Subsidies and Investments in the Solar Power Market

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Abstract

Over the last ten years, the solar photovoltaic (PV) market has grown rapidly due in part to government incentive programs. I estimate a dynamic consumer demand model to evaluate the effects of actual and counterfactual policies on residential solar installations. My results indicate that with a $72 social cost of carbon, the subsidy in California would be welfare neutral. This cost increases to $124 if I account for the tax credits. When comparing the two most frequently-used incentive schemes, I find that the upfront subsidy encourages more adoptions than the production-based subsidy, but the latter is more efficient. Overall, I find that the welfare costs of encouraging prolific solar adoptions in a suboptimal location are high.

JEL codes: D12, D61, H23, Q41, Q42, Q48.

Key words and phrases: optimal policy choice, dynamic discrete choice model, renewable energy subsidies, feed-in tariffs, technology adoptions.

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1 Introduction

"I'd put my money on the sun and solar energy. What a source of power! I hope we don't have to wait until oil and coal run out before we tackle that." -Thomas Edison, 1931

"Photovoltaics are threatening to become the costliest mistake in the history of German energy policy." -Der Spiegel, July 4, 2012

The solar power market has grown rapidly in the past decade, and solar photovoltaic (PV) systems (henceforth solar power system) have been the fastest growing renewable energy technology both in the U.S. and globally. On the supply side, because of lower input costs, learning-by-doing, and scale economies there is a sharp reduction in the costs of solar power. The costs of PV modules, the main components of solar systems, have halved during 2007-2012. However, even with this substantial decline in costs, most solar power systems are still not economically competitive; because the comparative electricity prices of coal and natural gas remain lower. The solar power market has overcome this cost difference through government incentive programs. In 2010 alone, the U.S. federal government spent $14.67 billion on subsidizing renewable energy while Germany, the world's leader in solar adoptions, invested over $13 billion on renewable subsidies in 2012.[1][2]

While various government entities in the U.S. and worldwide have spent prodigious amounts subsidizing solar energy technology, the cost-effectiveness and the net welfare costs associated with the subsidy programs remain unclear.[3] Many incentive programs, as in California, provide upfront capacity-based subsidies based on system size; other programs, as in Germany, provide production-based subsidies that depend on the amount of electricity produced. The success in stimulating PV systems adoptions in Germany

[1]The U.S. federal spending figure includes direct expenditure to producers or consumers, tax expenditures, R&D loans and loan guarantees. In particular, one billion dollars are spent on solar subsidies while 6 billion dollars go towards subsidizing biofuels. (EIA, 2011)

[2]Germany has on average half of the solar resources, one-quarter of the population and one-fifth of the GDP compared to the U.S. However its solar deployment (in cumulative installed PV capacity) is six times higher than that in the U.S.

[3]Cost-effectiveness is defined as the greatest number of solar power system purchased with the same amount of spendings.

had led to many inconclusive discussions on whether production-based subsidies are the best instruments for accelerating the diffusion of renewable energy technologies (Stern, 2007; Couture and Gagnon, 2010; Menanteau, et al., 2003; Ragwitz, et al., 2007; Butler and Neuhoff, 2008). It is important to address these issues because interests in renewable energy sources continue.

The quotes by Thomas Edison and the Spiegel magazine encompass the conundrum in solar subsidies faced by policy makers. On the one hand, there is consensus to expedite the transition from finite energy resources to renewable resources, with their reduced level of criteria pollutants and greenhouse gases. On the other hand, it is difficult to design and implement sustainable policy that balances growth with spending.

This paper develops a dynamic consumer demand model for rooftop solar power systems to examine such welfare implications of the subsidy programs in this fast-changing market. Each household solves an optimal stopping problem when making the investment decision in solar power systems. In other words, the households decide not only whether to purchase but also when to purchase. The model assumes that households can perfectly foresee future system prices and subsidies while evaluating the benefit of investing today versus the benefit of waiting.[4] I use a nested fixed-point maximum likelihood estimation on a 5-year data set from California to recover the underlying structural parameters in the consumer demand function. The model then evaluates the impact of price, capacity-based subsidies, tax credits, and the revenues raised by electricity production. From the viewpoints of the households making installation decisions, a production-based subsidy is equivalent to dollar for dollar decrease in the price of electricity.[5] I use a quasi-experimental setting with a preset subsidy schedule and exploit the variations through geographical locations and time to separately and jointly identify the impact of each variable.

I use this estimated model to answer questions concerning the economic

[4]The perfect foresight assumption can be easily relaxed by incorporating transition probabilities.

[5]The critical assumption here is that the demand for solar electricity in the relevant range is perfectly elastic such that there is no change to the equilibrium electricity price. The total solar electricity generated in 2012 contributes to less than 1% of the total generations.

value of solar incentive programs. I find that the capacity-based subsidy encourages more solar investments on the per dollar basis. Regarding welfare, however, production-based subsidies are more efficient as they encourage more adoptions in optimal locations for solar electricity production. Efficiency in this context is measured by the cost of displacing one ton of CO_2 (henceforth the implied CO_2 price). This efficiency result is particularly prominent with large geographic disparity in solar resources. The first force driving this result is that it requires a smaller amount of subsidies to stimulate adoptions to occur in a sunny location where the revenue from avoided electricity bills is higher compared to a less sunny location, holding everything else equal. Second, more CO_2 is mitigated by the greater amount of solar electricity production which drives the implied CO_2 price lower.

I also examine how households' investment decisions change with various subsidy policies. These changes include varying the subsidy level so that the implied CO_2 price (from subsidies) matches the social cost of carbon[6]. The equivalent CO_2 price of the CSI program subsidy during the studied period is \$62/ton to \$82/ton. The welfare cost of the program is relatively low compares to many other energy related programs that ranges from \$250-500 per ton $C0_2$ (Fowlie, Greenstone & Wolfram, 2015; Davis, Fuchs & Gertler, 2014; Beresteanu & Li, 2013; Knittel, 2009;). Meanwhile, the welfare cost considering both the California subsidy and the federal tax credits is around \$130. Jointly, the California program subsidy and the tax credits contribute to 76% to 87% of the installations. Without accounting for the change in consumer surplus, these costs can be 10-35% higher. An optimal subsidy policy should match the social cost of carbon (SSC). Interestingly, I find that it is infeasible to achieve the \$38/ton (Greenstone et al., 2013) welfare cost in two of electricity rate cases. This is because there are enough households who would choose to invest in solar power systems even without any subsidies when electricity rates are high. In this case, even an extremely small amount of subsidy would generate enough deadweight loss to exceed the \$38 optimal condition. In the lowest electricity

[6]The social cost of carbon (SSC) measures the economic damage that is associated with each additional ton of CO_2 released into the atmosphere. It requires significant assumptions that cover a wide range of fields which lead to a wide-ranging SSC value of \$5 to \$3000.

tier pricing model, lowering the aggregate subsidy to a level that matches the SSC results in a detrimental reduction in solar investments. Regarding the long-run elasticity, I find that demand elasticity is rather elastic (>3) at the 2011 price level. The elasticity is non-constant as it reduces to around two at the lower-end of the 2015 price level.[7]

Finally, I perform counterfactual analysis to consider the welfare loss in encouraging solar in less sunny locations. I find that the implied CO_2 price increased by about 50% when I introduce the solar radiation of Frankfurt, Germany, which is 35% less sunny than California, into the estimated model. This result is not immediately obvious since the number of investments and government spending reduces to a third of the original level. The welfare cost doubles to triples when I increase the subsidy level to reach the same level of investments as in the factual world.

The first contribution of this paper is to introduce a versatile model into environmental economics that allows researchers to conduct policy comparisons and welfare analysis in an environment where durable goods or other intricate dynamics are present. The flexibility of the model accounts for the change in consumer surplus from the infra-marginal consumers, which is a salient component of the total welfare. The estimation routine and the model are based on the single agent optimal stopping model as in Rust (1987). I further expand on the model to include multiple agents with observations at the aggregate market level, similar to Berry (1994). This analysis is, in spirit, similar to that of Gallagher and Muehlegger (2011), in which they examine how different forms of incentives affect consumers' hybrid vehicles purchase decisions and find that sales tax waivers have greater impact than tax credits. Beresteanu and Li (2011) uses a static structural model to study the demand for hybrid vehicle and finds that the rebate program costs less government revenue to achieve the same average fuel-efficiency of new vehicle fleet in 2006 than tax credits.

In particular, this paper is among the first papers to study the different outcomes under capacity-based subsidies versus production-based subsidies evaluated by their efficacy and social welfare implications using empirical data. The second contribution of this research is to improve understanding

[7]The average price at the end of 2011 is \$6.2 per watt in the data and a large installer in Arizona reported a price of \$3.2 per Watt in mid-2015.

of the demand side responses in the solar power market. Unlike Baker, et al. (2013) and Borenstein(2008) who provide a thorough economic analysis of the benefits and costs of solar from the supply side[8], this paper complements the studies of the solar home premium by Dastrup et al. (2012), and the peer effects of Bollinger and Gillingham (2012) by studying the consumer's behavior response to solar adoptions. Hughes and Podolefsky (2015) evaluate the effect of the capacity-based subsidy in California in a reduced form setting, which is the research most closely related to this paper. Using a regression discontinuity design, their result finds that the subsidy has a large effect on solar investments and a mild increase in subsidy (from \$5,600 to \$6,070) would increase investments by 13%.[9] A major difference between this paper and Hughes and Podolefsky (2015) is that the dynamic model capture consumer's foreward looking behavior such that consumers don't merely respond to the current subsidy level but also respond to the future system price and subsidy decline. This provides a much more complete description of the consumer's decision process in this fast-changing environment. Section 3 provides evidence of this forward looking behavior.

The following section builds the structural model, and section 3 describes the data used in this study. Section 4 presents the results and model validation. I present the counterfactual analysis in section 5 and section 6 concludes. Interested readers can consult Appendix A1 for additional information on solar power technologies and the development of solar power market in California.

2 The Structural Model

Next, the household's dynamic discrete choice model is developed. Each household has an infinite horizon and discount the future at the rate β. I proceed with constructing a general model with the least restrictions and

[8]Borenstein (2007) provides the economics of solar electricity from the households' perspective on the impact of mandatory time-of-use electricity pricing.

[9]The equivalent elasticity of 1.2 from Hughes and Podolefsky (2015) is low compared to estimates from this paper and two other recent papers, which may be explain by the difference in short-run (less elastic) and long-run elasticity (more elastic). Gillingham and Tsvetanov. (2016) use the 2008-2014 Connecticut data and find the demand elasticity estimate of 1.76. Arino et al. (2016) exploits exogenous change in electricity prices due to the Fukushima disaster to find the long-run demand elasticity of 1.5-2.3 in Japan.

later impose the perfect foresight restriction in the empirical section.

