Distributed Decisions
The Efficiency of Policy for Rooftop Solar Adoption

Evan Rogers [*]   Steven Sexton [†]

December 28, 2014

Abstract

Governments around the world provide direct capital subsidies for solar energy technology adoption in order to lessen the externalities associated with fossil energy consumption. This paper analyses the efficiency of the largest customer-oriented program in the U.S., the \$2 billion California Solar Initiative upon which programs in other states are modeled. An analytical model identifies limited conditions in which the programs declining rebate rate is preferred to a single, one-shot subsidy. Further, by exploiting exogenous changes in rebate levels over time, we estimate a rebate elasticity of approximately 0.4, suggesting a public cost per additional watt of more than half the total cost, and a cost per avoided ton of carbon of about \$200. Also, using high-resolution satellite imaging and ground-level weather data, we estimate that suboptimal siting of the programs installed solar capacity sacrifices 15-25% efficiency. These results indicate that greater emissions reductions could be achieved by public funding of optimally sited utility-scale solar projects.

JEL: Q21, Q42, Q48

Keywords: renewable energy, electricity, technology adoption

1   Introduction

Amid concerns about the depletion of fossil fuels and the unpriced damages their combustion imposes upon human and environmental health, authorities throughout the world promote renewable electricity generation technologies that can substitute for polluting power plants.

[*]North Carolina State University

[†]Duke University, 201 Science Drive, Box 90245, Duke University, Durham, NC 27708, steven.sexton@duke.edu.

In the United States and other Western countries, policy increasingly favors the small-scale, renewable generation of electric utility customers over large-scale generation undertaken by the utilities and independent generators. Whereas policy support for renewables is justified as second-best policy in the absence of pollution pricing, an economic rationale for the preferential treatment of distributed generation is less straightforward and virtually unexplored. The billions of public dollars devoted to such policies, however, are expected to induce a transformation of the electric power industry likened in scope and magnitude to that which remade the telecommunications industry beginning in the 1980s (EEI 2013, NARUC 2012, 2013).

Distributed renewable technologies are attractive because they avoid transmission costs and land-use changes associated with utility-scale projects. Whereas the small solar photovoltaic (PV) arrays that typify distributed renewable generation often occupy only rooftops of utility customers, utility-scale solar and wind farms occupy considerable land and require high-cost, high-voltage power lines to transmit electricity to load centers where it is demanded. While utility-scale infrastructure may complement agricultural production, causing only minimal displacement, or occupy marginal lands of little value, it may also crowd out farming and threaten natural habitat at the expense of other environmental objectives, like biodiversity preservation. Because these damages are themselves unpriced, policy intervention may be warranted.

The avoidance of land-use changes from large renewable generators, however, comes at the cost of potential efficiencies from utility-scale operations, including the economies of scale that have long-governed the electric power industry. As evidenced later in this paper, scale economies characterize today's renewable power even as the costs of distributed renewables decline. Further, utility-scale projects are typically sited to maximize the harvest of renewable energy, perhaps subject to constraints like transmission capacity. Distributed generation, on the other hand, is constrained by available rooftops and whatever sunlight

falls on them. Consequently, even individually rational adoption decisions may yield installed capacity that is suboptimal from society's perspective.

This paper evaluates the relative efficiency of a common policy for adoption of distributed renewables, namely taxpayer and ratepayer-funded rebates to utility customers who install rooftop solar energy systems. Thirty-four U.S. states offer such rebates, while a federal tax credit offsets up to 30 percent of distributed system cost. The efficiency of such policies is limited by the extent to which subsidy payments flow to inframarginal adopters and to adopters of low-value solar capacity. Information asymmetries preclude the government's identification of inframarginal adopters, limiting the cost-effectiveness of rebate policy generally. But the identification of high value solar capacity is relatively straightforward given information about the location of proposed capacity additions. Most state policies, however, do not discriminate according to location, limiting their cost-effectiveness.

Exploiting rich data from the California Solar Initiative, the largest of the state rebate programs, we estimate the responsiveness of distributed solar demand to rebates and to effective prices, and we derive estimates of the program cost per unit increase in generation capacity attributable to the program. We then employ high-resolution data on solar resource potential to model the power generated by solar capacity installed during the program. These results are compared to simulated generation under various assumptions about optimal capacity siting in order to estimate efficiency losses due to the program's reliance upon "distributed" adoption decisions that are suboptimal from the planner's perspective.

Distributed solar demand is shown to be inelastic with respect to rebates and effective prices, causing the program cost per additional unit of solar capacity to equal nearly half the total cost. Consequently, the cost of avoided criteria pollutant and carbon emissions is estimated to exceed the damages from those emissions by at least a factor of two. The cost of avoided carbon emissions alone exceeds the social cost of carbon by as much as $100 per ton. Moreover, reliance upon individual adoption decisions is estimated to forsake at least

13 percent efficiency in solar generation by producing a stock of solar capacity that is neither optimized to harvest solar energy resources nor to consume them. Combined, these results suggest a planner could yielded greater solar capacity by fully funding utility-scale projects rather than by subsidizing distributed capacity.

This paper proceeds in the following section with an overview of renewable energy and distributed generation policies, as well as their theoretical foundations. Section three considers the planner's objective and his choices in implementing renewable energy policies. Section four presents the data and methods employed to estimate the responsiveness of residential solar demand to rebates and effective price changes. Results of this analysis are reported in Section five, as are some immediate implications. The siting efficiency of the rebate program is explored in section 6. Section 7 combines the two empirical analyses to derive further policy implications. A final section concludes.

2   Renewable Energy Policy

Regulators across the United States and around the world seek to diminish demand for fossil energy by promoting substitution toward clean, renewable sources like solar generation. Electric power generation emits one-third of anthropogenic greenhouse gases, 60 percent of sulfur dioxide, and 13 percent of nitrous oxides in the United States (U.S. Environmental Protection Agency 2012). It is the largest producer of carbon emissions around the world. Solar electricity generation, in contrast, emits no pollution, but its supply is constrained by the availability of sunlight. The feedstock for solar generation is free, so variable costs are nil. Still, high fixed costs make solar more costly than all other forms of power generation except offshore wind (Energy Information Administration 2013; Borenstein 2012). Consequently, solar's small share of electricity generation has been induced by favorable policy regimes that date to the oil embargo and energy crisis of the 1970s. In the U.S., solar produced only 3.5

million megawatt-hours of electricity in 2012, less than one percent of renewable generation and less than one-tenth of one percent of total electricity supply (Energy Information Administration 2012).

The coal-fired power plant presents a textbook example of market failure. Absent policy, the plant operator ignores the damages his carbon and criteria pollutant emissions impose on the surrounding population and environment; he produces too much electricity relative to social optimality. The textbook policy response to such externalities is a tax on emissions equal to their marginal damages (e.g., Borenstein 2012; Pigou 1920). Were such a tax imposed, the pollution externality would be internalized by the plant operator and the cost of dirty electricity would rise. Solar generation, which emits no pollution, would become relatively cheaper. However, such pollution taxes are uncommon, as are tradable permit systems that can equivalently achieve efficient pollution abatement. Instead, command and control regulations are the norm in jurisdictions that regulate pollution at all. Such regulations often undervalue damages from some or all emissions and provide the wrong incentives for firms' marginal decisions, yielding too much pollution in equilibrium.

In the absence of policy that fully corrects the pollution externality, solar generation is undervalued; it displaces a portion of dirty electricity generation and avoids attendant pollution, the benefits of which do not accrue entirely (or even largely) to the solar electricity generator (Baker et al. 2013). Thus, much as the negative externality from coal-fired generation is optimally taxed, the positive externality from solar generation might be justifiably subsidized. Indeed, net-metering policies common to 43 U.S. states, including California, subsidize generation by requiring utilities to purchase exports to the electric grid at rates that typically exceed wholesale electricity prices. California utilities, for instance, must pay retail rates for distributed solar generation. The rates bundle a variety of charges beyond the marginal cost of electricity, including transmission and distribution cost recovery charges and conservation incentives. At $0.19 per kilowatt-hour, the average rate is more

than double prevailing wholesale prices for solar generation. The public benefits likely do not justify such substantial subsidy (Borenstein 2008); Muller et al. (2011) estimate that a one kilowatt-hour reduction in coal-fired generation avoids $0.036 of damages from local pollutant and carbon emissions.

A per-unit subsidy to solar generation can never be first-best because unpriced pollution leads to under-priced dirty generation, not over-priced clean generation. Because fossil-fired electricity generation and renewable electricity generation are (perfect) substitutes in end-use, a subsidy to solar power lowers the price of electricity that consumers face, inducing additional consumption where an optimal policy induces less consumption. The pollution externality makes dirty generation too cheap, not clean generation too costly. Moreover, the public benefit of solar generation is a function of the dirty generation it displaces, which varies by location and time (e.g., Fowlie and Muller 2013); a unit of solar generation avoids twice the greenhouse gas emissions when displacing a unit of electricity made from coal rather than natural gas.

Were externalities in environmental goods markets the only relevant market failures, then the imposition of Pigouvian prices would be sufficient to achieve efficient environmental outcomes. Importantly, polluters would demand technologies to lower their pollution tax burdens, inducing innovation in emissions abatement (or clean) technologies. The benefits of clean technology development, however, are likely not fully appropriated by the innovator, even if technology policy grants intellectual property protections. Competitors can reverse engineer technologies and processes upon the expiration of patents, if not before. Likewise, the full benefits of early technology adoption may not be fully appropriable because future adopters can learn about optimal deployment, risks, and benefits from technology leaders (Gillingham and Sweeney 2012; Nordhaus 2011). Such spillovers constitute positive externalities in the technology market that weaken incentives for innovation. Combined with the negative externalities from pollution, they likely cause clean technologies to be "doubly

6

under-provided" in the absence of policy (Fischer 2008; Fischer and Newell 2008; Jaffe et al. 2005). Amid technology market failures, environmental policy alone is likely insufficient to insure optimal clean technology investment; additional interventions are warranted to boost innovation. Further, while a pollution tax is the least costly single instrument for emissions reductions, costs are lowered when policy also directly corrects knowledge spillovers in clean technology markets (Fischer and Newell 2008).

2.1 Solar Policy

Direct subsidies for solar technology adoption, like those provided by the California Solar Initiative, are consistent with a portfolio strategy of emissions reductions and can constitute a first-best response to "learning by doing" (Fischer and Newell 2008; Jaffe et al. 2005; Arrow 1962). As noted by Borenstein (2012), however, policy is not justified merely by learning. Rather, the learning benefits must be largely non-appropriable, i.e. spillover to future innovators or adopters. Bollinger and Gillingham (2014) document strong evidence of learning that lowers the balance-of-system costs in California, but they find no evidence of learning spillovers that would justify policy.Van Benthem et al. (2008) also find some evidence of learning spillovers associated with non-hardware costs that include installation costs, while Bollinger and Gillingham (2012) and Graziano and Gillingham (2014) find peer effects in rooftop solar adoption that may be indicative of learning spillovers in adoption.

The solar adoption rebates offered by many U.S. states can be justified as a response to the externalities in environmental and technology markets. They are but one way authorities incentivize distributed solar generation investments. Twenty-four states offer tax credits for renewable generation investments. Twenty-eight states exempt renewable capacity expenditures from sales taxes or allow deductions against income taxes. Such tax credits, deductions, and rebates lower the upfront cost of solar adoption, and are, thus, first-order equivalent policies. Moreover, because the feedstock for solar generation

is free, the marginal cost of solar generation is essentially zero. Therefore, the incentives for solar capacity installation effectively operate as subsidies to solar generation, much as do net-metering policies in forty-three states that obligate utilities to purchase exports to the grid at regulated prices.

Solar adoption rebates increase generating capacity by inducing adoption by marginal utility customers. But those induced adoptions come at the additional expense of subsidies to those who would have adopted in the absence of incentives. These inframarginal adopters diminish the cost-effectiveness of subsidy regimes wherein marginal and inframarginal adopters are indistinguishable to policy makers. Therefore, the cost per additional adoption or installed unit solar generating capacity will exceed the subsidy received by the marginal unit. The more price (or policy) elastic is the subsidized behavior, the lower is the policy cost per additional unit capacity. The credible estimation of the solar adoption elasticity, then, is important to determining the cost effectiveness of solar incentives. It occupies the following two sections of this paper.

