percentage change in installation rate calculated for a $0.10 increase in the rebate rate. Standard errors clustered at the zipcode level . ***, ** and * denote significance at the 1 percent, 5 percent and 10 percent levels. Models 1, 2 and 3 use quarter and utility*year effects. Model 4 adds zip code fixed effects.