In each time period, households observe the price of the rooftop solar power system (p), the capacity-based subsidy (s), the net present value of the 25-year production revenue associated with solar electricity generation and the O&M cost (r), and the federal tax credits (τ).[10] These are the state variables observed both by households and econometricians. Denote $\mathbf{X} := \{p, s, r, \tau\}$. Given $\mathbf{X}$ and the other state variable, $\boldsymbol{\epsilon}$, each household decides whether to install an average size rooftop solar power system or to stay with the existing utility setup. The $\boldsymbol{\epsilon}$ is observed by households but not by econometricians. The discrete choice in time t can be formally expressed as, -p

$$d_t = \begin{cases} 1, & \text{install a solar power system} \\ 0, & \text{not install.} \end{cases}$$

The household exits the market forever once choosing to adopt. Given the states $(\mathbf{X}, \boldsymbol{\epsilon})$, the action d and the household income Y_i, the per-period utility can be decomposed into two components based on observability to econometricians - $\nu(\mathbf{X}, d; \boldsymbol{\theta})$ and $\epsilon(d)$. $\nu(\mathbf{X}, d; \boldsymbol{\theta})$ is the utility that a household receives from installing at state $\mathbf{X}$ where $\boldsymbol{\theta}$ is a vector of parameters to be estimated. Formally,

$$u(\mathbf{X}, d, \epsilon, \boldsymbol{\theta}) = \nu(\mathbf{X}, d, \boldsymbol{\theta}) + \epsilon(d) \tag{2.1}$$

where

$$\nu(\mathbf{X}, d, \boldsymbol{\theta}) = \begin{cases} \theta_0 + \theta_1(Y_i - p) + \theta_2 s + \theta_3 r + \theta_4 \tau, & d = 1 \\ \theta_1 Y_i, & d = 0. \end{cases} \tag{2.2}$$

The random error term $\boldsymbol{\epsilon} = \{\epsilon(0), \epsilon(1)\}$ is the idiosyncratic utility shock each individual receives at each time period, and follows a type I extreme value distribution. $\epsilon(1)$ is the unobserved component of installation cost. A positive $\epsilon(1)$ could reflect the case that a concurrent house renovation project reduces the cost of installing solar power systems, while a negative $\epsilon(1)$ may be attributed to sub-ideal roofing condition. $\epsilon(0)$ is the unobserved

[10]This refers to the total cost including the installation cost.

component of cost associated with staying with the existing utility setup. A positive $\epsilon(0)$ corresponds to the case of hearing negative reviews of solar power systems and a negative $\epsilon(0)$ can be the concern for climate change. I assume the additively separable error term as in Rust (1987). Note that in discrete choice models only the difference between choices matters so the income term drops out under the linear specification. Assume that households discount the future with a factor $\beta \in (0,1)$ and the states evolve following a Markov process, $(\mathbf{X}_{t+1}, \boldsymbol{\epsilon}_{t+1}) = p(\mathbf{X}_t, \boldsymbol{\epsilon}_t)$. Given the current state $(\mathbf{X}_t, \boldsymbol{\epsilon}_t)$, the household makes a sequence of decisions to maximize the sum of expected discounted values of future utilities over an infinite horizon. These optimal choices then define the value function as

$$V_\theta(\mathbf{X}, \boldsymbol{\epsilon}) = \max_{\{d_t\}_{t=0}^{t=\infty}} \mathbb{E}_{X', \epsilon'} \left[\sum_{t=0}^{\infty} \beta^t u(\mathbf{X}_t, d_t, \boldsymbol{\epsilon}_t; \boldsymbol{\theta}) \right]. \tag{2.3}$$

With the infinite horizon and the Markov transition function assumption, I can drop the time index and reformulate the infinite horizon optimal decision problem in (2.3) as a solution to the Bellman equation

$$V_\theta(\mathbf{X}, \boldsymbol{\epsilon}) = \max_{d=\{0,1\}} \left\{ \epsilon(0) + \beta \int_{\mathbf{X}'} \int_{\boldsymbol{\epsilon}'} V_\theta(\mathbf{X}', \boldsymbol{\epsilon}') p(\mathbf{X}', \boldsymbol{\epsilon}' | \mathbf{X}, \boldsymbol{\epsilon}) d\mathbf{X}' d\boldsymbol{\epsilon}', \nu(\mathbf{X}, 1; \boldsymbol{\theta}) + \epsilon(1) \right\} \tag{2.4}$$

where $(\mathbf{X}', \boldsymbol{\epsilon}')$ denotes the state variables in the next period. One critical assumption proposed by Rust (1987) is the conditional independence assumption on the transition probability p, to simplify the estimation complexity. This assumption together with the additively separable error term assumption provides the main identification strategy of the primitives.

Assumption 1. $p(\mathbf{X}', \boldsymbol{\epsilon}' | \mathbf{X}, \boldsymbol{\epsilon}) = p_\epsilon(\boldsymbol{\epsilon}' | \mathbf{X}') p_X(\mathbf{X}' | \mathbf{X})$

In another words, assumption 1 states that the unobserved state variable (by econometricians) doesn't affect the household's ability to predict the future states. Define the function, $\mathcal{F}_\theta(\mathbf{X})$, as[11]

$$\mathcal{F}_\theta(\mathbf{X}) = \int_{\mathbf{X}'}\int_{\boldsymbol{\epsilon}'} V_\theta(\mathbf{X}', \boldsymbol{\epsilon}')p_\epsilon(\boldsymbol{\epsilon}'|\mathbf{X}')p_X(\mathbf{X}'|\mathbf{X})d\mathbf{X}'d\boldsymbol{\epsilon}'. \tag{2.5}$$

and the choice specific value function as[12]

$$\begin{aligned} v_\theta(\mathbf{X}, d) &= \nu(\mathbf{X}, d, \theta) + \beta \int_{\mathbf{X}'}\int_{\boldsymbol{\epsilon}'} V_\theta(\mathbf{X}', \boldsymbol{\epsilon}')p_\epsilon(\epsilon'|\mathbf{X}')p_X(\mathbf{X}'|\mathbf{X})d\mathbf{X}'d\boldsymbol{\epsilon}' \\ &= \nu(\mathbf{X}, d, \theta) + \beta\mathcal{F}_\theta(\mathbf{X}), \end{aligned} \tag{2.6}$$

or explicitly as

$$v_\theta(\mathbf{X}, d) = \begin{cases} \theta_0 + \theta_1 p + \theta_2 s + \theta_3 r + \theta_4 \tau, & d = 1 \\ \beta\mathcal{F}_\theta(\mathbf{X}), & d = 0. \end{cases} \tag{2.7}$$

Note that the future value once installed is absorbed in the net present value of the revenue term and therefore there is only a future value associated with not installing. The Bellman equation (2.4) can be rewritten as

$$V_\theta(\mathbf{X}) = \max_{d=\{0,1\}} \left[v_\theta(\mathbf{X}, d) + \epsilon(d)\right]. \tag{2.8}$$

Assume $p_\epsilon(\boldsymbol{\epsilon}'|\mathbf{X})$ is a multivariate extreme value distribution. Then $F(\mathbf{X})$ has a closed form expression which is the expected value of the maximum of 2 *iid* random variables.[13]

$$\mathcal{F}_\theta(\mathbf{X}) = \int_{\mathbf{X}'} \ln \sum_{d\in 0,1} e^{v_\theta(\mathbf{X}',d)} p_X(\mathbf{X}'|\mathbf{X})d\mathbf{X}' \tag{2.9}$$

Rust (1988) and Rust et al. (2002) showed (2.9) is a contraction mapping using Blackwell's sufficient conditions. The conditional choice probability

[11]This function is sometimes called "expected future utility"(Su and Judd, 2012), the "social surplus function"((Rust, 1988); McFadden, 1981), or as the "Emax function" (**?**) and denoted as $EV_\theta(\mathbf{X}, d)$. In order to avoid confusion and to emphasize that $\mathcal{F}_\theta(\mathbf{X})$ is merely a function and not as a "value function", I denote it as $\mathcal{F}_\theta(\mathbf{X})$ instead.

[12]This term follows the common usage in the structural IO literature and with a slight abuse of terminology since the value function by definition is after choosing the optimal choice.

[13]See Anderson et al. (1992).

can now be characterized by the binary logit formula:

$$\mathcal{P}r(d|\mathbf{X};\boldsymbol{\theta}) = \frac{exp\{v_\theta(\mathbf{X},d)\}}{exp\{v_\theta(\mathbf{X},0)\} + exp\{v_\theta(\mathbf{X},1)\}} \tag{2.10}$$

$\mathcal{P}r(d=1|\mathbf{X}_t^z;\boldsymbol{\theta})$ represents the probability of adopting a solar power system and $\mathcal{P}r(d=0|\mathbf{X}_t^z;\boldsymbol{\theta})$ represents the probability of not adopting. The choice probablity is equivalent to the market share definition and is homogeneous across households in each zip code.

Rust (1987) proposed using the nested fixed point algorithm to estimate the structural parameter vector $\boldsymbol{\theta}$. The likelihood of observing data $\{\mathbf{X^z}, d^i\}$ for household i in zip code z is

$$\ell_i(\mathbf{X^z};\boldsymbol{\theta}) = \prod_{t=2}^{T} \mathcal{P}r(d_t^i|\mathbf{X}_t^z;\boldsymbol{\theta}) p_3(\mathbf{X}_t^z|\mathbf{X}_{t-1}^z, d_{t-1}^i) \tag{2.11}$$

The likelihood function over the whole data set is then

$$\ell_\theta = \prod_{z=1}^{Z}\prod_{i=1}^{n_z} \ell_i(\mathbf{X^z};\boldsymbol{\theta}) \tag{2.12}$$

which is usually expressed as a log-likelihood function:

$$L_\theta = \log \ell_\theta = \sum_t\sum_z\sum_i \log \mathcal{P}r(d_t^i|\mathbf{X}_t^z;\boldsymbol{\theta}) + \sum_t\sum_z\sum_i \log p_3(\mathbf{X}_t^z|\mathbf{X}_{t-1}^z) \tag{2.13}$$

The second term is zero under the perfect foresight assumption. This is the assumption I made in the empirical section and can be easily relaxed.

In Rust's nested fixed point algorithm, I optimize over (2.13) to find the deep structural parameters $\boldsymbol{\theta}$. Formally,

$$\max_{\boldsymbol{\theta}} \sum_t\sum_z \left[n_z(d_t^i=1)\log \mathcal{P}r(d_t^i=1|\mathbf{X}_t^z;\boldsymbol{\theta}) + n_z(d_t^i=0)\log \mathcal{P}r(d_t^i=0|\mathbf{X}_t^z;\boldsymbol{\theta})\right], \tag{2.14}$$

where $n_z(d_t^i = 1)$ denotes the total number of adopters in a zip code, z, and $n_z(d_t^i = 0)$ denotes the total number of non-adopters in z. Meanwhile, in the inner loop, the algorithm uses value function iteration to find a numerical value of $\mathcal{F}_\theta(\mathbf{X})$ computed for each value of parameters $\boldsymbol{\theta}$. Let $\mathcal{F}_\theta^\zeta(\mathbf{X})$ denote the numerical value during the ζ^{th} iteration. At $\zeta = 0$, I make an initial guess of $\mathcal{F}_\theta^0(\mathbf{X}) = 0$. At $\zeta = 1$, I can calculate $\mathcal{F}_\theta^1(\mathbf{X})$ based on (2.9) and $\mathcal{F}_\theta^0(\mathbf{X})$, such that

$$\mathcal{F}_\theta^1(\mathbf{X}) = T \cdot \ln \sum_{d \in 0,1} e^{\nu(\mathbf{X}',d,\theta)+\beta\mathcal{F}_\theta^0(\mathbf{X}')}, \tag{2.15}$$

where T is the state transition matrix. Then I check whether the iteration has converged by using the criterion

$$\sup_{\mathbf{X}} \left|\mathcal{F}_\theta^1(\mathbf{X}) - \mathcal{F}_\theta^0(\mathbf{X})\right| < \xi, \tag{2.16}$$

where ξ needs to be very small so that I can minimize the amount of error that propagates from the inner-loop into the outer-loop. Otherwise, it is less likely to converge in the outer-loop. Specifically, I set $\xi = 1e - 6$. If (2.16) is satisfied then I have found the $\mathcal{F}_\theta^1(\mathbf{X})$ to be used in (2.6) and (2.10), which go into the likelihood function (outer-loop). If not, then I repeat the iteration, with $\zeta = 2, 3...$, until the convergence criterion (2.16) is satisfied.