Because the aim of solar capacity subsidies is the displacement of dirty electricity generation, another margin of adoption decisions is also important to program effectiveness, namely the quality of the installed capacity. The value of solar electricity generation varies in signficant ways according to location and characteristics of the adopter. First, solar irradiance (or energy potential) varies by location; a solar array installed in high irradiance locales generates more solar electricity than an array installed at a low irradiance site, all else equal. Second, the value of solar generation depends upon the characteristics of the fossil-fired generation it displaces. It is far more valuable to displace coal-fired generation than natural gas-fired generation because of the relatively greater emissions intensity of coal. Moroever, solar capacity that alleviates grid congestion and thereby defers capital projects is of greater value than capacity that contributes to congestion. Finally, nontrivial losses are incurred when electricity is exported to the grid. Therefore, solar capacity installed by

8

utility customers who consume greater shares of their rooftop generation is more valuable. Thus, the characteristics of the induced capacity additions influence the cost-effectiveness of subsidy regimes intended to displace fossil-fired electricity generation. The planner would prefer to induce a high-value adoption by a marginal customer, but absent effort to target such customers, the value of capacity additions will not be maximized. We provide an estimate of the efficiency losses along this capacity-quality margin in Section X.

2.2   Distributed versus utility-scale capacity

Many renewable energy policies expressly favor small-scale, distributed generation. Net-metering policies, for instance, provide utility customers a regulated price for their solar generation that typically exceeds the wholesale, citygate price received by large solar producers. In California, the distributed solar price implicitly imposed by net-metering exceeds the wholesale price by a factor of two or more. The federal tax credit established by the Energy Policy Act of 2005 and revised by the Energy Improvement and Extension Act of 2008 and the American Recovery and Reinvestment Act of 2009 applies exclusively to solar generation that serves dwellings. The California Solar Initiative subsidizes at most one megawatt of capacity per customer, far less than the capacity of utility scale projects, which range from two to 2,700 megawatts (SEIA, 2014). Elected officials continue to pledge support for distributed renewables, which, today, are comprised nearly exclusively of rooftop solar PV because of its scalability. California Governor Jerry Brown, for instance, pledged to increase nearly ten-fold the distributed generation capacity in the state (LAT, April 2011). In 2014, the state of New York embarked on the New York Sun Initiative[1], a rooftop solar incentive program that rivals and mimics the California program. And in his 2013 and 2014 State of the Union addresses, President Barack Obama pledged support for rooftop solar.

Subsidies to distributed renewable generation, combined with technological change,

---

[1]http://ny-sun.ny.gov/

are expected to remake the electric power industry, threatening the survival of electric utilities and prompting predictions of a coming revolution (NARUC 2013, 2014). Because utilities typically recover at least part of the cost of generation capacity and electric grid development and maintenance through retail electricity rates, solar adopters can avoid payments for grid services upon which they rely to balance behind-the-meter generation with consumption needs. As solar adoptions increase, the base across which utilities can spread grid costs shrinks, precipitating a death spiral of rising rates and further solar adoptions by those seeking to avoid escalating utility rates. More generally, a distributed generation future diminishes demand for generation and grid services provided by the utilities. The pending transformation of the sector is compared to the magnitude of change that the telecommunications industry has experienced since about the mid 1980s (EEI 2013). Whereas the telecom revolution was induced by deregulation, the looming transformation of the electric power industry is induced by policies that not only distort prices between utility-scale and distributed generation but also rely on cross-subsidies from utility customers to distributed generators who avoid paying for an electric grid they consume in lieu of storage.

The planner who wishes to increase solar power generation may do so by directly investing public funds in solar generation capacity or by subsidizing private capacity investments. If the planner's objective is to minimize the public (or total) cost per additional unit of capacity, he should be indifferent between generating capacity that delivers equivalent units of electricity to load centers at equivalent cost. Sites for solar generation can differ in three primary respects: distance to load center, opportunity cost of space occupied by solar arrays, and solar irradiance. Utility-scale projects are typically located away from load centers and require land occupied by the generating unit as well as transmission capacity to deliver electricity to load centers. Moreover, transmission to load center entails power losses due to resistance of about 1-7% of generation. Thus, utility-scale projects located away from load centers produce less effective power per unit installed capacity and at greater cost

than distributed generation, all else equal. But load centers, and, therefefore, distributed generation sites, may not be located where solar energy potential is the greatest. For instance, rooftop solar systems may suffer from shading due to surrounding trees and structures that do not obscure sunlight at optimally sited large, solar arrays. And in California, solar irradiance is inversely correlated with population density; the greatest solar energy potential exists in relatively uninhabited deserts. Thus, distributed generation may sacrifice solar energy potential. Moreover, grid modeling work by Callaway and Cohen (IEEE 2013) demonstrates that energy losses also plague rooftop generation as it is exported to the local distribution system. These losses are expected to be as large a share of exported distributed generation as are losses to utility-scale generation. For these reasons, optimally sited utility-scale projects may be preferred to distributed generation, transmission losses not withstanding.

Given the planner's objective of minimizing the public cost per unit capacity, there is little ex ante reason to prefer investment by homeowners versus wholesale power generators and corporate investors. Admittedly, an oft-stated purpose of rooftop solar investment incentives is to lower electricity costs for households. However, as such policy is funded by electricity rate payers and taxpayers, there is little scope for net gains in aggregate household surplus. Of course, if solar investments generated savings to households, policy would not be required to induce adoptions. Hence, we consider under which circumstances it is optimal for the planner to directly invest in capacity or to provide incentives for private investment by households, corporations, or both.

Define effective solar capacity as nameplate capacity weighted by solar energy potential and transmission losses. Then the public cost per additional unit of effective solar capacity induced by residential, rooftop solar incentives is determined principally by the rebate elasticity of rooftop solar demand and by the efficiency of rooftop siting decisions. Specifically, let ρ^r denote the public cost per effective watt of additional solar capacity derived from a residential rebate. An effective watt is defined as a watt of installed capacity

multiplied by a siting efficiency parameter, α, that reflects solar generation potential relative to solar generation potential for optimally sited capacity. The siting efficiency parameter for rooftop solar is estimated in section 6. Hence,

$$\begin{aligned} \rho^r &= \frac{\Delta R \cdot (\Delta Q + Q)}{\Delta Q} \frac{1}{\alpha} \\ &\vdots \\ &= \left(\Delta R + \frac{R}{\varepsilon^r} \right) \frac{1}{\alpha}, \end{aligned}$$

where ε^r is the rebate elasticity of demand for residential rooftop solar, Q is the quantity of solar installed, ΔQ is the quantity of solar capacity induced by a change in the rebate, R, to $R + \Delta R$.

The public cost per additional effective watt due to unrestricted investment incentives, ρ^u, is similarly defined:

$$\rho^u = \left(\Delta R + \frac{R}{\varepsilon^u} \right) (1 - \beta) + L + T,$$

where ε^u is the rebate elasticity of solar demand among corporate investors, L is the rental rate of land per watt, and T is the transmission cost per watt. β is a transmission-loss parameter equal to the share of utility-scale generation lost in transmission to the load center relative to the share of distributed generation lost in distribution. Line losses are inevitable in moving electricity long distances. Engineering estimates suggest these losses are on the order of 6% in California and nationally (EIA, Borenstein, CPUC). While distributed generation is presumed not to incur line losses because the power is consumed on site, a substantial share of generation from residential rooftop systems is exported to the grid because instantaneous consumption is less than contemporaneous generation. Even though this generation needn't

travel great distances, losses are estimated at 7% (Calloway and Cohen 2014). Thus, we assume a share of total generation losses from rooftop solar equal to 7% multiplied by 0.58, the share of exports to the grid (Pecan Street Institute 2014). Then losses as a share of generation relative to distributed generation are $\beta = (.06 - .04) = 0.02$.

Land and transmission costs vary by site. In general, investors may sacrifice some solar energy potential in order to economize on land and transmission costs. A survey of utility-scale solar projects by the U.S. National Renewable Energy Laboratory reports that the typical solar PV project requires 3.3 acres per GWh per year (NREL 2013). The rental rate per acre of these lands varies considerably by location. Rates charged by the federal Bureau of Land Management vary from $94-314. We determine the land cost per watt over 20 years in order to equate the costs of the utility scale project capacity over the expected lifetime of rooftop solar capacity. For simplicity, we ignore discounting of future rental costs. The National Renewable Energy Laboratory also evaluates the cost of transmission. Based on these estimates, we assume a cost per watt of transmission services for 20 years of $x[2]. These costs can vary considerably depending on the distance to the load center or existing transmission infrastructure, the cost of the tranmission right of way, and the cost and duration of litigation by land owners, environmental groups, and other potential litigants.

Finally, the planner may choose to directly invest in utility-scale capacity. Then the public cost per effective watt is equal to the market price for utility-scale capacity divided by transmission efficiency, plus land and transmission costs per watt, ie.,

$$\rho^d = P^u (1 - \beta) + T + L,$$

where P^u is the market price per installed, utility-scale watt.

In general, $\varepsilon^u \geq \varepsilon^r$, i.e., investor demand for solar is at least as responsive to

---

[2]forthcoming

13

rebate changes as is household demand for solar. Investor demand is more responsive than residential demand if investors are less capital constrained or have lower cost of capital than households. If $\varepsilon^u > \varepsilon^r$, then $\rho^u < \rho^r$ if rooftop solar siting efficiency, α, is less than X. That is, even for very small siting efficiency losses from rooftop solar capacity, it is suboptimal to restrict investment incentives to residential, rooftop solar investments. Direct investment is never preferred to unrestricted, i.e., utility-scale, investment incentives, whenever solar demand exhibits some responsiveness to rebates and siting efficiency losses are small. Direct investment, however, may be prefered to rooftop capacity incentives if rebate responsiveness is low and siting efficiency losses are large. With direct investment, the planner gains siting efficiency improvements at the expense of fully funding the solar capacity and incuring transmission losses. As this discussion reveals, whether residential rooftop solar adoption incentives constitute an efficient program depends upon ε^r and α, the estimation of which is carried out in the next several sections.

2.3   California Solar Initiative

The California Public Utilities Commission (CPUC) established the California Solar Initiative (CSI) in 2006 as a continuation of state programming supporting solar photovoltaic implementation. The CSI covered three major Investor-Owned Utilities (IOUs) within California, Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDGE), and took effect starting January 1, 2007 with a 10 year planned budget of $2.167 billion. Under the program, each of the three IOUs administered a share of the total budget according for their respective service areas. This paper focuses on the 578 MW target for general market residential installed solar photovoltaic (PV) capacity, though the CSI program covered commercial general market and residential low-income capacity targets as well [3]. Though each IOU administered subsidy funds

---

[3]California Solar Initiative Handbook, 2012

independently, incentive amounts were standard as set by the CSI, and varied based on cumulative installed capacity with each service region. The program defined 10 rebate level amounts attached to an installed capacity target for each amount. As capacity amount milestones were recached, the rebate level "stepped down" to the next highest rebate level defined by the program.

Rebate amounts per watt are shown in 1, and they decline from $2.50 per watt to $0.20 per watt. For a sample-mean system size of 5.7 kW, the total subsidy amount at the initial rebate level of $2.50/watt would be $14,250, which declines to $1,140 at the $0.20/watt rebate level in the final incentive step. The mean rebate amount for residential installations is $5,600 (with standard error of 87.2 for the full sample of 96,355 adoptions). Discrete declines in the rebate occur as reserved capacity thresholds are achieved within each IOU. For example, PG&E could offer 27.4 MW worth of residential solar installations a rebate level of $1.10/watt. Once residential customers had met that threshold, the rebate level declined to $0.65/watt for the next 31 MW capacity. The CSI published weekly updates announcing the remaining amount of capacity in a current rebate step eligible for the corresponding rebate level, but an individual customer could not know with certainty whether waiting a week would definitively mean a lower rebate or not. Rebate levels were assigned to customers based on when those customers made a reservation with the CSI defining their planned system size and characteristics. Upon project completion, the resident or installer would submit project milestones, the project could be audited by the CSI, and then the rebate check would be disbursed. It is important to note that the rebate amount is determined at the time of the reservation, not at the time of project completion. Rebate level changes occur once the IOU determined that a step's capacity target had been reserved, and the dates of the change in rebate level for each IOU is also shown in 1.

Consumers have the option of choosing to receive their rebate as an up front rebate under the Expected Performance Based Buydown plane (EPBB) or the Performance Based

Incentive (PBI). This paper focuses only on EPBB adoptions, which provides a one time payment upon completion of the installation based on the reserved subsidy rate. The amount of the subsidy under the EPBB is determined by the prevailing rebate at the time the customer makes a reservation through their IOU with the CSI, but also by a number of system and geographical characteristics. The EPBB rebate was chosen by 99.44% of residential adopters.

The timing of the subsidy is as follows. First, a customer plans a PV installation with a contractor or installer. Second, the contractor sends a reservation to the IOU that includes all system characteristics, including module type, inverter type, system size, installation location, solar radiance and typical meteorological conditions at the site location, site shading if any, and system orientation. Third, these characteristics are run through a calculator that determines that systems "Design Factor," or the expected electrical output of the system relative to a reference system. This factor is multiplied by the rebate level at the time the reservation was made to determine the total subsidy amount for a system, which is then reported back to the customer. Mean Design Factor for the sample is 0.9475, and the distribution of Design Factors is shown in 7. Fourth, once the system has been installed and connected to the grid, the customer receives their subsidy check. If each contractor uses the best available module and inverter available for a household's budget and system size decision, Design Factor will be primarily determined by solar radiance and weather at a given geographical location. Design Factor was intended to discourage adoption, but to discourage poor system design. Reports on the justification for the EPBB design with regard to Design Factor stated, "Poor quality equipment as well as poor quality installations will be penalized, protecting the market from disreputable companies." (Hoff, Clean Power Research 2006). Contractors may have had some control over Design Factor, but the typical consumer would have minimal input affecting Design Factor.