3 Data

3.1 Data sources

The rooftop PV adoption pattern in California displays significant spatial discontinuity as shown in Figure A5.4. Adoptions are concentrated in the three largest metropolitan, namely: San Diego, Los Angeles and the San Francisco Bay area, in addition to Fresno and Sacramento. I focus on 344 zip codes in these three metropolitan, with over 2 million households, that belong to 9 counties: one in the San Diego Gas and Electric (SDG&E), two in the Southern California Edison (SCE), and 6 in the Pacific Gas and Electric (PG&E) service territory (Figure A5.5). About half of the zip codes and households are located in northern California and the remaining zip codes are in southern California. The finest geographic resolution I observe in the data is at the zip code level which defines the market in this study. I use the monthly data on the number of installations in each market (zip code), California Solar Initiative incentives, revenue generated from solar electricity and federal tax credits in order to recover the deep structural parameters in the utility function.

California Solar Initiative Incentives

The California Solar Initiative (CSI) is a solar incentive program, part of the 10-year, 3 billion dollars statewide Go Solar California Initiative that started in January 2007. The CSI goal is to reach 2 gigawatts of solar power system installations on existing homes and buildings.[14] The majority of the residential units receive a one-time, lump-sum, upfront payment. The amount of the subsidy depends on the size of the solar power system measured in watt (W) and the subsidy rate at the time of the application. The incentive starts at \$2.50/W and gradually reduces to \$0.25 at the end of the sampling period, by a prescribed schedule (Table A2.1 and Figure A5.1). For instance, at the start of the program, households in the SDG&E district receive \$2.50/W incentive payment; once there is a total of 2.4 megawatts of systems installed, the next applicant receives \$2.20/W. Therefore, an owner of a 5kW system in the above example receives \$12,500 CSI incentive at the beginning, compared to \$1,250 by December 2011. Since the solar module price continues to decline over time, a rational forward-looking consumer would always choose to adopt at a later date, if the subsidy stayed constant over time. The block schedule (or subsidy degression) is a strategy to account for the lower system cost in the future and encourage adoptions to occur sooner, rather than later.[15] These countervailing incentives on the timing of adoption provide a rich context for a dynamic analysis.

I aggregate the number of households that adopt solar power systems in each zip code in each month.[16] The data set also provides information

[14] 30% of the 2GW goal is designated for the residential sector while the remaining portion is satisfied by the commercial sector. While commercial sector could be potentially more important to study for its larger market share, its complex nature poses much more challenges than the residential households. The CSI program, for example, has a funding cap for the commercial applicants and therefore poses the identification problem - I can not distinguish whether firms decide not to install or would install if the funding were available.

[15] The rationale for the subsidy is that the government subsidizes the "early adopter" for the positive externalities that they provide to the later adopters either through the demand-side learning by doing effect or the network effect.

[16] I used the "first new reservation request date", the date when the application for subsidy is received, as the month when the households choose to invest solar. Although

on the prices of the systems and sizes; combined with the county specific weekly construction worker's wage from the Bureau of Labor Statistics and the monthly U.S. PV module prices from SolarBuzz, I am able to recover the unit price of solar power systems in the first stage regression analysis.[17] Figure 1 shows the system price trend and the number of installations over the studied period. During this period, the average system price decreases by 40% from \$8.40/W to \$5.67/W, while the solar module price underwent a much more precipitous decline of 57%. The declining system price explains the overall trend of the increase in solar power investments; meanwhile the subsidy schedule explains the peaks in the number of installations (Figure 2).

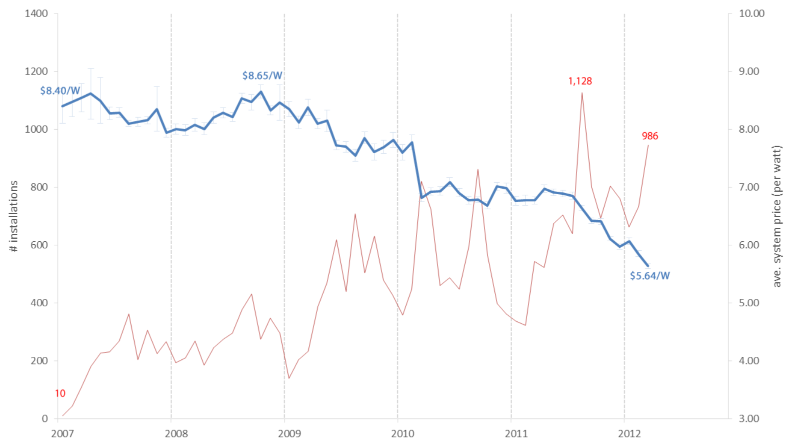


Figure 1: The average system cost versus the number of installations.

The system size varies greatly from one household to the next. However, the average system size remains relatively constant across the years (Figure A5.2 & A5.3). The average size in the data is 5.39kW, which is in line with the 4kW to 6kW size that an average household needs to supply its 100% of electricity based on the assumptions used in this research. One caveat concerning the binary logit model proposed here is that investments must

the "first reservation request review date", which is when the CSI subsidy application is reviewed, has less missing values. I believe that the first new reservation request date approximates the time when households make their investment decisions better. I construct the probability by utility districts using the empirical data to impute the missing dates (months).

[17]EIA also compiles the solar module price index albeit at the annual level. A simple bivariate regression analysis shows the EIA index and the annualized SolarBuzz index to be almost perfectly correlated.

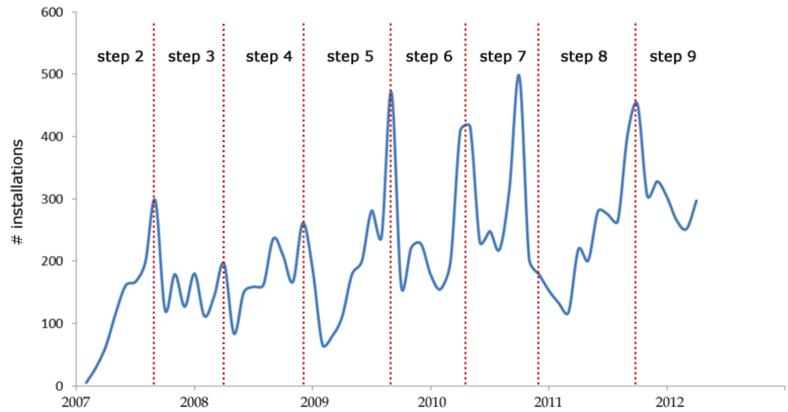


Figure 2: Monthly installations in PG&E service territory (vertical dashed lines represents one period before the decline in subsidy)

be made in a product that is a homogeneous in size and in the efficiency of the module and inverter. I reconstruct the price for this average-size system in each zip code-month pair from the first stage regression results including the city and county sales taxes.

Revenue (Lifetime Electricity Savings)

Assuming a 25-year system lifespan[18], I recover the present value of the revenue, R, generated from an average size system by the following equations,

$$R_{zt} = \frac{1 - r^{25}}{1 - r} Yrev_{zt}$$

and the annual revenue, $Yrev$

$$Yrev_{zt} = \sum_{m=1}^{12} Q \cdot IR_{zm} \cdot C^{e}_{umt}$$

where Q is the system size in (kW), IR is the solar radiation[19] in month, m, and C^{e}_{umt} is the monthly tier electricity price in utility district u in year t. There are (mostly) four electricity rate tiers during the studied

[18] The actual lifespan of the solar power system is unclear and some systems from the 1970's are still in operation today. Because the majority of manufacturers offer the 25-year standard solar panel warranty, I choose to use this as the lifespan of the system.

[19] Solar radiation (or irradiation) is measured in kWh/m^2/day. The solar electricity generated data used in the current draft is based on the PVWatts calculator provided by NREL, which uses the finer hourly data in a zip code measured in AC output.

period and I separately use the tier 1, tier 4 and a combination of all four tiers to compute the annual revenue, which I called "combined tiers" or "tier c". I calculate the monthly savings by allocating the solar production into the lowest to the highest tier pricing.[20] There are two issues with revenues calculated from the combined tiers. One is theoretical and one is practical. Theoretically, it is going to be less than the realized savings because actual savings would start from the top tier and move to the bottom tier as production increases. However, the calculation is the best I can do because I don't observe households' electricity consumption. The practical issue with the tier c savings is that it places more weight on the tier 1 pricing and this results in less variations. (See Figure A5.11 and A5.12 for average monthly and annual revenue by tiers)

Let α^D denote the module degrade factor, α^e be the electricity escalation rate, β be the annual discount factor, and finally $r = (1-\alpha^D)(1+\alpha^e)\beta$. The range of the present value of the revenue stream from tier 1 pricing is between \$9,000 and \$13,000 and increases to \$20,000 and \$36,000 from the tier 4 pricing.[21] The lifetime savings vary with the geographical location and also across the years due to the annual electricity rate adjustment by the utility districts.[22]

Federal Residential Renewable Energy Tax Credits

The Energy Policy Act of 2005 set in place a 30% federal tax credits for

[20] For example, during the summer season (May to October), the first 350 kWh of electricity generated would fall into the tier 1 price, the next 100 kWh falls into the tier 2 pricing, the next 255 kWh falls into the tier 3 pricing, the next 352 kWh falls into the tier 4 pricing and the remaining counts either as tier 4 or 5 depending on whether tier 5 pricing is available.

[21] Appendix A3 provides the details of the calibrated parameter values.

[22] Initially, the CSI rebate recipients are required to switch to the time-of-use (TOU) pricing. This TOU mandate is subsequently eliminated in June, 2007 after LA Times reports that the mandate decreases the economic value of solar power system in SCE district. Borenstein (2007) shows that the majority of PG&E adopters would be better off under the TOU rate, which is not the case for SCE adopters. The reason is that the SCE's original flat rate schedule is tiered (greater monthly electricity consumption is associated with higher electricity rate) but the TOU schedule is not tiered.

residential solar power systems, which expires at the end of 2016. Despite remaining at a constant level, there is a \$2000 cap prior to 2009 when the American Recovery and Reinvestment Act allows households to claim the full 30% credit. This is a significant change from an effective 5% tax credits prior to 2009 to the full 30% afterwards. The tax credits may be carried over for 5 years.[23] I compute the tax credits from multiplying the system price by 0.3 and cap this amount at \$2000 prior to 2009.

Table I provides the summary statistics of the data used in the second stage estimation. The unit of observation is at the zip code-month level. The average price for a 5.39kW system is about \$44,000. Households receive \$13,000 of CSI subsidy in January 2007 and receive a much smaller amount of \$1,300 at the end of the sampling period. I calculate the CSI subsidy using the size of the system, 5.39 kW, and the per watt subsidy at the month. All Table I values are either simulated and/or from the first stage regression, except the weekly labor wage and the number of installations are directly observe in the raw data.

[23] An example of how widely this tax credits can be utilized: A married taxpayers (filing jointly) with an income of \$67,901 has a tax liability of \$14,125 in 2009 (taken into account the standard deduction of \$11,400). This means the household in this example can use up the tax credits of \$13,688 in one tax year.

Table I: Summary (monthly) statistics (Jan. 2007- Dec. 2011, 344 zip codes)

Variable	Mean	Std. Dev.	Min	Max	Obs.
System price[24]	43,934	3,921	32,567	51,155	20,640
Capacity-based subsidy	8,061	4,283	1,348	13,475	20,640
Present value of 25-year revenue (Tier 1)					
10%:	10,667	969	9,186	13,125	20,640
Present value of 25-year revenue (Tier 4)					
10%:	27,672	3,988	20,728	35,879	20,640
Present value of 25-year revenue (Combined tiers)					
10%:	15,974	1,420	13,513	19,755	20,640
Tax credits	7,683	4,694	2,000	13,764	20,640
Annual electricity output (kWh)	8,472	404	7,777	9,948	20,640
Weekly wage rate[25]	1,085	120	930	1,253	20,640
Installed cost/watt	7.51	0.68	5.59	8.78	20,640
# installations	1.24	2.14	0	36	20,640

4 Empirical implementation

The estimation of the primitives is carried out in the following steps: In the first stage, I recover the relationship between the (dollar-per-watt) price of the solar power system and its component costs. The estimated price per watt, by month and zip code, is used in the second stage to aggregate the data from the individual level to the zip code level (the finest geographical resolution) and in effect to conform to the proposed binary logit model as discussed in the previous section.[26] This allows me to convert each installation observed in the data into a homogeneous average size system (5.39 kW) and to derive the final system price in every zip code by month. In the second stage, I use the maximum likelihood estimation to recover the structural parameters in the consumer's utility function.

[24]Total upfront PV system price after city and county taxes

[25]Weekly wage of construction worker by county

[26]The individual level data contains only the zip code and not street address information.

4.1 Recovering solar power system unit price

The (per-watt) system price is assumed to be a function of the system size (x), the solar module cost (P^{pv}), the inverter cost(P^{inv}), the labor cost of installation (L), the permit fee (c^{fee}), and the costs of electric wires and connectors (BOS). The expression for the unit price, dollar per watt (D) as,

$$D_{izt} = f(x_i, x_i^2, P_t^{pv}, P_t^{inv}, L_{cty}, c_i^{BOS}, c_{cty}^{fee}) + \epsilon_{izt}$$

The unit price is generally higher for small systems as the result the economies of scale. Therefore, system size is a major determinant of the unit price. Let x denote the system size (in kilo-Watts) observed in the data and x^2 be the square of x to capture nonlinearities. The permit fee, inverter, and the BOS cost are not included in the regression analysis because I don't have good measures of these variables. During this time period, the inverter cost remains roughly the same ($.70/W according to SolarBuzz inverter retail price index) as does the cost of wires and connectors. In this case, the constant term captures the combined effect of these two factors. The construction workers weekly wage, published by the Bureau of Labor and Statistics each month, is a proxy for the labor input cost. I also include the total amount of installations in each zip code prior to implementation of the CSI program, pre_z and use it to control for unobserved factors such as age and types of roofs and the proximity to installers.

Table II reports the first stage estimation results. All estimated coefficients have the expected signs and are significant at the 1 percent level. Table I reports reconstructed system price of an average size system. This cost is used in the second stage maximum likelihood estimation and also serves as the basis of the calculation of the 30% federal tax credits.

Table II: Regression Analysis on Installed Cost per watt

	cPw	Std. Err.
pre2007	-.0009***	(.0002)
size (kW)	-.2039***	(.0045)
size^2 (kW^2)	.0038***	(.0001)
wages ($1,000)	1.4701***	(.1334)
module cost ($)	0.821***	(16.31)
constant	3.056***	(13.03)
Year FE	Yes	
Utility FE	Yes	
N	25,262	
F(11, 25250) = 722.40		

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

4.2 Recovering structural parameters

I use two specifications in the second stage structural estimation. The first specification estimates the parameters in (2.2) separately; and the second specification aggregates all dollar terms into a single variable.[27] The second model assumes that consumers weight cost and various forms of benefits equally. Therefore only net costs (i.e. net present values) enter into the model. This reflects a scenario where there is no consumer behavioral response to paying versus receiving, and assumes no transaction costs or timing differences associated with different forms of subsidies.

Within each specification, I use fixed effects at the utility company and the year level to control for potential omitted variables. I also include the interaction term between the utility and the year to capture the differences

[27]This is the net present value of each system.

in trends in each utility district. I estimate the log-likehood function (2.13) in Matlab using the nested fixed point maximum likelihood estimation.[28] In the inner loop, the fixed point algorithm finds the expected future utility (2.5) and the outer-loop searches over the whole parameter space to find the parameter values that maximize the log-likelihood function. It's well known that there is no unique maximum in this type of model where the parameters enter into the expected future utility. I use multistart algorithm to randomly select starting points and find the parameter combinations that yields the highest likelihood value. To ensure that the *fminunc* algorithm converge successfully, the Matlab first-order optimality condition is manually checked such that it approaches zero in each successive iteration.

Table III(a) and Table III(b) reports the results from the three electricity tiered pricing.[29] Standard errors of the estimated coefficients are calculated by bootstrapping over the two stages. The first to third columns in Table III(b) report the results with the fixed effects and utility specific time trends, whereas the fourth to the sixth column report the result from estimating a net cost term. Most estimates have signs as expected, that costs are associated with negative coefficients while subsidies, tax credits and revenues are associated with positive coefficients, which conform with the intuition that consumers prefer lower cost and greater subsidies.

The coefficient of the system price is consistently and significantly higher than the other forms of benefits across models. This result agrees with the anecdotal evidence that the upfront system cost is the greatest entry barrier to solar PV adoptions. The magnitude of the CSI subsidy coefficients becomes greater when more fixed effects are included. The fixed effects also take away most of the variations from the revenue variable. Tier 1 electric-

[28]The unconstrained nested fixed point MLE is identical to the constrained maximization with equality constraint (See Su and Judd (2012)). Due to the concern of including nearly 30,000 constraints in a non-strictly concave objective function, I opt for a slower repeated fixed point iterations.

[29]Table A2.4 and A2.5 include the full estimation results.

ity pricing, in particular, is usually very stable and this lack of variations leads to the lost of significance when fixed effects are included. When controlling for the year fixed effects, the residual variations in post-2009 tax credits are perfectly correlated with system prices because tax credits are 30% of the system prices by design. This means as the system price declines over time, tax credits are also lower while the number of investments increases. Tax credits also seem to be correlated with the utility specific time trends. The associated coefficients are negative when the fixed effects and interaction terms are included.

Table III (a): Maximum Likelihood Estimation Results without Utility Specific Time Trends

Variables	Lowest Tiered Pricing (Tier 1)	Highest Tiered pricing (Tier 4)	Combined Tiered Pricing	Highest Tiered pricing (Tier 1)	Highest Tiered pricing (Tier 4)	Combined Tiered Pricing
system price	-0.132***	-0.146***	-0.14***	-0.363***	-0.376***	-0.353***
	(0.022)	(0.025)	(0.024)	(0.038)	(0.058)	(0.047)
CSI subsidy	0.035*	0.057***	0.055***	0.066***	0.110***	0.102***
	(0.020)	(0.022)	(0.020)	(0.0145)	(0.0176)	(0.0131)
revenue	0.01	0.024***	0.088***	0.074	0.049***	0.040**
	(0.016)	(0.005)	(0.036)	(0.060)	(0.008)	(0.018)
tax credits	0.026***	0.022***	0.018***	0.388***	0.397*	0.322*
	(0.004)	(0.005)	(0.005)	(0.108)	(0.215)	(0.165)
net cost						
constant	-3.364******	-3.401***	-4.134***	5.477***	4.834**	4.709***
	(0.848)	(0.909)	(1.272)	(1.704)	(2.422)	(2.350)
Year FE	N	N	N	Y	Y	Y
Utility FE	N	N	N	Y	Y	Y
Utility x Year	N	N	N	N	N	N
N observations	20640	20640	20640	20640	20640	20640
LR chi2	5409	5541	5587	7450	8709	8451

standard errors in parentheses

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

Table III(b): Maximum Likelihood Estimation Results with Fixed Effects and Utility-Time Trends

Variables	Lowest Tiered Pricing (Tier 1)	Highest Tiered pricing (Tier 4)	Combined Tiered Pricing	Highest Tiered pricing (Tier 1)	Highest Tiered pricing (Tier 4)	Combined Tiered Pricing
system price	-0.185***	-0.183***	-0.201***			
	(0.059)	(0.061)	(0.060)			
CSI subsidy	0.147***	0.146***	0.147***			
	(0.012)	(0.012)	(0.012)			
revenue	-0.056	-0.026	-0.014			
	(0.047)	(0.018)	(0.015)			
tax credits	-0.485**	-0.486**	-0.43**			
	(0.214)	(0.212)	(0.212)			
net cost				-0.189***	-0.128***	-0.153***
				(0.025)	(0.014)	(0.033)
constant	-0.749	-0.291	-0.491	-4.091***	-7.827***	-5.719***
	(2.304)	(2.327)	(2.335)	(0.633)	(0.068)	(0.552)
Year FE	Y	Y	Y	Y	Y	Y
Utility FE	Y	Y	Y	Y	Y	Y
Utility x Year	Y	Y	Y	Y	Y	Y
N observations	20640	20640	20640	20640	20640	20640
LR chi2	8,615	8,619	8,609	7,177	6,715	6,949

standard errors in parentheses

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

4.3 Discussions

4.3.1 Subsidy comparisons

I run a hypothesis test on the estimated coefficients (of specification I) to investigate the cost-effectiveness of capacity-based subsidy and production-based subsidies. Because production-based subsidies, such as feed-in tariffs, pays consumers a premium over the electricity retail rates, its effect on consumer's preference is equivalent to the effect of revenues generated by solar electricity. I define the null hypothesis such that the effects of the CSI subsidy and revenue are equal ($\theta_2 = \theta_3$), and the alternative hypothesis is CSI subsidy has a greater impact than the revenue on a per-dollar basis ($\theta_2 > \theta_3$). Using the two-sampled hypothesis test, I find that the capacity-based subsidy has statistically significant greater impact than the (would-be) production-based subsidy under the tier c and the tier 4 pricing. I am unable to reject the null hypothesis using the tier 1 pricing because there is not enough variation in tier 1 pricing to identify the effect of revenue on the household's utility function.[30] This provides some evidence that the capacity-based subsidy such as the CSI subsidy induces more household to invest than the feed-in tariffs.

4.3.2 Endogeneity

A potential omitted variable bias concern in the second stage is that the positive shock in the utility function may lead to an increase in the system price and/or a decrease in the subsidy rate. However, the shock by specification occurs at the individual level whereas the module cost, the largest portion of the system cost is determined in the international market (See Appendix A1.2 for more detailed discussions on the component costs.). Because the US solar market accounts for less than 10% of the worldwide demand (in total capacity), it lessens the concern that an individual utility shock can influence the solar module price. However, the bias on the installation cost, the second largest component in the system cost (Figure A5.6), poses a challenge because I don't observe the market structure of solar installers. Friedman et al. (2011) observe there is some evidence of excess supply in the solar installation labor market during this period.[31] In which case, an *i.i.d.* shock at the household level is unlikely to increase the equilibrium price for the installation. Even if the shock affects the final installed price, the bias concern would be greatly lessened because

[30] Across different calculations of lifetime revenues, the null hypothesis can be rejected at the 10% significance level under tier 4 electricity pricing with no fixed effects. Similarly the null is rejected at the 1% significance level under the tier c prices with utility and year fixed effects. There is no statistical significance difference between the effect of revenue and subsidy under combo pricing and no fixed effects.

[31] A future project is to incorporate the supply side (installers) data.

I don't use the actual price in the second stage but instead using the predicted values from the first stage regression. As for the subsidy, because the number of households required for the subsidy to be lowered to the next level is large- on average, 4000 households are required before meeting the capacity threshold set for each subsidy level. Therefore, each household's investment decision has a negligible effect on the overall subsidy level.