3 Rebate Responsiveness: Data and Methods

In order to assess the responsiveness of solar adoption to rebates, we employ public data on program-funded solar installations maintained by the utilities and published by the California Public Utilities Commission. These data include the timing of each rebate application to the California Solar Initiative, the zip code of the solar installation, its size, performance rating, rebate rate, total cost, and incentive payment. Observed daily rebate activity is aggregated to weekly counts of applications per utility service area and mean characteristics. Weekly rebate rate is assigned according to the prevailing rate received by applications in a week in which the rebate level changed. [4] This aggregation eliminates substantial zeros in the data that reflect the absence of solar adoptions in a given utility region on a given day. Because solar market characteristics, like panel prices, are not likely to evolve daily, little information is lost in this aggregation step. Following this aggregation, we observe 990 weekly observations in the three utility regions from January 2007 to October 2013. The average weekly number of adoptions across the three regions is 87. PG&E, the largest of the three utilities by number of customers, averaged 125 weekly rebate applications, compared to 101 in the Southern California Edison service area, and 32 in the San Diego Gas and Electric territory. The average system size is 5.7 kilowatts and cost \$38,373, or \$6.75 per watt. The mean rebate received by applicants was \$1.39 per watt and the mean total incentive was \$6,130. Summary statistics by utility region are reported in table 2.

We are interested in estimating the expectation of weekly solar adoptions conditional on rebate and a suite of fixed effects. Our outcome variable, thus, is a count variable, which is constrained to non-negative integer values. Standard (linear) models estimated by OLS are problematic for count data because they usually predict negative values of the outcome for some plausible values of regressors. Moreover, the normal distribution assumption is typically

---

[4]A map of utility service areas is reported in figure 1.

violated in count data models. Rather, as is characteristic of count data, the weekly number of solar adoptions in a utility region is right-skewed as shown in figure 2. The residuals of the linear model are not normally distributed, making standard linear estimators inconsistent. However, because we observe only two zero values for the dependent variable following the aggregation to weekly counts by utility area, a log transformation of the dependent variable is sufficient to overcome the major limitations of the linear model. As shown in figure 3, the distribution of residuals from the nonlinear model are approximately normally distributed. Thus, we proceed by specifying an exponential conditional mean function and estimating by OLS and maximum likelihood with Poisson and negative binomial distributions, as is common for count data.

Specifically, we estimate the regression equation:

$$\text{Adoptions}_{it} = \exp\left(\beta \cdot \text{lnRebate}_{it} + \gamma_t + \xi_i + \omega_{im}\right) + \epsilon_{it}, \tag{1}$$

where $Adoptions_{it}$ is a count of solar adoptions in utility region i and week t, γ_t is a fixed effect for each week (or month in some specifications) of the sample, ξ_i is a utility-region fixed effect, and ω_{im} is variably a region-by-month or region-by-year fixed effect. $lnRebate_{it}$ is the log-transformation of the rebate level (in dollars per watt) in region i and week t. The log-transformation is undertaken in all preferred specifications because it is expected that the effect of a rebate change on adoptions is greater in large regions than small regions. Moreover the log-transformed rebate exhibits better fit in all models than rebate level, and the log transformation permits the convenient interpretation of β, the coefficient of interest, as an elasticity in all specifications. The foregoing model exploits within-region, exogenous, temporal variation in the rebate level. It is robust to secular trends, e.g., declining solar technology prices, time-constant region heterogeneity, e.g., solar irradiance, and region heterogeneity that varies annually or monthly, e.g., utility marketing and policy.

18

3.1 Pull Forward Effect

Without additional controls, the foregoing model is biased by a "pull forward" effect that reflects consumers' strategic responses to announced reductions in solar rebates. Because consumers are typically in the market for durable goods like cars, homes, and home appliances for several months, they may "pull forward" their purchases of durable goods ahead of anticipated effective price increases. This results in a spike in sales just before the price increase and lower-than-average sales following the price increase as future sales were "stolen" by earlier periods. For instance, Mian and Sufi (2012) document a substantial pull forward effect in response to the U.S. government's 2009 "Cash for Clunkers" program, which offered incentives for vehicle scrappage during a limited period of time: a "peak" in new car sales during the policy resulted in a sustained "trough" following the policy.

There is similar evidence of a pull-forward effect on solar adoptions in California. Figure 4 depicts weekly solar adoptions in each utility region along with the dates of rebate changes in the Pacific, Gas and Electric service territory over the duration of the program. It shows that adoptions spike during the few weeks before rebate program administrators begin awarding lower rebates to applicants, as depicted by vertical lines in the figure. Shallow troughs follow the rebate changes. It is not surprising that the peaks precede the administrative rebate changes by several weeks because the rebates changed not at dates certain, but rather when benchmark installation capacities were achieved. Thus, consumers were able to only imperfectly anticipate the rebate changes. As region capacity neared thresholds, consumers in the market with sufficient willingness to pay would rationally purchase sufficiently ahead of rebate changes to minimize the risk of applying after capacity thresholds were achieved. Moreover, some administrative delay causes the processing of applications (and assignment of rebate levels) to lag rebate applications.

If adoptions are summed according to their proximity to a rebate change, evidence of a distinct pull-forward effect emerges. Figure 5 depicts the sum of all adoptions

19

across all rebate changes and all regions that occur τ weeks after a rebate change for $\tau = \{-12, -11, \cdots, 0, 1, 2, \cdots, 12\}$. In the weeks that precede rebate changes by four or five weeks, i.e., $\tau = \{-5, -6\}$, 80% more adoptions occur than in the two weeks that follow a rebate change, i.e., $\tau = \{1, 2\}$. Were it not for a pull-forward effect, it is expected that the distribution of adoptions relative to rebate changes would be approximately uniform, particularly near the rebate change. Instead, the distribution varies substantially from uniformity; there are far more adoptions just before the rebate changes than after. This is unlikely to be due to chance. Comparing the sums for $\tau = \{-5, -6\}$ to the sums for $\tau = \{1, 2\}$ yields a p-value of less than 0.00001 that the counts are drawn from a uniform distribution.

Failure to control for the pull-forward effect leads to estimated rebate effects that are biased up, as some sales at higher rebate levels would have occurred at lower rebate levels were it not for consumers' ability to anticipate effective price increases. The pull-forward effect is controlled by incorporating into (1) a suite of fixed effects designed to absorb the variation due to the effect. Adapting the technique common to event studies, we create an "event time" variable, τ_{it}, whose value corresponds to the temporal position of observations relative to the event. In the present context, the "event" is a rebate change. Thus, each observation is first assigned to the nearest rebate change in the appropriate region. Then τ_{it} is defined to be equal to the temporal position of week t in region i relative to the most proximal event. Thus, τ_{it} is equal to j if week t follows the nearest event in region i by j weeks, where j takes on negative values for observations that precede the nearest event. For example, for the second week of 2008 in the San Diego Gas and Electric territory, τ equals 1 because the most proximal rebate change occurred during the first week of 2008.

In order to characterize the pull forward effect and calibrate controls for estimation of (1), we estimate by OLS:

20

$$\text{Adoptions}_{it} = \sum_{j=-15}^{15} \alpha_j 1 \left[\tau_{it} = j \right]_{it} + \rho_l + \eta_{ig} + \gamma_t + \xi_i + \epsilon_{it}, \tag{2}$$

where ρ_l is a fixed effect for each rebate level, l, and η_{ig} is a region-specific fixed effect for each rebate change. It is defined to be equal to one for all observations in region i that are assigned to the event g. The rebate-level and event-group fixed effects are intended to improve precision of our estimates of α_j, which reflects the change in adoptions due to the anticipated rebate change j weeks earlier. The estimates of α are plotted in figure 6 along with 95-percent confidence intervals. Figure 6 evidences a strong affect of consumer ability to anticipate rebate changes on the pattern of adoptions. Importantly, these estimates reflect the affect of proximity to a rebate change, not the affect of the rebate change, itself, which we estimate in (1). The pull forward effect significantly increases adoptions 3,4, and 5 weeks before a rebate change and significantly decreases adoptions 0, 1, 4, and 6 weeks after a rebate change. Thus, we proceed to control for the pull forward effect in our estimation of (1) by incorporating event time indicators. We include event time indicators for $j \in [-5, 11]$ based on inspection of figure 6 and goodness of fit. Results are robust to the inclusion or exclusion of other event time indicators. Thus, our preferred estimating equation is given by:

$$\text{Adoptions}_{it} = \exp \left(\beta \cdot \ln\text{Rebate}_{it} + \sum_{j=-5}^{11} \alpha_j 1 \left[\tau_{it} = j \right]_{it} + \eta_{ig} + \gamma_t + \xi_i + \omega_{im} \right) + \epsilon_{it}. \tag{3}$$

The event-time indicators in (3) control for the average pull-forward effect across regions, but would permit bias to the extent the effect varies systematically by region. It is for this reason, and to control for the pull-forward effect and other time effects non-parametrically, that we exploit a plausible source of exogenous, within region and within time-period variation in rebate levels.

3.2   Performance-weighted rebates

While the econometric models already proposed control for time-constant region heterogeneity, secular trends, and a common pull forward effect, one may nevertheless be concerned about region-specific time effects. A unique characteristic of the California rebate programs allows that such effects may also be controlled. In particular, the rebate program issued individual rebates that were scaled according to the performance of individual solar PV systems. The greater the performance relative to a reference system's performance, the greater the effective rebate. Performance is measured according to expected solar irradiance, expected typical weather, panel tilt and orientation, and several technical specifications. These characteristics comprise the *design factor* by which the statuary rebate is multiplied. For example, the average design factor of 0.947 reduces the average rebate rate of $0.954/watt to $0.907/watt. For the average residential system, this equates to an incentive reduction of $221. Figure 7 shows the distribution of design factors for residential PV systems. It is this variation in design factor which produces variation in effective rebate within region and within week or month.

The PV system design factor is plausibly exogenous. In particular, so long as households do not choose their design factor, then the use of this performance measure in rebate calculations introduces exogenous variation in rebate levels. Given that the California Solar Initiative applied exclusively to existing homes, it is unlikely households chose their homes due to performance considerations. Households cannot affect solar irradiance or weather, two important components of the design factor calculus. While they can choose system orientation, tilt, and technical specifications, these decisions are either dictated by characteristics of the house, i.e. roof shape, or are trivial (in terms of cost and labor) to optimize, i.e. tilt. Thus, there are few margins along which households can adjust their design factors, short of moving homes.

As before, we aggregate observations of individual adoptions into counts and associated

mean characteristics by region, week, and design factor bins. Bin sizes of 0.005 translate to approximately a $25 difference in rebate between marginal groups for the average PV system. This aggregation step yields 23,849 region-design factor-week observations. (Results reported in the following section are robust to alternative design-factor bin-widths.)

Thus, the following is estimated:

$$\text{Adoptions}_{it} = \exp\left(\beta \cdot \ln(\text{Rebate}_{it}) + \psi_g + \gamma_t + \xi_i + \psi_g \times \gamma_t + \psi_g \times \xi_i + \gamma_t \times \xi_i\right) + \epsilon_{it}. \quad (4)$$

This adaptation of (1) includes the interactions of region, week and design-factor bin indicators, where ψ_g, is a vector of indicators for each design factor bin[5]. This specification differs from (3) by excluding the event time indicators; the pull forward effect and other region-specific time effects are absorbed by the interaction of the region and time fixed effects.

Finally, inspection of raw residuals plotted against predicted values reveals several outliers in each model. These plots are shown in figure 8. We drop observations that are poorly fit by any of the three models, namely those with raw residuals more than four standard deviations from the mean. Twelve observations are omitted in this procedure. While ad hoc and subject to over-fitting critiques, such corrections are justified in count data models and defensible when omitted outliers are few relative to sample size (Cameron and Trivedi 1998).

4   Rebate Elasticity Results

Estimation of (3) by OLS, Poisson, and negative binomial models yields estimates, β, of the responsiveness of solar adoption to rebates, where β is directly interpretable as an elasticity. Table 3 reports estimated elasticities for three specifications of time fixed effects for each

---

[5]Equation (4) is estimated with varying bin widths, and, thus, the quantity of bins varies from 10 to 40.

of the three models. In columns 1, 4, and 7, (3) is estimated with week fixed effects and year-region interactions. Columns 2, 5, and 8 include instead a monthly fixed effect and year-region interaction. And columns 3, 6, and 9 report results with week fixed effects and month-region interactions. Across all specifications, elasticity estimates are similar and small, indicating that solar demand in California is relatively unresponsive to the rebate. Estimated elasticities range from 0.40 to 0.50, and from 0.4 to 0.44 in our preferred specification that includes year-region and week fixed effects. Results are robust across model specifications.