4.4 Model verification

I use five zip codes that are not part of the data for estimation as the out-of-sample verification. I compare the actual installation counts with the predicted numbers from the estimated model during 2007 and 2011. Table IV reports the percentage differences in adoptions between the predicted and the actual numbers. The model over-predicts the number of solar adoptions in the zip code 92673 across the estimated models using the three electricity tiered rates. I exclude certain zip codes in both the estimation and the verification steps. These zip codes, such as Ladera Ranch (92694), which locates in the San Diego Gas & Electric district, have well-documented large new housing developments with pre-installed solar panels. Since solar panels on new homes are not part of the CSI program discussed in this paper, the presence of these new homes creates an under-count on the number of installations observed in the CSI dataset. In other words, given the number of homes, I would expect to see more installations were these home not already pre-installed with solar panels. This is likely to explain the higher (than actual) predicted adoptions in the zip code 92673, which is very close to Ladera Ranch geographically. There is a higher (than predicted) number of adoptions in 93420, which can be caused by any idiosyncratic shock at the zip code level. This positive shock may be explained by a tight-knit community with the demographics that highly values solar or simply better informed on solar rebates and solar technology at this particular zip code although the specific reason requires further case study. Overall, the difference between predicted adoptions and actual adoptions range from 1 to 8%, on average. The model estimated using tier 1 pricing produce the best match with an average 2% difference between the actual and predicted adoptions. Figure A5.13 shows the actual and predicted installations by month. Not surprisingly, the predicted number explains the general trends but not the occasional spikes in demand.

Table IV: Out-of-Sample predictions

zip code \ electricity pricing	Lowest Tier	Highest Tier	Combined Tiers
93420	-13.2%	-23.7%	-5.4%
95129	-9.3%	1.0%	-0.6%
90230	-12.8%	4.4%	-9.5%
93257	9.3%	6.3%	9.9%
92673	34.6%	52.9%	33.6%
average	1.7%	8.2%	5.6%

5 Counterfactual Analysis

This section uses counterfactual analysis to investigate 1) the welfare costs associated with the subsidy programs and encouraging adoptions in the suboptimal locations; 2) the impact of policy changes on the solar power market. All subsequent analysis is based on the estimated model II with the nest cost term. While the analysis can be made using any of estimated models, this is the preferred model to address the differences in policies by taking away any behavior responses and timing issues.

5.1 Welfare Analysis of the Incentive Programs

To create a meaningful measure of the cost of solar incentive programs, I first clarify the purpose of such programs. Demand side subsidies are designed to offset various market failures such as switching costs, liquidity constraints, externalities (both positive and negative), imperfect information, etc. Meanwhile, the argument for subsidies are of basically three types: securing energy independence, creating new jobs, and reducing pollution. The first two justifications are problematic. The main carbon-based fuels that solar electricity replaces are coal and natural gas and yet the U.S. is a net exporter of these fuels. Although the green industry will create new jobs, the shrinking fossil fuel sectors will also lose jobs. Instead of creating jobs, expansion of the solar industry shifts jobs. Therefore, the only benefit that I consider in this paper is pollution reductions. In particular, I focus on GHG emission reductions, which would lead to an upper bound on the cost estimates.[32] I convert the various greenhouse gasses emissions into a unifying CO_2 equivalent measure. I use GHG and CO_2 interchangeably throughout the paper.

The most common approach to assessing program cost is to sum up the total program costs and divide this sum by total amount of pollutants, such as GHG, mitigated from the program implementation. This straightforward calculation doesn't require a structural model but fails to capture the change in consumer surplus from owning a solar power system. I propose instead to derive the program cost by finding the change in total surplus per unit pollutant avoided from policy implementation. Under the assumption of a perfectly elastic supply function of solar power sys-

[32]At the same time, I'm also not accounting for the hazardous chemicals used in producing the panels. Although not addressed in this paper, the life-cycle analysis (LCA) of the technology is critical in accessing the overall reduction in GHG emissions. NREL surveyed the past LCA studies and found that PV power production is similar to other renewables and much lower than fossil fuel in total life cycle GHG emissions

tems, the loss in surplus is the difference between total program spending (in 2011 dollar) and the gain in consumer surplus.[33] A household makes the investment decision depending on which of the two options (investing in solar power systems versus investing in an outside option) provides the greatest utility. However, because part of utility remains unobserved to the econometrician, the best I can do is to find the expected consumer surplus (for each individual) over all possible values of $\boldsymbol{\epsilon}$.

$$E(CS) = \frac{1}{\theta} E\left\{\max_d \left[v_\theta(\mathbf{X}, d) + \epsilon(d)\right]\right\} \tag{5.1}$$

where θ is the marginal utility of income, which equals marginal utility of net system cost in this setting. The division by θ translates utility into a dollar measure.[34] Given the error specification of the multivariate extreme value distribution, the expected consumer surplus has a closed form expression:

$$E(CS) = \frac{1}{\theta} \ln\left[\sum_{d=0,1} e^{v_\theta(\mathbf{X}, d)}\right] \tag{5.2}$$

Then, I aggregate the expected consumer surplus (5.2) over each household in each zip code. Because the change in consumer surplus is derived from the dynamic model that captures the effect of a permanent change, government spending should be measured over the same time horizon. To match this long-term change in consumer surplus, I sum over the government spending over the next 50 years and discount it with the actual annual inflation rate until the end of 2015. From 2016 to 2061, I use the 30-year expected inflation rate derived from the Treasury Inflation-Protected Securities, which has an annual inflation rate of approximately 2%. I assume

[33]In the case when the supply function is not perfectly elastic, the number derived here provides an upper bound.

[34] $\theta = \frac{\partial U}{\partial Y} \Longrightarrow \frac{1}{\theta} = \frac{\partial Y}{\partial U}$

inflation stays constant after the first 30 years.

$$P_{CO_2} = \frac{G - \triangle CS}{\gamma \times \triangle Q}, \tag{5.3}$$

where G is the present value of the total government spending, $\triangle CS$ is the change in consumer surplus as measured by the difference in the sums of (5.2) before and after implementation of the incentive policy. γ is the amount of CO_2 displaced by the solar power system over its lifetime and $\triangle Q$ denotes the installations that is due to the subsidy. The complete description of the forward simulation and the derivation of the break-even CO_2 price, P_{CO_2} is provided in Appendix A3.[35]

Table A2.6 reports the long-run welfare cost or the implied welfare-neutral CO_2 price. Assuming households with a 10% discount rate, the CO_2 prices associated with the CSI subsidy are \$62/ton using the tier 1 rate, \$82/ton using the tier 4 rate and \$72/ton using the combined tiered rate. The Tier 1 and Tier 4 welfare costs can be viewed as the lower and upper bounds on the welfare cost. This cost is calculated using the actual cost and benefits in the first five years and then holding the values in the last observed time period (Dec. 2011) constant for the next 50 years. The combined welfare costs of CSI subsidy and the federal tax credits increase to \$117/ton using the tier 1 rate, \$132 using the tier 4 rate and \$127 using the combined tiers. Program costs without considering the change in consumer surplus are about 10% to 35% higher depending on the total subsidy level (See Table A2.7). In general, cost difference is U-shaped in the size of the subsidy. The difference is the greatest when the subsidy is either very low or very high and reaches the lowest point at the intermediate subsidy level. This peculiar shape is a direct result of the type 1 extreme value error specification. On average, households gain \$375 per solar power

[35] I use the average GHG emission rate of 0.348 ton/MWh or 767 lb/MWh published by the California Air Resources Board to calculate γ.

system installed in consumer surplus with the CSI subsidy and $975 with both the CSI subsidy and the tax credits. In comparison, the average CSI subsidy and tax credits at the end of 2011 are around $1800 and $10,000 per system, respectively.

More electricity produced means more CO_2 abated, which lowers the program cost per unit of CO_2 and therefore Southern California tends to have lower welfare cost from subsidy than the North.[36]

5.1.1 Feed-in Tariffs vs. Upfront Subsidies (Production-based vs. Capacity-based Subsidies)

To compare the efficiency of a production-based subsidy and a capacity-based subsidy, I conduct a counterfactual analysis by investing the same amount of money in a production subsidy as in a capacity-based subsidy and observe the change in implied welfare-neutral CO_2 prices.[37] I use a fixed capacity-based subsidy rate of $1.1/W while keeping the 30% tax credits. This means each adopter would receive almost $6000 per system. Then, I calibrate the feed-in-tariff rate such that the present value of government spending matches that in the capacity-based subsidy. I maintain the assumption that a rational consumer will keep the solar power systems in the optimal electricity production condition throughout the paper.[38]

[36]In the current calculation, the average CO_2 associated with each unit of electricity production is an exogenously given constant. It's easy to see that this value, γ, should go down as more solar power systems are installed. However, given the solar electricity only contributes to 0.4% of total electricity generation currently, the change in γ would be insignificant for most of the years considered here.

[37]This is a "revenue-neutral" approach. In reality the Feed-in-Tariff rate is designed to reflect either the utility avoided cost or the project cost (and return) of the renewable energy technology. In particular, I use a market-independent, fixed feed-in tariff design which is independent of the retail electricity rates. Similar design is in use in Germany, for example.

[38]Despite this assumption may lead to biased preference towards capacity-based subsidies, I also do not incorporate the additional cost from the third-party electricity monitoring system that is sometimes required to report the electricity production under the production-based subsidy. The simpler design of a capacity-based subsidy can potentially overcome this inefficiency. The latter assumption thus leads to biased preference

Intuitively, a production subsidy encourages more adoptions in sunny locations and results in a lower CO_2 price.

This is indeed what I observe in the counterfactual simulations. Conditioning on the same level of government spending, the welfare cost of the subsidy program in Northern California reduces by about $1.50 when moving from capacity-based to production-based subsidy (See Table V and Table A2.8 to A2.10). The overall welfare difference between the capacity-based and the production-based subsidy, however, is minuscule (around $0.10).

There are two reasons that may cause the small efficiency gains from using the production-based subsidy. The first is the revenue-neutral subsidy assumption. Per-system subsidy under production-based subsidy has to increase for households located in Southern California to reach the same level of government spending because fewer households would adopt in Northern California. The production-based subsidy reduces the subsidy in N. California by $216, while increases the S. California subsidy by $135 per unit, Therefore, the welfare cost also increases by almost $1 in Southern California from the higher subsidy level. In fact, the efficiency outcome would be identical between these two types of subsidies in a location with no solar radiation variation using the revenue-neutral approach. This is simply the result of the number of installations (or purchase probability) being monotonically increasing in subsidy. Because total spending is the product of the subsidy and number of adopters, the subsidy amount and the number of adoptions have to be the same under the two schemes to reach the same level of spending. The second reason is the relatively small difference in solar radiation between Northern and Southern California. There is only 8% of solar resource difference, on average, between Northern and Southern California.

towards production-based subsidies.

To gain deeper insights on the efficiency outcomes under the two subsidy schemes when applying to a large geographical area with greater solar radiation differentials, such as what would happen in a federal subsidy program, I replace the solar resource in Northern California by that in Alaska while replacing the solar resource in Southern California by that in Arizona. This increases the North-South solar radiation difference from 8% to 90%. Table V reports the welfare costs in each utility districts To match the government spending in capacity-based subsidy program, the equivalent per-unit production-based subsidy decreased by 40% to $3000 in Northern California and increase mildly by 5% in Southern California. Naturally, the number of households that invest in solar reduces by one-third in the North and increases by 5% in the South. Total number of installations reduces by 1-2% under the production-based subsidy but the amount CO_2 emission abatement increases by 4% because the higher level of investments occurs in the sunnier South. I find the welfare costs of the production-based subsidy indeed reduce more in this setting by about two dollars. In particular, the welfare cost in Northern California reduces by twenty-four dollars using the production-based subsidy relative to the capacity-based subsidy.

Table V: Welfare costs of production and capacity-based subsidies (Tiers C)

Utility	Factual World		AK & AZ Solar	
	Capacity	Production	Capacity	Production
PG&E	$72.21	$70.9	$117.7	$93.98
SCE	$67.31	$68.04	$63.63	$65.54
SDG&E	$68.15	$69.16	$64.34	$66.27
Overall	$69.78	$69.68	$69.13	$67.15

5.1.2 Deadweight loss resulting from suboptimal siting

To address the question raised by Der Spiegel magazine and to study the effect of encouraging large adoptions in a suboptimal location, I conduct a counterfactual analysis using the estimated model but with German solar radiation data. Suppose that the whole California is endowed with the solar resource in Frankfurt, Germany, which is 35% less than the average CA solar resources. Holding the subsidy at $1.1/W or $5,920 per system, the number the adopters under German solar radiation would reduce to a third of the amount as in the factual world (with the actual solar resources). Meanwhile, the total amount of CO_2 abated also drops to one-fifth of the factual world for the reduced solar resources. The average consumer surplus per solar power system decreases slightly to $755 per system because of the higher final price (net cost) under the German solar radiation. I find that the welfare cost of encouraging solar adoption in a suboptimal location is 50% more costly than in the factual world.

The welfare cost increases significantly when greater number of adoptions is required (Table A2.11-A2.13). To reach the same number of installations as in the factual world, the government would have to double to triple the per-unit subsidy, which leads to the welfare neutral CO_2 price nearly tripled. Furthermore, in order to have the same level of electricity production as in the factual world, the government has to increase the subsidy amount to more than three times the current level. The welfare neutral CO_2 price also increases more than three-fold. The result provides the first look into the potentially high welfare cost associated with the suboptimal siting. However, the actual cost of the German subsidy program is very likely to be smaller which ultimately depends on consumer preferences and the amount of CO_2 produced during electricity generation.[39]

[39] In 2011, the CO_2 emission per kWh of electricity generation in Germany was 1.6 times higher than in California. Therefore, the break-even German CO_2 price here is

5.2 Impacts from Policy Changes

The next series of counterfactual policy experiments explore how various policy designs and levels affect equilibrium demand.

Pending Tariffs on Imported Chinese Solar Modules

The US is in the midst of the second solar tariff ruling on imported Chinese solar panels. In October 2011, a coalition led by SolarWorld filed an unfair competition complaint with the US Department of Commerce, which led to a ruling that imposes duties of 30% to 265% on imported solar panels containing Chinese solar cell. However, most Chinese companies were able to avoid these duties by shifting the cell manufacturing to Taiwan while keeping the rest of the supply chain in China. The new complaint filed in 2013 is meant to extend the scope of the previous ruling and close the loophole.

The case splits the US solar industry between domestic manufacturers and solar installers; the first group has been squeezed to bankruptcy by the cheaper Chinese solar panels, whereas the latter group has been benefited from the increased demand due to the cheaper solar products and are concerned that higher costs will reduce the growth in the solar power market.

The flexibility of the structural model can also provide a quantitative (upper-bound) prediction on the potential impact of the solar tariffs.[40] Using the estimated model and the panel cost at the end of 2011, I predict the system price from the first stage regression equation given a worst case 30% increase in module price (GreenTech Media, 2014). Then I use this predicted price in the second stage structural model to simulate the long-run demand. The increase in panel price leads to a relatively small 8% increase

biased upward.

[40]This is an upper-bound of the impact because I assume homogeneous products and no heterogeneous consumer responses to price in this paper. In reality, there is a much smaller subset of consumers who will be affected by the increased price of Chinese imported solar products.

in system price, which results in a large 22% to 31% reduction in quantity demanded (Table VI). This is the scenario in which firms do nothing to avoid the new tariffs. If Chinese manufacturers move cell production back to China and pay the 2012 tariff instead, the GreenTech report estimates that this will lead to a milder 14% increase in module prices. Given the 14% permanent system price increase, my model indicates that we can expect a 3.6% increase in the system price and 11% to 16% reduction in quantity demanded.

Table VI: Potential impact of the pending tariff on imported Chinese solar cells

	14% increase in module price	30% increase in module price
Increase in system price	3.6%	7.7%
% change in installations (Tier 1)	-15.9%	-31%
% change in installations (Tier 4)	-11%	-22.08%
% change in installations (Tier Combo)	-13.05%	-25.88%

The analysis above raises the issue of using the end of 2011 panel price to evaluate the impact of imposing tariffs in 2015 because the price elasticity of demand is likely to be non-constant given the large price change. While I cannot predict the impact using the 2015 panel price due to the extrapolation concern in the first stage, I'm able to calculate the price elasticity at the different system price levels (Table VII). Given a 1% permanent increase in price at the 2011 level, I find the long-run demand to change by 4.7% using the tier 1 electricity pricing. Not surprisingly, the demand is less elastic at the lower system price level of \$3/W. This result indicates that the impact from tariffs would be smaller in 2015 than in 2011.

Table VII: Demand Elasticity with Prices in 2011 and 2015

	2011 price (\$6.23/W)	2015 price (\$3/W)
ϵ_D (Tier 1)	4.7	2.1
ϵ_D (Tier 4)	3.2	1.6
ϵ_D (Tier Combo)	3.8	1.8

Matching the Social Cost of Carbon

In 2013, the U.S. government interagency working group estimated the social cost of carbon to be $38/ton.[41][42] It is then of interest to understand the impact of lowering the subsidy to $38/ton because this is the optimal level of subsidy, where the marginal cost of subsidy equates the marginal benefit of displacing one ton of CO_2. A subtle result arises from the counterfactual exercise is that it's possible that no subsidy level is low enough to match the $38/ton carbon price when electricity prices are high. This is because there are enough households who would invest in solar at the end of 2011 market condition even without any subsidies or tax credits. The change in consumer surplus induced by the subsidy is not enough to offset the spending on these households. *Figure 3(a)* shows that (program) welfare costs follow a near linear relationship with the subsidy. At the lower end of the subsidy, however, the welfare cost converges to $40/ton of CO_2. *Figure 3(b)* shows the aggregate number of households choose to adopt solar over the 50-year time period. It follows an S-shape curve that adoptions are slow at the lower level of subsidies, then increase at a faster rate as subsidy get higher, and then slow down again at the high subsidy level.[44]

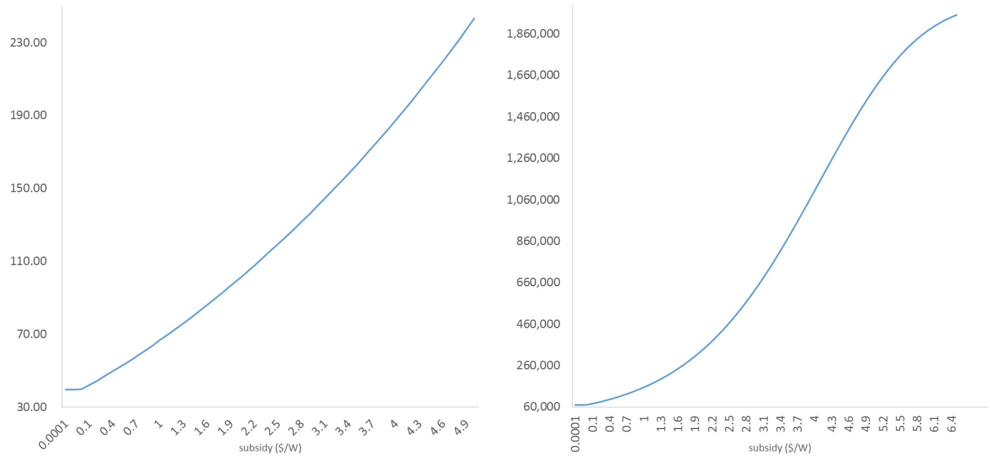
6 Conclusion

This study uses the investment decisions in solar power systems from a large pool of households in California during the 5-year period to recover the con-

[41]This is the central value (in 2007 dollar) of each additional ton of CO_2 emitted in 2015 based on the outputs of three Integrated Assessment Models-PACE, DICE and FUND. This value increases as time evolves to $52 by 2030 and $71 by 2050. (Interagency Working Group, 2013)

[42][43]

[44]This S-shape adoption curve is another artifact of the extreme value error assumption.



(a) Welfare Costs (\$/ton CO_2) *(b) Number of Solar Adoptions*

Figure 3: Welfare costs and the number of adoptions at different subsidy levels

sumer demand function. It provides one of the first economic evaluations of solar incentive programs to address both normative and positive policy concerns. The result suggests that an upfront capacity-based subsidy has greater impact than an equivalent amount of production-based subsidy on a household's decision to invest in a PV system. From a policy perspective, this implies that a capacity-based subsidy encourages more solar adoptions than a production-based subsidy such as the feed-in tariff program, holding the amount of government spending equal. On the other hand production-based subsidies are more efficient than capacity-based subsidies. One insight from this counterfactual experiment is that in a location with homogeneous solar resource across the geographical boundary, the two type of subsidies would have exactly the same efficiency implication.

The flexibility of the structural model also allows me to assess the potential effect of the on-going solar trade war. I find that if the tariffs lead to an increase in the system price, it would have a significant impact on the solar adoptions. The long-run demand elasticity for solar is less elastic in the recent times when the prices are low but a 1% increase in price can still lead to 1.8% decrease in the solar demand. The model shows that most of the investments in solar power systems would not have been made without the CSI upfront subsidy and the residential renewable energy tax credits. To respond to the concern raised by *Der Spiegel*, this study also shows that the German subsidy program for solar electricity could indeed be highly expensive due to Germany's suboptimal solar resources. We may agree with Thomas Edison's vision of switching to the solar power generated electricity before the exhaustion of fossil fuel resources. This should, however, occur in a sustainable manner that balances the benefits and the costs of the programs. This paper provides the quantitative results to address these overarching questions.

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Appendix

A1. Background Information (For Online Publication)

A1.1 The Characteristics of Solar Technology

Solar power systems can be broadly separated into two categories - PV technologies and concentrated solar power technologies. PV technologies commonly referred to as "solar panel" systems feature an unusual attribute among all electricity generation technologies inasmuch as they provide distributed power generation.[45] Photovoltaic technologies convert sunlight directly into electricity using semiconductors that exhibit the photoelectric effect. This effect was first observed by Becquerel in the 19th century and in 1921 a Nobel Prize was awarded to Albert Einstein for his mathematical description of the effect. When Chapin, Fuller and Pearson patented their PV cell in 1954, while working at Bell Laboratories, they adopted silicon as the semiconductor material of choice. It achieved 6% efficiency at a cost of $1,720/W. Since then, crystalline silicon (c-Si) cells have been the most widely deployed PV technology reaching an average efficiency of 14.4% (Hand et al. 2012).

The dominant PV cell manufacturers in the U.S. include the Phoenix-based First Solar Company that uses different semiconductor materials, such as cadmium telluride (CdTe) or copper indium gallium selenide (CGIS) to produce solar cells. These products are often called thin-film PV cells because of their physical characteristics as they are thinner than traditional c-Si cells. Thin films are generally cheaper to produce and easier to integrate into a housing structure. However, due to their relatively low efficiency rate[46] they currently do not have a cost advantage over c-Si solar cells. PV panels or PV modules are connected assemblies of multiple PV

[45]Solar power systems can generate electricity on-site unlike the common setup where electricity is generated at a central station and subsequently transmitted to each household through transmission lines and substations.

[46]Thin-film efficiency rate is around 10% for most commercially available cells depending on the material that is used. Prof. Yablonovitch used gallium arsenide (GaAs) as the solar cell material and reached a record of 28.3% efficiency approaching the 33.5% Shockley-Quiesser efficiency limit of single junction solar cell. Thin-film PV cells are considered by many to be the technology of the future, and are sometimes referred to as "second generation" solar cells.

cells which make up components of a larger PV system. These PV systems can be installed on any residential rooftop to generate electricity to supply household electricity needs. They are referred to as distributed generation systems since the electricity is generated at each node without the need of transporting electricity from a central power generation plant to individual users through power transmission lines. PV technologies always have an economic advantage in rural areas due to the high fixed cost of setting up transmission lines (or the off-grid systems).