Table 3 includes a number of model diagnostic and goodness of fit statistics used to identify our preferred model. Following Cameron and Trivedi (1998), we use the Pearson residual as a goodness of fit measure with which to compare the parametric Poisson and negative binomial models. The Pearson residual is smaller in each of the negative binomial models than in the corresponding Poisson model, suggesting that the negative binomial distribution better fits the data. Over-dispersion that violates the Poisson assumption of equal mean and variance also favors negative binomial, though our Poisson estimation with cluster-robust standard errors is consistent, if inefficient, amid over-dispersion. Figure 9 demonstrates that the negative binomial variance function better characterizes the data than does an over-dispersed Poisson variance function. Specifically, figure 9 depicts group mean and variance of *Adoptions* for 100 groups defined by similarity of predictions from negative binomial estimation of (3). The figure also plots the Poisson and negative binomial functions using estimated parameters from (3). The Poisson variance function is necessarily linear, even when allowing for a dispersion parameter. The negative binomial variance function is quadratic, and, thus, better captures the variation in adoptions. The negative binomial model, therefore, is preferred to the Poisson even though it requires estimation of an additional parameter.

Following Cameron and Trivedi (1998), we use information criteria to select from

among the non-nested negative binomial and log-transformed OLS models. In essentially each specification, the OLS model outperforms the negative binomial and the Poisson models, exhibiting less information loss according to either Akaike's Information Criterion or Bayesian Information Criterion. Log-transformed OLS is of little use in many count data applications because the log of the dependent variable is undefined for zeroes, which characterize such data. Our aggregation step, however, eliminates all but two zeros in the data, permitting reliance upon exponentiated OLS. We find little reason to prefer the negative binomial maximum likelihood estimator to the nonlinear OLS estimator. Thus, our preferred estimates of the rebate elasticity are 0.40 (OLS) and 0.41 (Negative Binomial). Given these elasticity estimates, the marginal effect of the rebate evaluated at the mean is 24.97-25.85 adoptions per week, i.e. 29-30 percent of all adoptions were induced by the policy. Given the program cost, this implies a public cost per additional watt installed due to the rebate equal to $3.36 or $3.48, or about 49-52 percent of the average total cost per installed watt.

Estimation of (4), which exploits exogenous variation in the design factor, yields results similar to those above. Table 5 shows estimation results by OLS, Poisson, and negative binomial specifications. Results are significant across specifications and range from 0.26 to 0.41, within the range of the results in Table 3. Given the design-factor analysis results in less aggregation of the data than the other specifications, zeros in the the outcome variable are more common. The non-linear OLS estimate may be less reliable in estimating (4) than (3).

In order to demonstrate the bias induced by the pull forward effect, and the consequence of ignoring it in estimating the rebate elasticity, we report estimates from (1) in table 5 for week and region-year fixed effects. For each model, the estimated elasticity is considerably larger than the elasticities estimated by (3) and (4). Estimates from the preferred models without controls for the pull forward effect are 90 and 95% larger than estimates from the

preferred models and preferred specification in (3). They imply a public cost per additional watt of \$1.75-\$1.78. Thus, failure to account for the strategic response of consumers to pre-announced rebate reductions causes one to substantially overestimate the responsiveness of solar demand to rebates and over-estimate the cost effectiveness of the rebate program.

5 Efficiency of Rooftop Solar Siting

A discussion of the foregoing empirical results is postponed until the subsequent section in order to present empirical results related to the efficiency of rooftop solar siting. As Baker et al. (2013) noted, the private and public benefit of a solar photovoltaic installation varies spatially according to solar irradiance, i.e. sunlight, the generation displaced by the solar project, and the transmission capacity benefits. In California, two-thirds more sunlight falls in the zip code with greatest average annual irradiance (Jacumba in San Diego County) than in the zip code with the least solar irradiance (Dillons Beach in Marin County). And nearly twice as much carbon pollution is avoided by a unit of solar power that displaces coal-fired generation rather than natural gas-fired generation. Thus, the public benefits from New Jersey solar exceed those of Arizona solar: although an Arizona project generates more electricity, it largely displaces natural gas generation whereas New Jersey solar largely displaces coal. Virtually no coal power plants operate in California. The bulk of the state's energy is supplied by natural gas plants. Moreover, all solar in the state is interconnected through the electric grid, so that solar anywhere in the state effectively displaces the same type of generation. And, as Borestein 2008 notes, solar capacity has not been installed in order alleviate congenstion on transmission infrastructure. Thus, in evaluating the efficiency of California's solar capacity, solar irradiance is the predominant consideration. [6]

---

[6]Solar generation can also alleviate or eliminate transmission bottlenecks–locations in the grid where transmission demand exceeds infrastructure capacity. Solar projects located behind a bottleneck may avoid or delay transmission investments to alleviate the bottleneck, making certain solar projects more valuable irrespective of solar irradiance. Borenstein (2008), however, assumes away any transmission benefits from

As noted previously, rooftop solar generation is likely to sacrifice solar electricity generation for proximity to the load because load centers may not be located at sites with greatest solar irradiance and because sunlight may be obscured from rooftop systems by surrounding trees and structures. This is particularly true in California, where the most sunlight falls in the desserts in the southern part of the state. If households were identical except with respect to their locations, rooftop solar would deliver the greatest return to those households located in the sunniest locations. They should, therefore, preferentially adopt solar, minimizing potential efficiency losses relative to optimally sited, or utility-scale, projects. Because such households would have higher willingness to pay for solar photovoltaics, the planner's most cost-effective program would pay the difference in cost and willingness to pay among those households in the highest solar irradiance parts of the state. Absent information on individual household willingness to pay, however, the planner is constrained to offer the same subsidy to all potential adopters. Induced adoptions should occur predominantly in high irradiance areas, though for sufficient subsidy, low irradiance households may also adopt.

Figure 11 depicts the location of solar photovoltaics installed under the California rebate program. It reveals a high concentration of solar along the coastline, and particularly in the San Francisco Bay Area, Santa Barbara, Los Angeles, and San Diego. The quantity of solar installed per detached home in the least sunny zip code in the state, Dillons Beach near San Francisco, is an order of magnitude greater than the adoption rate in the sunniest zip code in the state, Jacumba, outside San Diego. This spatial pattern of adoption indicates household heterogeneity beyond solar irradiance exposure is an important determinant of adoption. Though it is beyond the scope of this paper to formally explore the determinants of individual household adoption decisions, we consider possible explanations for preferential

solar because there is little evidence any solar installations have impacted infrastructure investments or that they are strategically sited to reduce bottlenecks.

adoptions away from high irradiance areas. First, variation in retail electricity prices would induce variation in expected returns as self-generation displaces consumption from the grid and generation in excess of instantaneous demand is sold to the grid at retail rates. However, there is little variation in retail rates across the major utilities in the state (FERC, 2013). Second, the cost of funds may be greater in high irradiance areas. However, while it is true that incomes are higher in coastal areas than inland areas, there is little reason to believe inland households are credit constrained or face higher cost of funds. They should prefer to access credit to generate the return to solar as opposed to forgo the solar investment [7]. Finally, rooftop solar may not be viewed strictly as an investment. Households may adopt solar for reasons other than expected returns, including, for instance, desire to contribute to pollution abatement or to signal environmental preferences (Sexton and Sexton 2013). Regardless, figure 11 indicates that more solar power could be generated from the solar photovoltaics installed under the program if the capacity were sited to maximize the investment return. Solar installed along the coastline would be located, instead, in the inland desert.

In order to estimate the efficiency losses due to potentially rational individual adoption decisions that are nevertheless suboptimal from the perspective of the planner, we simulate power generation under the existing capacity and under alternative siting scenarios. First, we assume that the entire capacity installed under the program could have been installed in the highest solar-irradiance areas of the state, irrespective of the number of rooftops in those areas. This scenario assumes solar photovoltaics could be mounted to structures other than residential rooftops. A second scenario assumes the installed capacity can only be located on residential rooftops. Thus, using 2010 data on detached homes by zip code from

---

[7]Back-of-the-envelope calculations indicate that a system in San Francisco of average size receiving an average rebate ($1.28 per watt) and a post-2009 federal subsidy generates a 5 percent internal rate of return, which exceeds the cost of funds over the period of the California rebate program. Absent the California subsidy, the system generates a 2 percent return. Without the federal subsidy, it generates a 1 percent return. And without either subsidy, the return is a 2-percent loss.

the U.S. Census Bureau, this scenario assigns the solar capacity first to all residences in the highest-irradiance zip code. Unassigned solar is then allocated to each rooftop in the second-highest-irradiance zip code until all rooftops are occupied by one solar installation each. Remaining unassigned solar is then allocated to the third-highest-irradiance zip code, and so on, until the solar capacity is fully allocated.

These first two simulation scenarios ignore grid stability concerns derived from the intermittent and unpredictable nature of solar energy. Reflecting customer preferences for "always on" electricity, regulators require utilities to maintain grid stability to minimize the likelihood of blackouts and damage to equipment connected to the grid. A system that relied entirely on solar generation would be highly unstable and susceptible to outages unless temporal variation in solar generation across the interconnected grid were sufficiently negatively correlated, i.e., so that low generation in one part of the grid were offset by high generation elsewhere. As the number of solar energy systems increases, so, too, do concerns about the ability of low-capacity distribution lines to handle the additional load. The Federal Energy Regulatory Commission recommends that power sourced from solar exceed no more than 15 percent of peak load in any particular generation circuit in order to avoid "unintentional islanding" and voltage fluctuations that present safety risks and degrade the quality of electric power delivered through the grid (Federal Energy Regulatory Commission 2014). The standard was introduced by the California Public Utilities Commission and most states because it is believed negative effects are minimal if the distributed generation capacity on a section of the grid is less than the minimum load. Some suggest the standard is conservative and that greater than 15-percent penetration has not wrought major risks in other countries, e.g., Braun et al. (2012). Nevertheless, for a conservative simulation scenario, we adopt the 15-percent standard and assign solar to rooftops as in the second scenario, but limit assignment in any zip code to only 15 percent of homes. This necessarily requires installation in areas with less solar irradiance than the installation areas of the other

two simulation scenarios.

Estimates of the direct current power output of solar photovoltaics rely on high-resolution modeling of solar irradiance by collaboration of universities and the National Renewable Energy Laboratory. Unique estimates of typical generation are obtained for every 10-square kilometers in the state The data are modeled according to the methods of Perez et al. (2002) and Dunlap et al. (1994) using hourly radiance images from weather satellites, daily snow cover data, and monthly averages of water vapor, trace gases, and atmospheric aerosols. Because weather characteristics affect the performance of solar photovoltaics, the 10-kilometer, satellite-based irradiance data are combined with surface weather station data from the National Solar Radiation Database to estimate direct current electricity output, assuming typical parameters for the solar photovoltaic system. Specifically, for each of California's 1,700 zip codes, a weighted mean solar irradiance is calculated using GIS software to aggregate the 10-kilometer satellite data to zip code boundaries. Each zip code is mapped to the nearest weather station and to "typical meteorological year" data derived there from. These are inputed to the PVLib model developed by the Sandia National Laboratory and the PVPerformance Modeling Collaborative [8], which parameterizes conversion of solar irradiance to direct current electricity output.

Estimates of the energy losses from the existing installed capacity relative to these three optimal adoption scenarios are presented in table 7. If the installed capacity were sited in the highest solar potential areas without consideration for rooftop availability or grid stability, 184,000 megawatt-hours of additional electricity would be generated, or 25 percent more generation than under the existing capacity siting. The additional generation could power 30,600 additional average California homes annually. If the solar capacity were sited on available rooftops in the sunniest zip codes in the state, irrespective of grid stability concerns, the solar projects could generate 17 percent more electricity, or power 20,400

---

[8]See http://pvpmc.org

more typical California homes. Finally, if the solar capacity were optimally sited accounting for rooftop availability and grid stability concerns, 13 percent more electricity could be generated, powering 15,900 homes.

The optimal locations of the solar capacity under this last, conservative scenario are depicted in figure 12 (in blue) alongside the locations of projects installed under the California rebate program (in black). As the figure shows, it is optimal not to site any solar capacity in the San Francisco and Los Angeles areas. Moreover, there is little overlap between the actual and the optimal siting. This suggests divergence between the planner's objective to maximize solar generation per unit cost and the consumer's objective. Consumers are presumed to make adoption decisions that are individually rational even if they are not efficient from the planner's perspective. Intrinsic motivations and prosocial behavior may explain the over-adoption of solar along coastal areas relative to optimality. As Kahn (2007) noted, adoption of Toyota Prius hybrid vehicles occurs disproportionately among coastal California populations, which are observed to support Democratic candidates at high rates. In contrast, the low fuel efficiency Chevrolet Hummer enjoys relatively high market share in inland California. Reputational and signaling benefits, i.e. extrinsic motivations, may also motivate greater solar adoption along the California coast because signaling value of conspicuous conservation effort is presumed to increase in the relative preference for the environment of one's neighbors and peers (Sexton and Sexton 2013).