The main disadvantage of PV technologies is that they only generate electricity when the sun is shining.[47] PV systems cannot support modern household electricity needs without an electrical storage system, which can be extremely expensive. Therefore the systems of interest in this paper are "grid-connected" systems. These systems generate electricity to supply a household but when the demand is higher than the solar system can deliver or during the night time, the residual demand is supplied by the usual sources through grid/transmission lines.

Concentrated solar power (CSP) technologies use mirrors or lenses to focus sunlight onto a receiver. The receiver contains a working fluid which transfers the thermal energy to a heat engine that drives an electrical generator. Examples of CSP technologies include the Solar Two, a 10 MW Department of Energy demonstration solar tower project, and parabolic trough systems. CSP experienced very little growth since the mid-90s and its utility-scaled deployment excludes this technology from the consideration in this paper.

A1.2 Solar Power Markets

In analogous to retailers and wholesalers in the conventional markets, the solar supply-side can be characterized by two interdependent markets- one is the market with PV installers as suppliers and the other is the market with wafer, cell and module manufacturers as suppliers. The most important distinction between the two markets is that the former is organized as a domestic market whereas the latter is an international market. For exam-

[47]The intermittency and integration issue with solar and wind power which is not in the scope of this study is discussed in Gowrisankaran et al. (2014), EnerNex Corp (2010), and GE Energy (2010).

ple, manufacturers in China and Taiwan produced 61% of the global supply of PV modules in 2011 and on average merely 6% of the solar power system capacities are installed in the US. This observation shows that the price of solar modules doesn't depend on the domestic activity to a large extend and avoids the potential endogeneity concern. One potential endogeneous variables are the unobservables that encourage installations that also leads to higher module prices. Since US contributes only a small percentage of the total world demand, it's conceivable that the local increase in demand in California doesn't translate a global module price spike (However, the extend of the influence should be further studied empirically.). The production capacity followed a period of rapid expansion, as worldwide module manufacturing capacity increased 100-fold from 2007 to 2011 after the relief from the global bottleneck in raw silicon production. During this period, the supply capacity is 50% to 200% higher than the demand size. The excess built-up in capacity finally lead to numerous bankruptcies and consolidations in 2011, and this led to the DoC complaint filed by Solar World, discussed above.

The solar PV demand-side market can be broadly divided into three sectors - utility, commercial and residential, based on the ownership of the solar power system. Residential systems are generally less than 10 kW due to the limited rooftop space available whereas commercial systems are generally between 10 kW and several MW in size and utility systems are often several hundred MW. The residential market contributes to one-fifth of the operating capacities in the U.S. In this paper, we will focus on residential grid-connected systems.[48]

[48]While commercial sector could be potentially more important to study for its larger market share and potential, its complex nature poses much more challenges than the residential households. For example, consider a company rents an office building from the owner and pays its own electricity bills. The owner might has incentives to install solar power systems to differentiate their office building from the others and charge a premium in the rent but conceivably a rare situation. Meanwhile, the renter may not have the right to install solar power systems or unwilling to invest due to the uncertainty in the length of the lease. In addition, many subsidies programs have a funding cap thus poses a problem in identification. The CSI residential program is one of the few programs that doesn't have such a constraint.

A1.3 California Solar Initiative Program

California, with its scenic coastline and rich natural resources, has long exercised progressive environmental policies. For example, California passed the Solar Rights Act back in 1979. This establishes the right of homeowners and businesses to access sunlight in order to generate solar energy and limits the ability of local governments or homeowner associations to prevent solar system installations.[49] In 1998, California was one of the first states to provide a capacity-based solar incentive policy following the electricity deregulation. The funding for these programs is supported by the Public Benefit Fund. It is collected by each investor-owned utility (IOU) company based on the ratepayer's electricity usage[50] through a "public good charge", created by AB1890 in 1996. There were two parallel subsidy programs that were in effect from 1998 to December 31, 2006. California Energy Commission's (CEC) Emerging Renewable Program (ERP) which targets residential and small commercial solar systems that are under 30 kW. Larger commercial systems are funded through California Public Utilities Commission's (CPUC) self-generation incentive program (SGIP). There were very few adoptions in the market despite the initial $3/W subsidy[51] and the preexisting net-metering rule. Cumulative installation increased by a mere 43% from 6 MW in 1996 level to 8.7 MW at the end of 1999.

The 2000-2001 electricity crisis presented itself as a turning point for the solar power market in California. It heightened the awareness of the benefits of self-generated electricity and shifted the public opinion on renewable energy policy. Following the crisis, California provides a 15% state tax credit for renewable energy investments and increased the capacity-based subsidy to $4.50/W in 2001. Later that year, funding for mid-sized and large projects were depleted. Within the three-year timespan from 2000 to 2003, the cumulative grid-tied PV capacity increased by 300% (see Figure

[49] In addition, California also enacted the Solar Shade Control Act in 1978 which guarantees PV system with access to sunlight from the neighboring trees and buildings.

[50] This additional charge varies by utility and customer type. It is around 0.85 cents/kWh in addition to the electricity rate. 18% of the fund is used to support renewable energy technologies while 63% is used for energy efficiency related programs and the remaining 18% is for research and development projects.

[51] Compare this to the average $10/W total system price. Note that in 1998 there was a 50% cap on the total subsidy amount relative to the total system cost however it's not a binding constraint in most cases.

A5.8).

Since 2007, the two programs had been replaced by the Go Solar California campaign with a goal of installing 3 GW of solar generating capacity over 10 years with a budget of $3.35 billion. A third of the goal is designed to be fulfilled by the New Solar Homes Partnership program that focuses on integrating solar power systems into new housing constructions thus at a lower installation cost. The rest of the capacity is to be met under the California Solar Initiative (CSI) program.[52] Systems larger than 30 kW[53] are required to take the 5-year performance-based incentive to receive monthly payments while smaller systems are to take the expected performance-based buydown (EPBB) subsidy and receive a one-time lumpsum upfront payment.[54] This upfront capacity-based rebate starts at $2.50/W and declines to nil following a block schedule as shown in Figure A5.1. When the aggregate installed capacity reached a preset amount, the subsidy level moves down to the next level. The block schedule (or subsidy degression) is a method to reflect the declining system cost in the future and additionally it encourage adoptions to occur sooner, rather than later. Since the panel price continues to decline over time (See Figure A5.9 and A5.10), a rational forward looking consumer will always choose to adopt at a later date, should the subsidy stay constant over time. Each of the three IOUs receives a pre-allocated target and follows its own subsidy schedule (Table A2.2). The particular block schedule adopted by CSI means that the financial incentive declines as more capacity is installed. This particular design also means the policy makers have precise information on the amount of subsidy that is required to reach the 1.94 GW target level of adoption. This is in contrast to the production subsidy where the subsidy amount depends on the realized production amount.

[52] Within the CSI, a third of the installed capacity are to be fulfilled by the residential sector and the rest to be fulfilled by commercial, government and non-profit sectors jointly.

[53] When the CSI launched in 2007, this threshold is set at 100kW. Subsequently, this is lowered to 50 kW during 2008-2009 and 30 kW starting in 2010.

[54] The EPBB program is essentially a capacity-based subsidy but it weights the final subsidy amount based on the quality and installation orientation of the solar power systems. Systems less than 10 kW in size have to take the capacity-based subsidy while systems between 10 kW and 30 kW have the option to opt into the PBI program.

A2. Tables

Table A2.1 CSI rebate rate schedule

Step	Statewide MW in each step	Residential subsidy rate (per Watt)
1	50	n/a
2	70	$2.50
3	100	$2.20
4	130	$1.90
5	160	$1.55
6	190	$1.10
7	215	$0.65
8	250	$0.35
9	285	$0.25
10	350	$0.20

Table A2.2: First stage regression result

	cost/W	Std. Err.
pre2007	-0.0009***	(.0002)
size (kW)	-0.2037***	(.0045)
size^2 (kW^2)	0.0038***	(.0001)
wages	1.4702***	(.0435)
Module cost	0.6557***	(.1338)
2007	– omitted –	
2008	0.0763**	(.0390)
2009	-0.1700***	(.0396)
2010	-0.4594***	(.0599)
2011	-.3688***	(.0922)
PG&E	– omitted –	
SCE	0.7456***	(.0426)
SDG&E	0.3206***	(.0284)
_cons	4.127***	(.2685)
N	25,038	

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

Table A2.4: Maximum Likelihood Estimation Results without Utility Specific Time Trends

Variables	null	Lowest Tiered Pricing (Tier 1)	Highest Tiered pricing (Tier 4)	Combined Tiered Pricing	Highest Tiered pricing (Tier 1)	Highest Tiered pricing (Tier 4)	Combined Tiered Pricing
system price		-0.132***	-0.146***	-0.14***	-0.3626***	-0.3762***	-0.3525***
		(0.022)	(0.025)	(0.024)	(0.0375)	(0.0575)	(0.0471)
CSI subsidy		0.035*	0.057***	0.055***	0.0664***	0.1099***	0.102***
		(0.020)	(0.022)	(0.020)	(0.0145)	(0.0176)	(0.0131)
Revenue		0.01	0.024***	0.088***	0.0736	0.0486***	0.0397**
		(0.016)	(0.005)	(0.036)	(0.0601)	(0.008)	(0.0179)
Tax Credits		0.026***	0.022***	0.018***	0.3876***	0.3967*	0.3219*
		(0.004)	(0.005)	(0.005)	(0.1084)	(0.2153)	(0.1647)
net cost							
D2008					0.8164***	0.8864***	0.85***
					(0.1096)	(0.0799)	(0.082)
D2009					-3.3754***	-3.6386	-2.6715
					(1.1937)	(2.3645)	(2.3776)
D2010					-4.2081***	-4.244*	-3.2885
					(1.1583)	(2.3655)	(2.3670)
D2011					-4.5697	-4.4337	-3.5666
					(1.1419)	(2.3744)	(2.3696)
SDGE					-0.2632	0.1222	-0.1977
					(0.1340)	(0.1347)	(0.1461)
SCE					-0.6186***	0.3988***	0.1175***
					(0.1203)	(0.0637)	(0.0522)
constant	-8.4466***	-3.3638******	-3.401***	-4.134***	5.4766***	4.8343**	4.709***
		(0.848)	(0.909)	(1.272)	(1.7038)	(2.4216)	(2.3497)
N observations	20640	20640	20640	20640	20640	20640	20640
Log- Likelihood	-241985	-239281	-239215	-239192	-238260	-237631	-237760
LR chi2		5409	5541	5587	7450	8709	8451
prob > chi2		0	0	0	0	0	0

standard errors in parentheses

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

Table A2.5: Maximum Likelihood Estimation Results with Fixed Effects and Utility-Time Trends