6 Discussion

Solar technology adoption subsidies comprise one component of energy and environment programs implemented by authorities to reduce environmental damages. Indeed, they constitute one among many potential and actual policies to promote solar electricity generation. Others include renewable portfolio standards, feed-in tariffs, and net-metering

policies that respectively mandate solar generation and subsidize its generation by large-scale and distributed sources. More generally, common environmental objectives like carbon and criteria pollutant emissions reductions can be, and are, pursued by renewable energy policies, pollution quotas, pollution taxes, innovation incentives, and policies specific to sectors other than the power sector, like fuel economy standards and standards for the carbon intensity of fuels, e.g. renewable fuel standards. Given uncertainty about the optimal level of environmental damage, it is common practice to evaluate environmental programs according to a cost effectiveness criterion that seeks to achieve given objectives at least cost. Evidence on the costs and benefits of alternative policies is necessary for achieving the cost-effectiveness criterion.

This paper has considered the efficiency of the California Solar Initiative (ignoring the optimality of objectives), including the optimality of a unique characteristic that other states in the United States are emulating: a subsidy that declines over time. Several lessons emerge from the foregoing analysis. First, there is little economic rationale for rebates to decline over time. Were regulators able to provide unanticipated increases in rebate rates, they may find it optimal to do so, much as the durable goods monopolist would rationally reduce prices. As public authorities are unlikely to be able to commit to such a program in secret, they are subject to the Coase conjecture and can do no better than offer a single subsidy rate unless consumer entry is an important part of the problem. This is true in the stylized model of section ?? even amid unappropriated learning and regardless of the evolution of prices over time. Notably, there is no advantage to delaying learning by reserving budget for subsidies in a later period. Subsidies across multiple periods can be optimal if sufficient consumers enter the market in successive periods. In California, however, household formation declined over the duration of the California program.

Second, econometric results in section 4 indicate the rebate program induced additional solar adoptions at a high cost equal to 50 percent of total system cost. The program induced

28 percent of solar adoption observed in program data. There are few analyses of "green" rebate programs with which to compare these results, however, Bennear et al. (2013) find low additionality due to rebates for adoption of high efficiency toilets. The rebate program induced 34 percent of high-efficiency toilet purchases over the study period.

The effectiveness of solar adoption rebates can be compared to other programs for air pollution reductions by estimating the cost per unit of avoided emissions. We do this by assuming a 20-year lifespan of an installed kilowatt of solar capacity and ignoring discounting. We assume a capacity factor of 0.22 to translate nameplate capacity into generated electricity per hour[9]. We also assume a derate factor of 0.04 to reflect losses in electricity during conversion from direct current to alternating current power[10]. Thus, 1 kilowatt of installed solar capacity is assumed to generate 37,000 kilowatt-hours of electricity over its lifetime.[11] The estimated public cost per kilowatt-hour is thus $0.091. In order to compare the public cost per additional capacity to estimated benefits from avoided pollution, we adapt the Muller et al. (2011) estimates of external damages from carbon and criteria pollutant emissions per kilowatt-hour of coal or natural gas-fired generation to reflect the U.S. government's estimated social cost of carbon of $37 per metric ton. Doing so yields estimated public benefits from avoided damages equal to $0.039 if coal-fired generation is displaced and $0.016 if natural gas-fired generation is displaced. Even were California solar to displace coal entirely, the cost of avoided emissions more than doubles the benefits of avoided emissions. Costs are more than five times greater than benefits if natural gas generation is displaced. These calculations assume no increase in consumption due to the price effect of increased electricity supply. A price effect would limit the displacement of dirty generation and erode the public benefits of incremental solar capacity.

---

[9] See National Renewable Energy Laboratory (2011).

[10] A default derate factor of 0.04 is assumed in the National Renewable Energy Laboratory's "PVWatts" solar electricity calculator. See http://pvwatts.nrel.gov.

[11] $1 \text{ kilowatt} \times 0.22 \times (1 - 0.04) \times 20 \text{ years} \times \frac{8760 \text{ hours}}{\text{year}} = 37,000 \text{ kWh}$.

Subtracting the criteria pollutant damages per kilowatt-hour of dirty generation (in Muller et al. (2011)) from the estimated public cost per kilowatt of program solar capacity, we derive an estimate of the value of avoided carbon emissions necessary for the program to deliver positive net benefits. We assume a carbon dioxide emissions rate equal to the average rate of the Western Electricity Coordinating Council interconnection (0.00038 metric tons per kilowatt-hour) [12].If avoided criteria pollutant emissions are high (e.g. from a coal plant), then the public cost per avoided ton of carbon dioxide emissions is $144. If avoided criteria pollutant emissions are low, the public cost per avoided ton of carbon dioxide is $202. If the benefit of avoided criteria pollutant emissions are ignored, i.e. it is assumed the only public benefit of solar adoption is avoided carbon emissions, then the cost of an avoided ton of carbon dioxide is $238. If future avoided emissions are discounted at a 5% rate, the cost per ton of avoided carbon dioxide ranges from $270-$328. The U.S. Office of Management and Budget (2013) estimates that the social cost of carbon is $37 per ton of carbon dioxide emissions.

The California rebate program fares poorly when compared to alternative carbon abatement programs. Johnson (2014) estimated the cost of marginal carbon emissions reductions of $45-160 from a renewable portfolio standard in the Northeast United States. Parry and Williams (2011) estimated the carbon abatement costs from economy-wide and power-sector-only pricing policies to be $16-18 per ton of emissions.

The foregoing analysis also suggests the California rebate program is not efficient among solar energy policies. In particular, whereas the California program and other California energy policy favors distributed solar generation, utility-scale projects accomplish carbon abatement at far less cost. The capacity-weighted average cost per watt for utility scale projects larger than 10-megawatt capacity was $3.1 in 2012; the capacity weighted cost per watt of utility-scale projects less than 10-megawatts was $3.5 (Barbose et al. 2013).

---

[12]See Zivin et al. (2012).

Utility scale capacity differs from the distributed generation capacity installed under the rebate program in two respects. First, the utility-scale projects can be sited to optimize generation, so, drawing on results from section 5, distributed capacity sacrifices 25 percent generation relative to utility-scale projects. The utility-scale generation, however, must be transmitted from the solar project site to end-users. Energy losses equal to about 7 percent occur along the transmission lines. The cost of distributed capacity, then, is $4.48-4.64 per equivalent watt capacity, whereas the price of an equivalent utility-scale watt of capacity is $3.33-3.76. Hence, the equivalent cost of a large utility-scale project is lower than the public cost of program capacity even if the former is penalized for line losses and the latter is not penalized for sub-optimality of siting. Thus, greater carbon abatement could be accomplished at the same public cost if regulators fully funded and optimally sited large solar installations. Examining data in system and installation costs for rooftop and utility-scale projects, Barbose et al. (2013) identify significant reductions in technology costs in recent years. Balance of system costs that are largely composed of installation costs, however, have stalled despite declining from 1999-2005. Installation costs, therefore, are becoming an increasing share of the cost of rooftop systems, suggesting increasing scale economies that favor large solar projects.

Given spatial variation in solar irradiance and evidence of increasing returns to scale, policy preferences for distributed generation are difficult to explain. Because electricity is a quintessential homogeneous product in its end-use, the neoclassical economist views solar adoption as an investment decision in which dividends are paid in the form of avoided utility costs. If solar generation capacity is viewed as an investment, then households should be indifferent to the location of their solar investment. In particular, one can imagine Coasian transactions whereby households in areas with low solar irradiance areas rent rooftops of households in high irradiance areas in exchange for the incremental generation benefits. More generally, policy should not constrain households to investing in solar capacity on

their own rooftops. Households in foggy, cloudy, and shaded areas, and households that do not own rooftops, are disadvantaged in solar investments. Greater efficiency in solar generation could be achieved by policies that permit these and other households to invest in community solar projects or even utility-scale projects that can capitalize on scale economies and high irradiance areas.

7   Conclusion

This paper has evaluated the cost-effectiveness of a large solar technology adoption program in California. We find that the signature characteristic of the program, a system of declining rebates that is emulated by other jurisdictions, is inefficient unless consumer entry is an important phenomenon. Moreover, it is shown that the announcement of rebate reductions permits anticipatory investments by consumers who "pull forward" their demand in order to capture the relatively more generous subsidies. The effect of the rebate alone is shown to be quite low, as the rebate elasticity is estimated to be 0.40. This indicates that the program achieves carbon emissions abatement at a cost that is conservatively 3-5 times greater than the estimated social cost of carbon. Finally, the siting of solar capacity installed under the program is shown to be suboptimal from the planner's perspective as 13-25 percent more solar generation (and, therefore carbon abatement) could be achieved by shifting the installed capacity to areas that receive more sunlight. These combined results suggest the same solar generation could be achieved at less total cost and less public cost were regulators to fully invest in optimally sited, utility-scale projects, rather than distributed solar generation.

References

Arrow, Kenneth J, "The Economic Implications of Learning by Doing," *The Review of*

Economic Studies, 1962, *29* (3), 155–173.

Baker, Erin, Meredith Fowlie, Derek Lemoine, and Stanley S Reynolds, "The economics of solar electricity," *Annual Review of Resource Economics*, 2013, *5* (1).

Barbose, Galen, Naim Darghouth, Samantha Weaver, and Ryan Wiser, "Tracking the Sun VI: An Historical Summary of the Installed Price of Photovoltaics in the United States from 1998-2012," Technical Report, Lawrence Berkeley National Laboratory, Berkeley, CA July 2013.

Bennear, Lori S, Jonathan M Lee, and Laura O Taylor, "Municipal Rebate Programs for Environmental Retrofits: An Evaluation of Additionality and Cost-Effectiveness," *Journal of Policy Analysis and Management*, 2013.

Benthem, Arthur Van, Kenneth Gillingham, and James Sweeney, "Learning-by-doing and the optimal solar policy in California," *ENERGY JOURNAL-CAMBRIDGE MA THEN CLEVELAND OH-*, 2008, *29* (3), 131.

Bollinger, Bryan and Kenneth Gillingham, "Peer effects in the diffusion of solar photovoltaic panels," *Marketing Science*, 2012, *31* (6), 900–912.

Borenstein, Severin, "The Market Value and Cost of Solar Photovoltaic Electricity Production," *UC Berkeley Center for the Study of Energy Markets Working Paper Series*, 2008, (176).

_ , "The Private and Public Economics of Renewable Electricity Generation," *The Journal of Economic Perspectives*, 2012, *26* (1), 67–92.

Braun, Martin, Thomas Stetz, Roland Bründlinger, Christoph Mayr, Kazuhiko Ogimoto, Hiroyuki Hatta, Hiromu Kobayashi, Ben Kroposki, Barry Mather, Michael Coddington et al., "Is the distribution grid ready to accept large-scale

photovoltaic deployment? State of the art, progress, and future prospects," *Progress in Photovoltaics: Research and Applications*, 2012, *20* (6), 681–697.

Cameron, A Colin and Pravin K Trivedi, *Regression Analysis of Count Data* number 30, Cambridge University Press, 1998.

Dunlap, MA, W Marion, and S Wilcox, "Solar radiation data manual for flat-plate and concentrating collectors," Technical Report 463-5607, National Renewable Energy Laboratory, Golden, CO 1994.

Energy Information Administration, "Electric Power Monthly," Technical Report, U.S. Energy Information Administration, Washington, DC December 2012.

_ , "Levelized Cost of New Generation Resources in the Annual Energy Outlook 2013," Technical Report, U.S. Energy Information Administration, Washington, DC May 2013.

Federal Energy Regulatory Commission, *Small Generator Interconnection Procedures* Federal Energy Regulatory Commission, order no. 792 ed. January 2014.

Fischer, Carolyn, "Emissions pricing, spillovers, and public investment in environmentally friendly technologies," *Energy Economics*, 2008, *30* (2), 487–502.

_ **and Richard G Newell**, "Environmental and technology policies for climate mitigation," *Journal of environmental economics and management*, 2008, *55* (2), 142–162.

Fowlie, Meredith and Nicholas Muller, "Market-based emissions regulation when damages vary across sources: What are the gains from differentiation?," NBER Working Paper 18801, National Bureau of Economic Research, Cambridge, MA February 2013.

Gillingham, Kenneth and James Sweeney, "Barriers To Implementing Low-Carbon Technologies," *Climate Change Economics*, 2012, *3* (04).

Graziano, Marcello and Kenneth Gillingham, "Spatial Patterns of Solar Photovoltaic System Adoption: The Influence of Neighbors and the Built Environment ," 2014.

Jaffe, Adam B, Richard G Newell, and Robert N Stavins, "A tale of two market failures: Technology and environmental policy," *Ecological Economics*, 2005, *54* (2), 164–174.

Johnson, Erik, "The Cost of Carbon Dioxide Abatement from State Renewable Portfolio Standards," *Resource and Energy Economics*, 2014.

Kahn, Matthew E, "Do greens drive Hummers or hybrids? Environmental ideology as a determinant of consumer choice," *Journal of Environmental Economics and Management*, 2007, *54* (2), 129–145.

Mian, Atif and Amir Sufi, "The Effects of Fiscal Stimulus: Evidence from the 2009 Cash for Clunkers Program*," *The Quarterly Journal of Economics*, 2012, *127* (3), 1107–1142.

Muller, Nicholas Z, Robert Mendelsohn, and William Nordhaus, "Environmental accounting for pollution in the United States economy," *The American Economic Review*, 2011, *101* (5), 1649–1675.

National Renewable Energy Laboratory, "2010 Solar Technologies Market Report," Technical Report, National Renewable Energy Laboratory, Golden, CO November 2011.

Nordhaus, William, "Designing a friendly space for technological change to slow global warming," *Energy Economics*, 2011, *33* (4), 665–673.

Parry, Ian and Roberton Williams, "Moving US climate policy forward: Are carbon taxes the only good alternative?," *Resources for the Future Discussion Paper*, 2011, (11-02).

Perez, Richard, Pierre Ineichen, Kathy Moore, Marek Kmiecik, Cyril Chain, Ray George, and Frank Vignola, "A new operational model for satellite-derived irradiances: description and validation," *Solar Energy*, 2002, *73* (5), 307–317.

Pigou, AC, "The Economics Of Welfare," 1920.

Sexton, Steven E. and Alison L. Sexton, "Conspicuous Conservation: The Prius Halo and Willingness to Pay for Environmental Bona Fides," *Journal of Environmental Economics and Management*, 2013, *Forthcoming.*

U.S. Environmental Protection Agency, "Cleaner Power Plants," Online at http://epa.gov/airquality/powerplanttoxics/powerplants.html April 2012.

U.S. Office of Management and Budget, Technical Report Executive Order 12866, Interagency Working Group on Social Cost of Carbon November 2013.

Zivin, Joshua S Graff, Matthew Kotchen, and Erin T Mansur, "Spatial and Temporal Heterogeneity of Marginal Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies," Technical Report 18462, National Bureau of Economic Research, Cambridge, MA 2012.

Table 1: CSI Rebate Levels

Rebate Level ($/watt)	Date First Issued		
	PG&E	SCE	SDG&E
2.50	Week 45, 2006	Week 36, 2006	Week 7, 2007
2.20	Week 43, 2007	Week 20, 2008	Week 1, 2008
1.90	Week 15, 2008	Week 25, 2009	Week 41, 2008
1.55	Week 51, 2008	Week 30, 2010	Week 26, 2009
1.11	Week 37, 2009	Week 10, 2011	Week 44, 2009
0.65	Week 19, 2010	Week 40, 2011	Week 17, 2010
0.35	Week 44, 2010	Week 16, 2012	Week 46, 2010
0.25	Week 43, 2011	Week 46, 2012	Week 40, 2010
0.20	Week 29, 2012	Week 20, 2013	Week 18, 2012

Table 2: Summary Statistics

	California	PG&E	SCE	SDG&E
Weekly Solar Adoptions	87	125	101	32
Average System Size (kilowatts)	5.7	5.68	5.95	5.39
Average System Cost ($)	38,373	37,993	40,383	36,513
Average Rebate ($/watt)	1.39	1.12	1.51	1.23
Average Subsidy Payment ($)	6,130	5,137	7,648	5,465

Table 3: Effect of Rebate on Rooftop Solar Adoption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Exp. OLS			Poisson			Neg. Bin.	
Dependent variable: *Adoptions*									
$ln(Rebate)$	0.399***	0.414***	0.444**	0.442***	0.423***	0.500*	0.413***	0.457***	0.467*
	(0.096)	(0.107)	(0.217)	(0.059)	(0.044)	(0.257)	(0.049)	(0.074)	(0.263)
Constant	0.588*	1.370***	0.980***	-0.368*	0.215	-1.644***	-0.484**	0.050	-1.677***
	(0.321)	(0.331)	(0.199)	(0.209)	(0.075)	(0.263)	(0.215)	(0.134)	(0.391)
Week FE	Y	N	Y	Y	N	Y	Y	N	Y
Month FE	N	Y	N	N	Y	N	N	Y	N
Region*Year FE	Y	Y	N	Y	Y	N	Y	Y	N
Region*Month FE	N	N	Y	N	N	Y	N	N	Y
AIC	0.738	0.664	0.599	9.942	11.845	8.917	8.927	8.849	8.751
BIC	-3979.753	-5366.080	-3016.671	5021.26	5568.455	5118.172	4033.781	2643.283	4960.953
Pearson	–	–	–	3089.74	5580.587	1602.859	982.007	1016.473	956.601
$R^{2\dagger}$	0.942	0.906	0.968	0.839	0.795	0.865	0.256	0.212	0.315

Cluster-robust standard errors in parentheses. *** p ¡ 0.01, ** p ¡ 0.05, * p ¡ 0.1; $N = 978$

Coefficients are interpreted as rebate elasticities of solar adoption.

†McFadden pseudo R-squared reported for maximum likelihood estimation; R-squared for OLS.

Table 4: Effect of Rebate on Rooftop Solar Adoption Controlling for Design Factor

	(1) Exp. OLS	(2) Poisson	(3) Neg. Bin.
Dependent variable: *Adoptions*			
$ln(Rebate)$	0.259**	0.411***	0.398***
	(0.029)	(0.033)	(0.035)
Constant	-2.270***	-2.775***	-2.764***
	(0.193)	(0.338)	(0.342)
AIC	35,412	3.622	3.618
BIC	35,444	$-221*10^3$	$-223*10^3$
Pearson		20,092	18,663
$R^{2\dagger}$	0.629	0.367	0.221

Cluster-robust standard errors in parentheses. *** p ¡ 0.01, ** p ¡ 0.05, * p ¡ 0.1, N= 23,848

Coefficients are interpreted as rebate elasticities of solar adoption.

†McFadden pseudo R-squared reported for maximum likelihood estimation; R-squared for OLS.

Table 5: Effect of Rebate on Rooftop Solar Adoption Ignoring Pull Forward Effect

	(1)	(2)	(3)
	Exp. OLS	Poisson	Neg. Bin.

Dependent variable: *Adoptions*

	(1)	(2)	(3)
$ln(Rebate)$	0.781***	0.758***	0.786***
	(0.124)	(0.087)	(0.088)
Constant	0.552***	0.592***	0.547***
	(0.110)	(0.077)	(0.079)
N	978	978	978
AIC	0.793	10.572	9.005
BIC	-4141.189	5423.218	3895.075
Pearson	–	3807.100	971.387
$R^{2\dagger}$	0.933	0.826	0.240

Cluster-robust standard errors in parentheses. *** p ¡ 0.01, ** p ¡ 0.05, * p ¡ 0.1

Coefficients are interpreted as rebate elasticities of solar adoption.

†McFadden pseudo R-squared reported for maximum likelihood estimation; R-squared for OLS.

Table 6: Effect of Behavioral "Bargain-seeking" on Solar Adoptions

	(1)	(2)	(3)
	Exp. OLS	Poisson	Neg. Bin.

Dependent variable: $Adoptions$

	(1)	(2)	(3)
$lnNetPrice$	-.320***	-.167**	-0.277***
	(0.065)	(0.075)	(0.081)
$lnSubsidy$	0.117***	0.057**	0.097**
	(0.042)	(0.025)	(0.041)
Constant	3.209***	1.198***	1.845***
	(0.409)	(0.432)	(0.416)
AIC	0.734	9.968	8.928
BIC	-3978.834	5052.202	4040.107
Pearson	–	3115.149	976.957
$R^{2\dagger}$	0.942	0.834	0.256

Cluster-robust standard errors in parentheses. *** p ¡ 0.01, ** p ¡ 0.05, * p ¡ 0.1; $N = 978$.

Coefficients are interpreted as rebate elasticities of solar adoption.

†McFadden pseudo R-squared reported for maximum likelihood estimation; R-squared for OLS.

Table 7: Electricity Gain from Optimal Capacity Sting

	Additional Annual DC Electricity (1,000 MWh)
Scenario 1: Site in highest irradiance locations	184 +25% (30,600 homes)
Scenario 2: Site only on rooftops	122.6 +17% (20,400 homes)
Scenario 3: Site only on 15% of rooftops	95.4 +13% (15,900 homes)

Figure 1: Service Areas of California Investor Owned Utilities
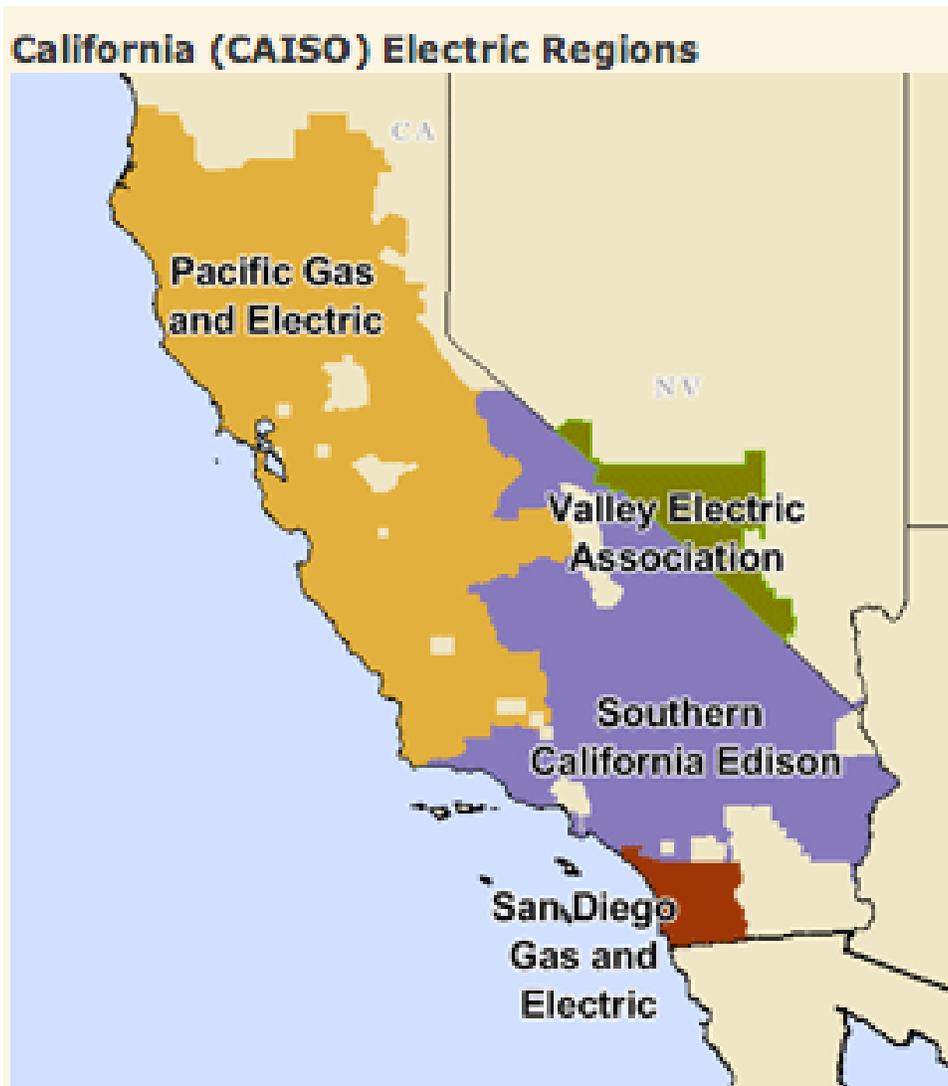
Figure 2: Distribution of Weekly Number of Solar Adoptions
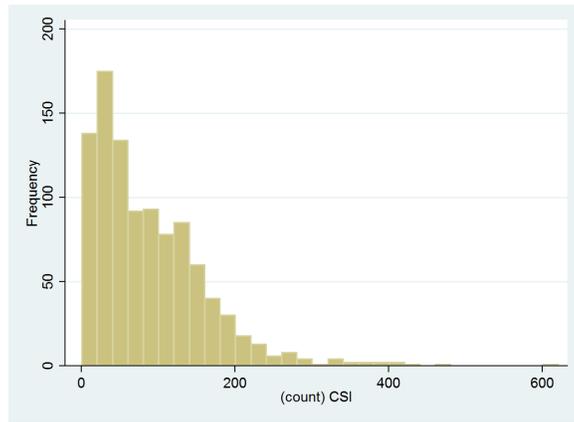
(a) Distribution of Adoptions (CSI)
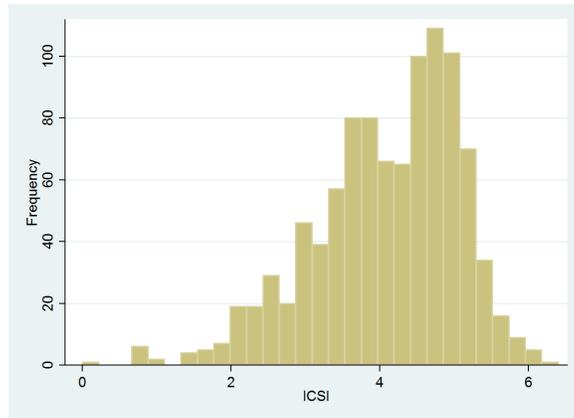
(b) Distribution of Ln(Adoptions) (CSI)

Figure 3: Residuals from Main OLS Estimation
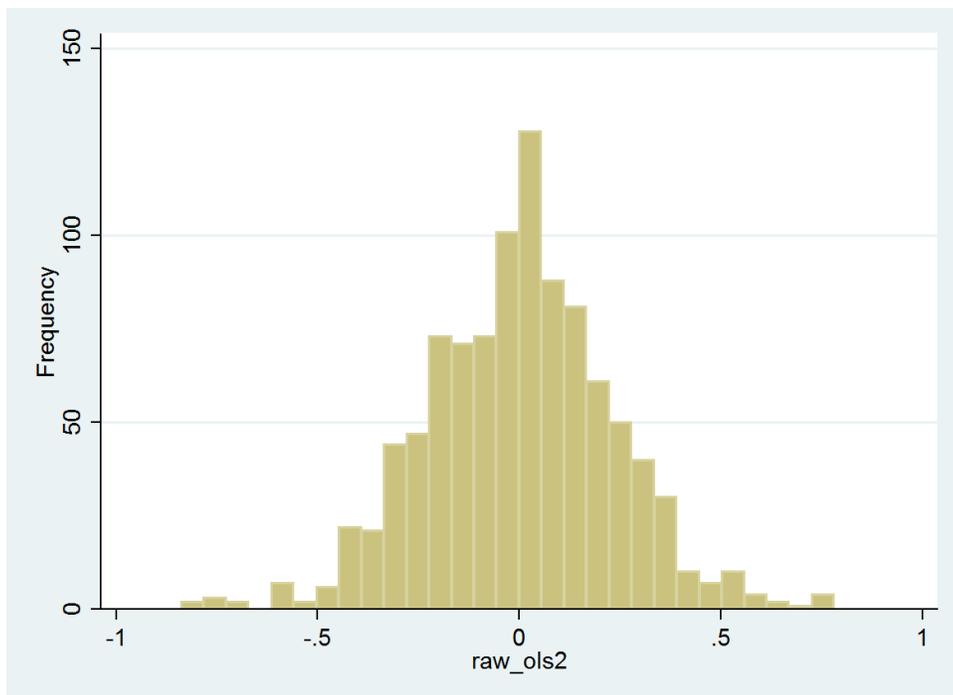
This figure shows the distribution of residuals from estimation of (3) by OLS.

Figure 4: Weekly Solar Adoptions and PG&E Rebate Changes
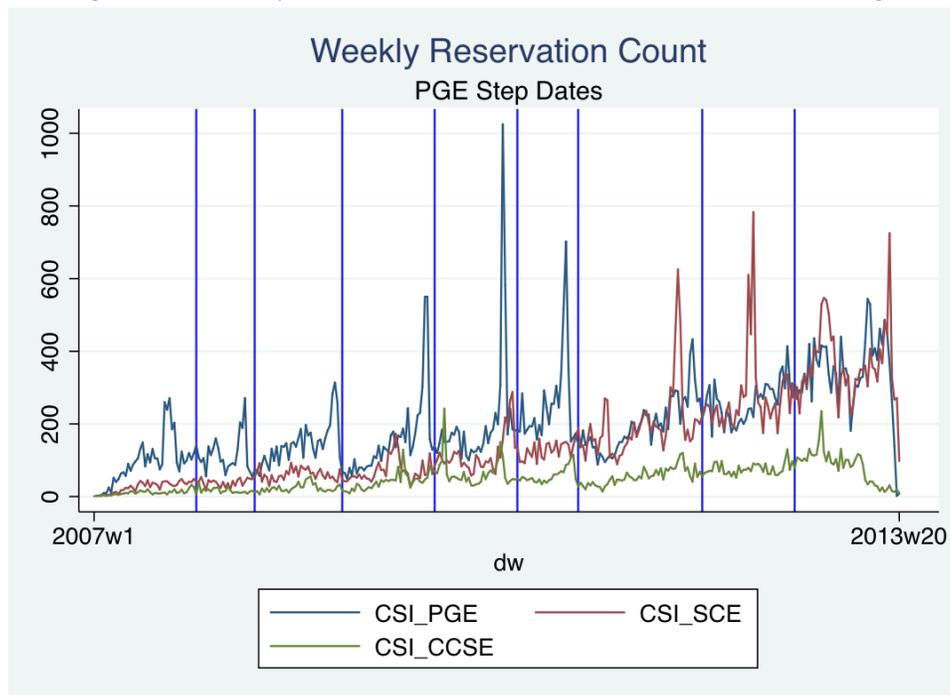
This figure shows the number of solar adoptions per week in the territories of Pacific Gas and Electric (in blue), Southern California Edison (in red), and San Diego Gas and Electric (in green). Vertical blue lines designate the dates that rebate rates were lowered in the Pacific Gas and Electric territory. Adoptions in that territory tend to spike shortly before the rebate changes, suggesting a pull forward effect caused by consumer anticipation of rebate reductions.

Figure 5: Total Adoptions by Week Relative to Rebate Change
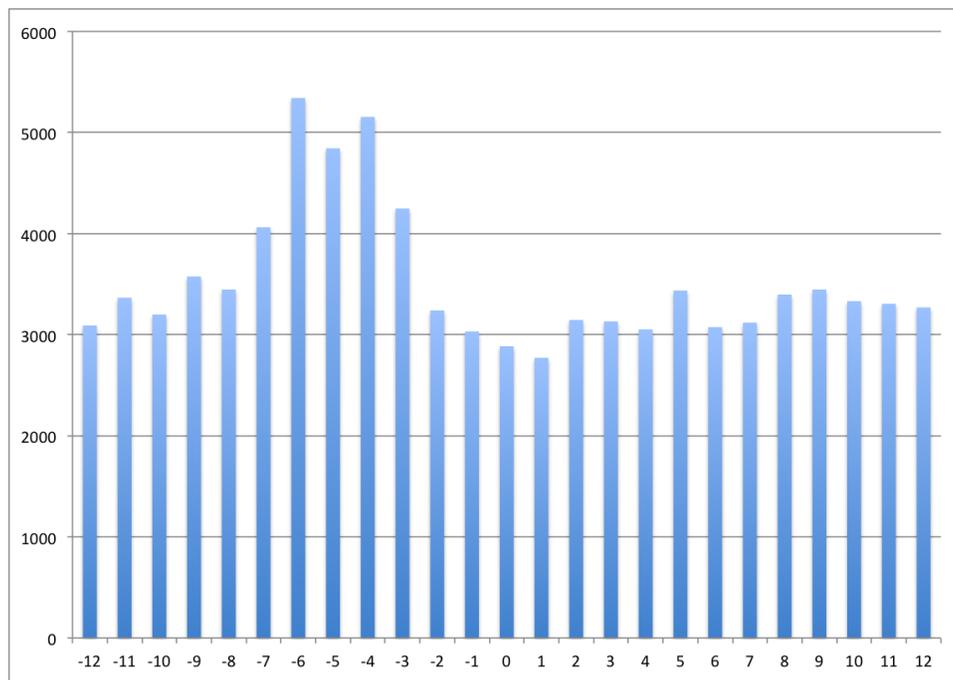
This figure shows the total number of adoptions per week starting twelve weeks before a rebate change through 12 weeks after a rebate change for all three Investor Owned Utility regions in the sample.

Figure 6: Event time plots
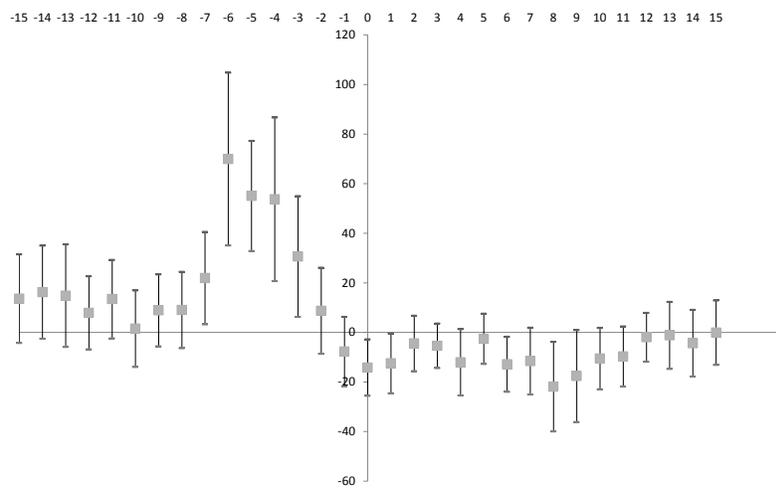
This figure shows the point estimates and 95-percent confidence interval for α_j in (2). It provides evidence of a substantial pull forward effect that confounds estimation of a rebate elasticity.

Figure 7: Design Factor Distribution
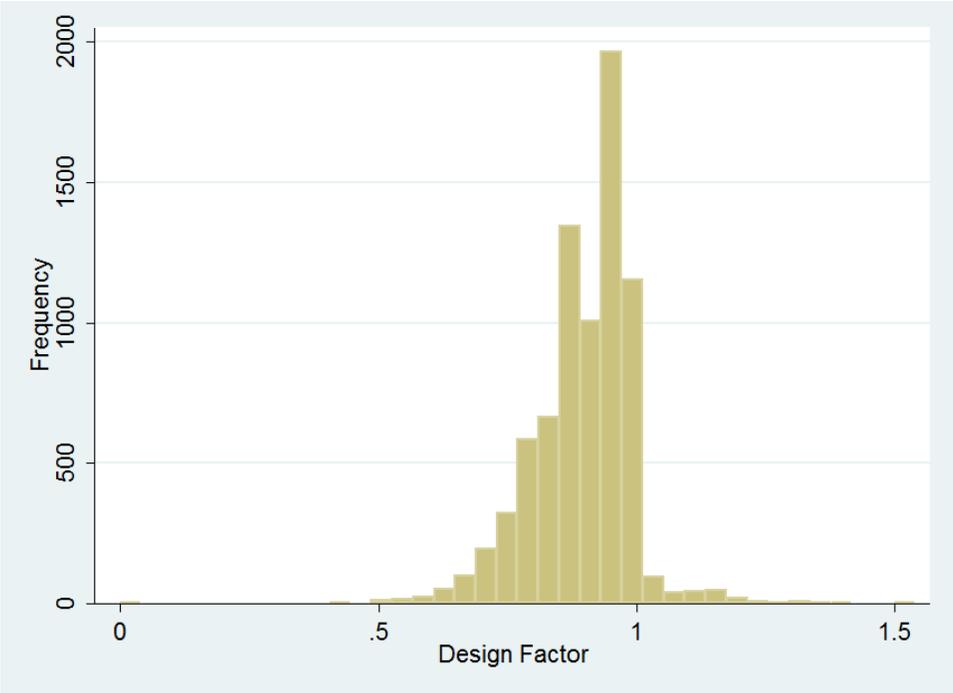
This figure shows the distribution of design factors for installed residential solar PV systems under the California Solar Initiative.
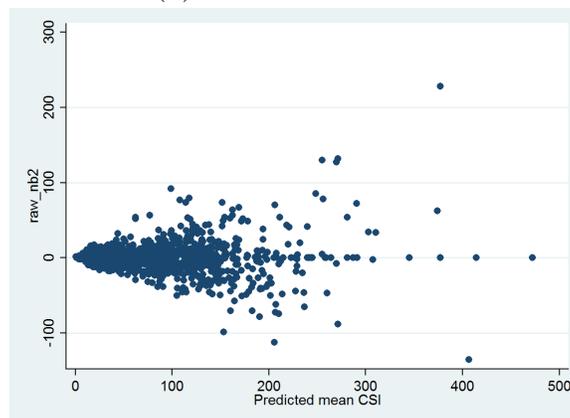
Figure 8: Raw Residuals Plotted Against Predicted Adoptions
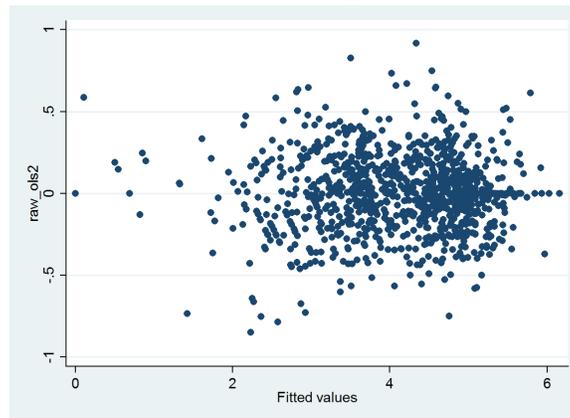
(a) OLS Residuals
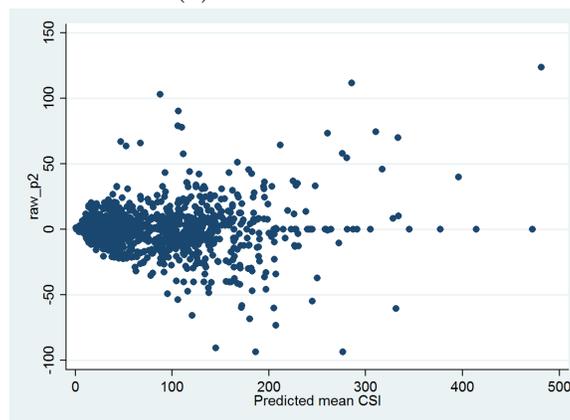


(b) Poisson Residuals

(c) Negative Binomial Residuals

Depicted are the raw residuals from estimation of (3) by OLS in panel (a), Poisson-distributed maximum likelihood in panel (b), and negative binomial distributed maximum likelihood in panel (c). All residuals are plotted against respective fitted values.

Figure 9: Mean-Variance Relationship
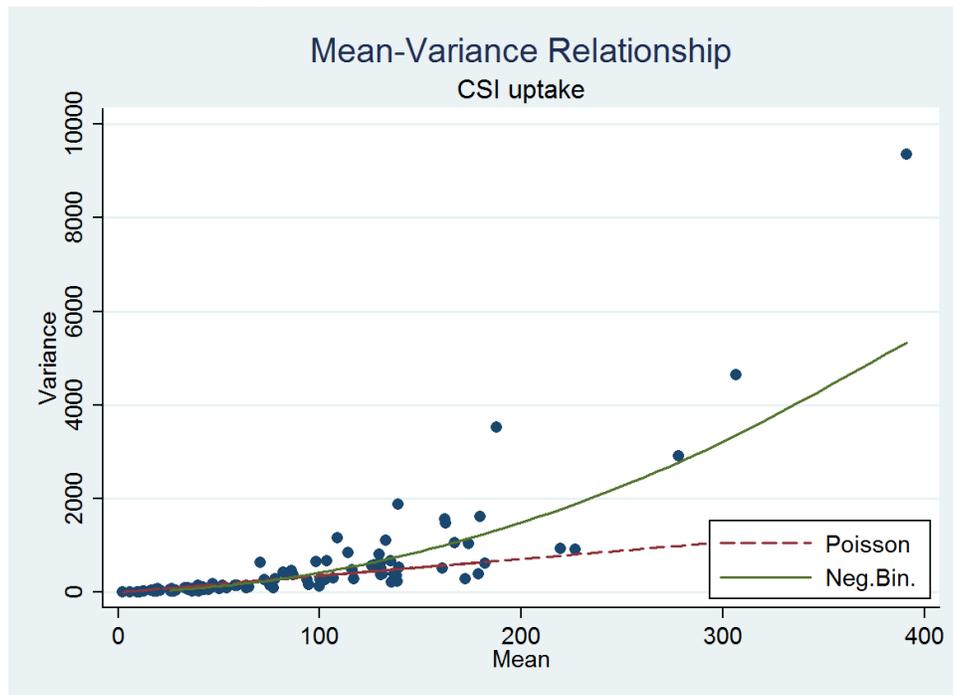
Shown is the average mean versus variance of adoptions for 100 groups defined by the similarity of predicted values from negative binomial regression of (3). These are plotted alongside the assumed Poisson and negative binomial mean-variance relationship using parameter estimates derived from respective estimation of (3). It evidence the relative advantage of the negative binomial assumptions in fitting the data. The Poisson, even an over-dispersed Poisson model is constrained to a linear mean-variance relationship that poorly fits the data.

Figure 10: Solar Irradiance in California
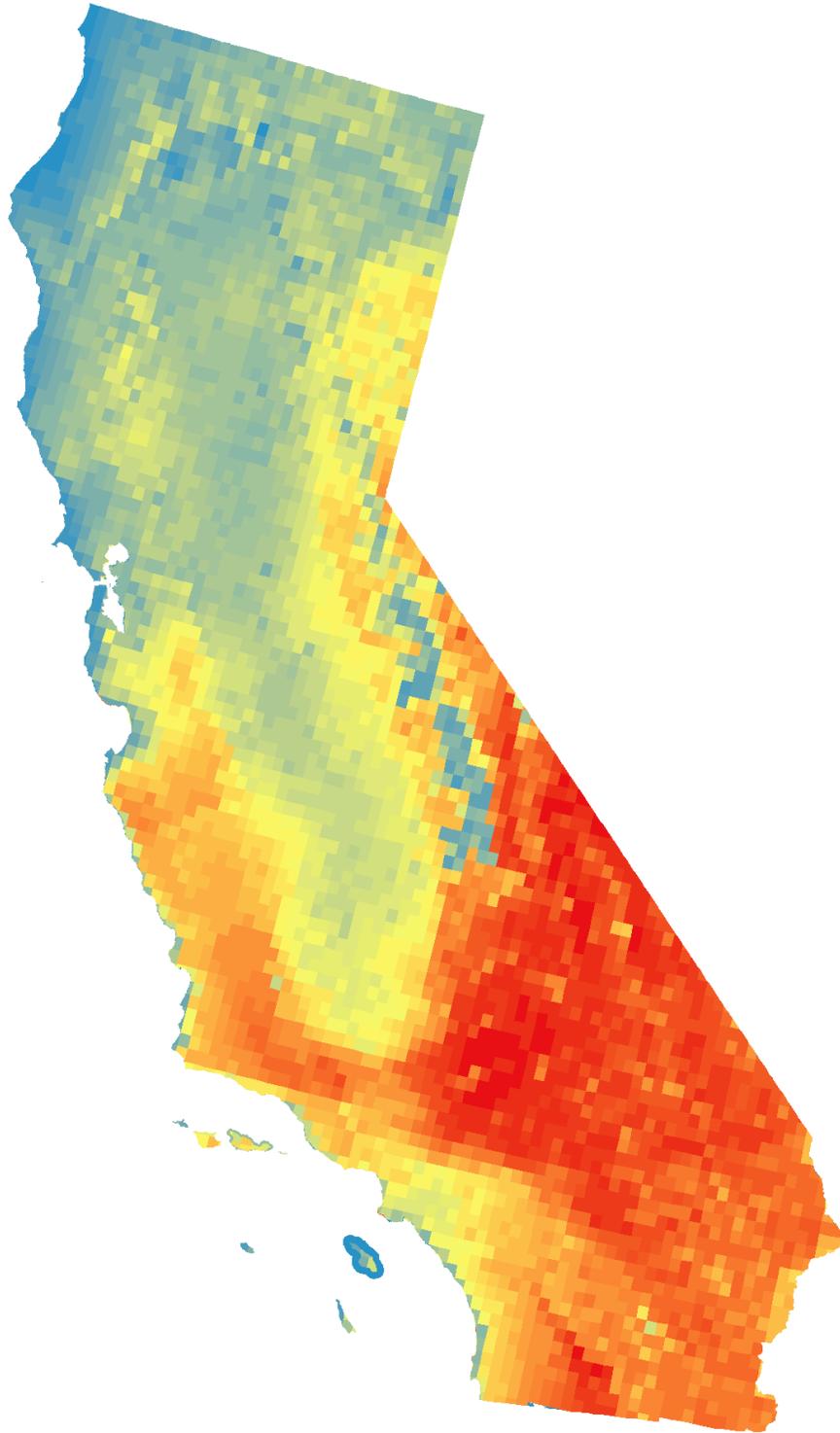
Mapped is the annual solar output of a modal system for the California Solar Initiative given solar radiance measured at a resolution of 10 square kilometers. Weather data is linked to each system based on Typical Meteorological Year data from weather stations operated by the National Renewable Energy Laboratory as part of the National Solar Resource Database. Darker red areas depict greater solar irradiance (scale coming soon). Yellow areas reflect less solar irradiance. Blue areas reflect the lease solar irradiance.

Figure 11: Solar Installations Under California Rebate Program
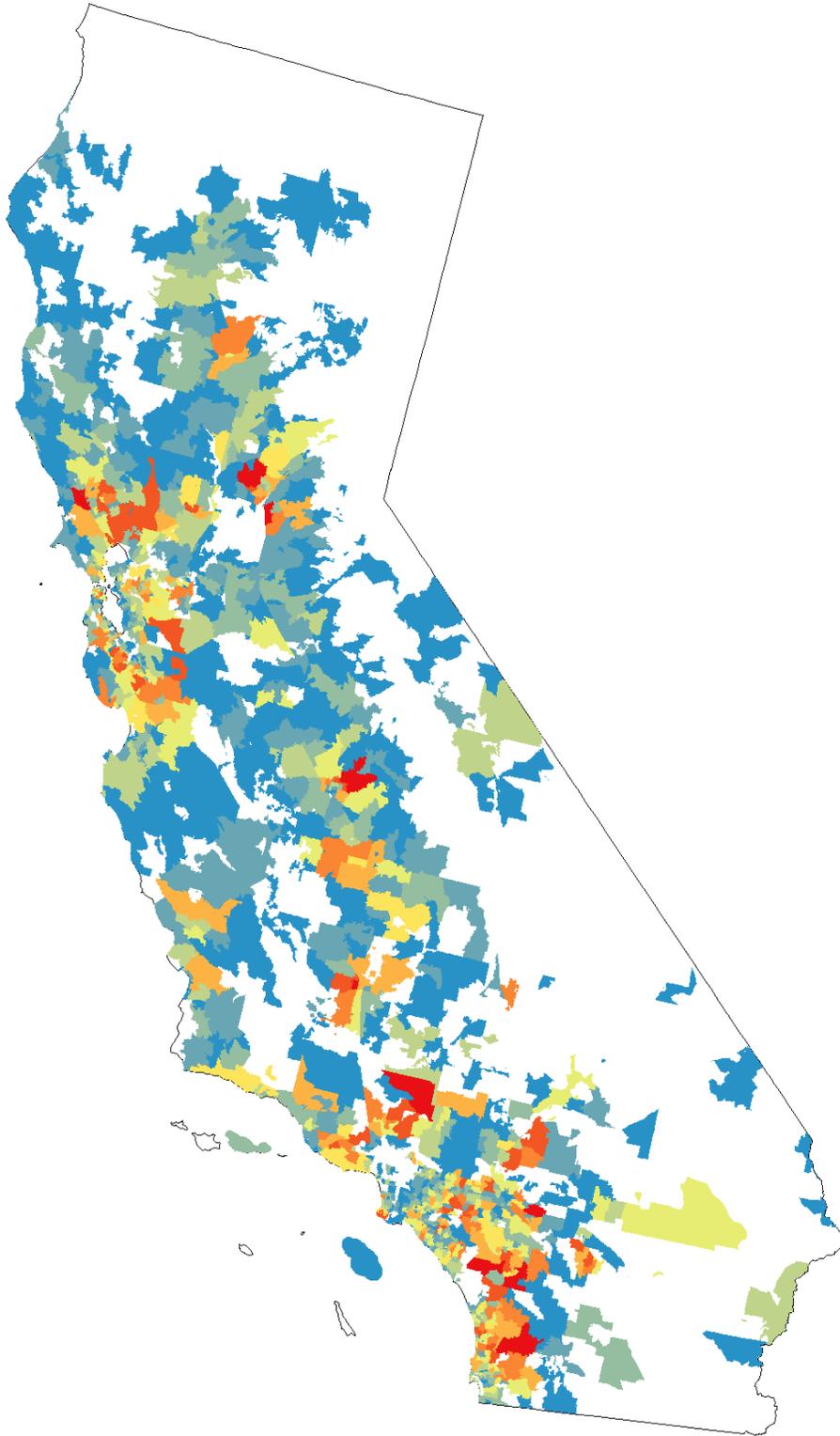
Locations of residential solar adoptions under the California Solar Initiative. One dot represents 5 installations.

Figure 12: Locations of Optimal Solar Capacity Siting

Locations of residential solar adoptions under the California Solar Initiative (in black) and location of optimal siting of rooftop solar accounting for grid stability concerns (in blue). One dot represents 5 installations.