Variables	null	Lowest Tiered Pricing (Tier 1)	Highest Tiered pricing (Tier 4)	Combined Tiered Pricing	Highest Tiered pricing (Tier 1)	Highest Tiered pricing (Tier 4)	Combined Tiered Pricing
system price		-0.1847***	-0.1834***	-0.2007***			
		(0.0594)	(0.0605)	(0.0598)			
CSI subsidy		0.1467***	0.146***	0.147***			
		(0.0123)	(0.0118)	(0.0122)			
Revenue		-0.0560	-0.0259	-0.0143			
		(0.0474)	(0.0178)	(0.0153)			
Tax Credits		-0.4854**	-0.4855**	-0.4296**			
		(0.2138)	(0.2107)	(0.2124)			
net cost					-0.1889	-0.1276***	-0.153***
					(0.0249)	(0.0142)	(0.0330)
D2008		0.7677***	0.7645***	0.7787***	0.8477	0.6429***	0.754***
		(0.0751)	(0.0781)	(0.0730)	(0.0817)	(0.0416)	(0.1147)
D2009		5.8226**	5.9469**	5.2569**	-0.8134	-1.0606***	-0.7814***
		(2.2991)	(2.2859)	(2.2862)	(0.1664)	(0.1614)	(0.2507)
D2010		5.2047**	5.3843**	4.6395**	-0.4933	-1.0496***	-0.5851**
		(2.2771)	(2.2920)	(2.2591)	(0.1673)	(0.1969)	(0.2816)
D2011		4.6442**	4.7220**	4.0513*	-0.5599	-0.631***	-0.5868
		(2.2786)	(2.2802)	(2.2571)	(0.1680)	(0.1486)	(0.2693)
SCE×08		0.0998**	0.0563*	0.0921***	0.0364	0.3459***	0.1372***
		(0.0340)	(0.0417)	(0.0275)	(0.0377)	(0.0521)	(0.091)
SCE×09		0.4525***	0.3184*	0.3921***	-0.1136	0.7755***	0.2402*
		(0.1507)	(0.1635)	(0.1517)	(0.0939)	(0.0468)	(0.125)
SCE×10		0.4025***	0.1965	0.3201**	-0.3134	1.0276***	0.231
		(0.1578)	(0.1881)	(0.1591)	(0.1450)	(0.0538)	(0.1736)
SCE×11		1.3707***	1.2649***	1.3144***	0.7342	1.4852***	1.1154***
		(0.1466)	(0.1518)	(0.1475)	(0.0980)	(0.0393)	(0.1318)
SDGE×08		0.1724***	0.1766***	0.1778***	0.1556	0.1647***	0.1145
		(0.0076)	(0.0100)	(0.007)	(0.0115	(0.0225)	(0.0983)
SDGE×09		0.9983***	1.0969***	1.0191***	0.8366	0.437***	0.5782***
		(0.0500)	(0.0837)	(0.0556)	(0.0347	(0.0720)	(0.1923))
SDGE×10		0.9015***	0.8681***	0.8982***	0.7877	0.9552***	0.7337***
		(0.0500)	(0.0512)	(0.0491)	(0.0124)	(0.0272)	(0.0861)
SDGE×11		1.2027***	1.2447***	1.1974***	1.0427	0.7961***	0.9801***
		(0.0511)	(0.0617)	(0.0496)	(0.0126)	(0.0308)	(0.0965)
SDGE		-0.9089***	-1.0347***	-0.6118***	-1.0248	0.0857	-0.7525
		(0.0965)	(0.1321)	(0.0605)	(0.0565)	(0.0808)	(0.1062)
SCE		-0.5293***	-0.7896***	-0.9191***	-1.1299	-0.6854***	-1.1023***
		(0.1557)	(0.1769)	(0.1509)	(0.0784)	(0.0884)	(0.072)
constant	-0.9660	-0.7487	-0.2909	-0.4914	-4.0907	-7.8227***	-5.7191***
		(2.3042)	(2.3267)	(2.3351)	(0.6334)	(0.0684)	(0.5516)
N observations	20640	20640	20640	20640	20640	20640	20640
Log-Likelihood	-241,985	-237,678	-237,676	-237,681	-238,397	-238,628	-238,511
LR chi2		8,615	8,619	8,609	7,177	6,715	6,949
prob > chi2		0	0	0	0	0	0

standard errors in parentheses

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

Table A2.6: Welfare Costs of the Solar Incentive Programs

	Tier 1		Tier 4		Tier C	
	CSI Subsidy	CSI & Tax Credits	CSI Subsidy	CSI & Tax Credits	CSI Subsidy	CSI & Tax Credits
△ num. adoptions						
PGE	22%	87%	18%	76%	19%	81%
SCE	46%	91%	34%	80%	40%	86%
SDGE	21%	85%	16%	73%	18%	79%
Overall	27%	87%	21%	76%	23%	81%
Total Installations ('000)						
PGE	178	178	121	121	172	172
SCE	82.8	82.8	80.6	80.6	80.3	80.3
SDGE	133	133	120	120	131	131
Overall	394	394	321	321	383	383
Change in CS ($ per system)						
PGE	337.5	882.7	481	1259	367.8	1026
SCE	456.2	789.4	512	1029	490.5	919.9
SDGE	290.2	811.8	349.9	1071	314.5	942.2
Overall	346.5	839.1	439.9	1131	375.3	975.4
Implied CO_2 price ($/ton)						
PGE	63.43	120	83.57	135	73.56	126.7
SCE	62.55	125.2	81.83	137.5	71.92	130.6
SDGE	59.02	108.7	79.28	124.2	69.33	115.9
Overall	61.9	117.3	81.64	131.7	71.8	123.7

All dollar values are in 2011 dollar. The unit, ton, refers to metric ton.

I keep the tax credits in the background even when evaluating only the CSI subsidy for the reason to be closest to the reality.

Table A2.7: Welfare Costs of the Solar Incentive Programs Without Adjusting for Consumer Surplus

	Tier 1		Tier 4		Tier C	
	CSI Subsidy	CSI & Tax Credits	CSI Subsidy	CSI & Tax Credits	CSI Subsidy	CSI & Tax Credits
Implied CO_2 price ($/ton)						
PGE	85.42	134.7	122.8	159.2	101.9	145.2
SCE	75.97	137	102.2	155	88.78	145.2
SDGE	77.59	121.6	109.8	144.2	93.36	132.2
Overall	79.8	130.8	110.6	152.6	94.7	140.7

All dollar values are in 2011 dollar.

Table A2.8: Welfare comparison between capacity- and production-based subsidies (revenue neutral, Tier 1)

	Capacity-based subsidy	Production-based subsidy	Capacity-based subsidy with AZ solar in S. CA and AK solar in N. CA	Production-based with AZ(S. CA) and AK (N. CA) solar
△ num. adoptions				
PGE	60.56%	76.04%	53.84%	26.28%
SCE	62.70%	94.03%	120.40%	145.30%
SDGE	58.71%	146.20%	179.20%	213.80%
Overall	60.33%	60.29%	60.61%	59.53%
Total Installations ('000)				
PGE	322	244	204	203
SCE	133	91.7	77	75.4
SDGE	242	101	85.2	82.7
Overall	697	696	586	571
Subsidy ($/W)				
PGE	$1.1/W	$1.06/W	$1.1/W	$0.656/W
SCE	$1.1/W	$1.12/W	$1.1/W	$1.23/W
SDGE	$1.1/W	$1.13/W	$1.1/W	$1.23/W
Overall	$1.1/W	7.914 ¢/kWh	$1.1/W	8.142 ¢/kWh
Public spending ('000)	$2,646,265	$2,646,265	$2,221,709	$2,221,709
Change in CS			$627.2	$295.2
PGE	$819.5	$1022	$1534	$1894
SCE	$776.3	$1170	$2745	$3400
SDGE	$857.2	$2154	$1310	$1340
Overall	$824.3	$1315		
Lifetime CO2 abatement				
PGE	13	13	4.6	2.2
SCE	6.1	6.3	7.2	8.5
SDGE	10	11	12	14
Overall	30	30	24	25
Implied CO_2 price				
PGE	$71.26	$69.77	$111.5	$87.23
SCE	$64.79	$65.66	$61.42	$65.9
SDGE	$68.75	$70.05	$66.32	$71.26
Overall	$69.07	$69.01	$73.51	$70.83

Table A2.9: Welfare comparison between capacity- and production-based subsidies (revenue neutral, Tier 4)

	Capacity-based subsidy	Production-based subsidy	Capacity-based subsidy with AZ solar in S. CA and AK solar in N. CA	Production-based with AZ(S. CA) and AK (N. CA) solar
△ num. adoptions				
PGE	47.57%	58.92%	21.41%	10.21%
SCE	48.81%	75.65%	112.30%	121.70%
SDGE	45.41%	117.20%	166%	179.60%
Overall	47.03%	46.99%	46.25%	45.66%
Total Installations ('000)				
PGE	251	194	150	150
SCE	112	74.4	56.9	56.5
SDGE	207	83.1	63.3	62.5
Overall	570	570	435	430
Subsidy ($/W)				
PGE	$0.696/W	$1.06/W	$1.1/W	$0.618/W
SCE	$0.691/W	$1.12/W	$1.1/W	$1.16/W
SDGE	$0.704/W	$1.13/W	$1.1/W	$1.16/W
Overall	$1.1/W	7.898 ¢/kWh	$1.1/W	7.671 ¢/kWh
Public spending ('000)	2146438	$2146438	$1642808	$1642808
Change in CS				
PGE	$904.9	$1117	$338.4	$159.8
SCE	$879.9	$1369	$2103	$2295
SDGE	$949.5	$2463	$3717	$4064
Overall	$916.2	$1489	$1502	$1517
Lifetime CO2 abatement				
PGE	8.2	7.9	1.3	0.63
SCE	4	4.1	5	5.4
SDGE	6.9	7.2	8.2	8.8
Overall	19	19	15	15
Implied CO_2 price				
PGE	$86.81	$85.44	$132.2	$108.7
SCE	$79.73	$80.48	$76.2	$78.13
SDGE	$85.08	$86.2	$83.23	$85.37
Overall	$84.71	$84.66	$85.31	$83.74

Table A2.10: Welfare comparison between capacity- and production-based subsidies (revenue neutral, Tier C)

	Capacity-based subsidy	Production-based subsidy	Capacity-based subsidy with AZ solar in S. CA and AK solar in N. CA	Production-based with AZ(S. CA) and AK (N. CA) solar
△ num. adoptions				
PGE	58.18%	56.86%	59.28%	39.83%
SCE	58.72%	59.58%	58.36%	60.49%
SDGE	57.65%	58.72%	57.74%	59.84%
Overall	58.07%	58.04%	58.19%	57.87%
Total Installations ('000)				
PGE	75.1	72.8	19	12.8
SCE	26.9	27.5	37.6	39.7
SDGE	63.9	65.6	61.4	64.6
Overall	166	166	118	117
Subsidy ($/W)				
PGE	$1.1/W	$1.06/W	$1.1/W	$0.619/W
SCE	$1.1/W	$1.12/W	$1.1/W	$1.16/W
SDGE	$1.1/W	$1.13/W	$1.1/W	$1.16/W
Overall	$1.1/W	7.898 ¢/kWh	$1.1/W	7.689 ¢/kWh
Public spending ('000)	$609325	$609325	$433155	$433155
Change in CS				
PGE	$774.4	$755.9	$753.4	$504.4
SCE	$764	$776	$770.8	$800.6
SDGE	$784.5	$800.4	$782.8	$813.8
Overall	$776.6	$776.8	$774.3	$775.4
Lifetime CO2 abatement				
PGE	3	2.9	0.47	0.21
SCE	1.2	1.2	1.7	1.9
SDGE	2.7	2.8	2.8	3
Overall	6.9	6.9	4.9	5.1
Implied CO_2 price				
PGE	$72.21	$70.9	$117.7	$93.98
SCE	$67.31	$68.04	$63.63	$65.54
SDGE	$68.15	$69.16	$64.34	$66.27
Overall	$69.78	$69.68	$69.13	$67.15

Table A2.11: Counterfactual analysis with solar irradiation for Frankfurt, Germany (Tier 1)

	Baseline (Factual World Solar Radiation)	Frankfurt irradiation	Frankfurt radiation/ same num. installations	Frankfurt radiation/ same electricity prod.
△ num. adoptions				
PGE	66.24%	66.77%	83.68%	89.38%
SCE	66.71%	67.06%	84.04%	89.77%
SDGE	66.01%	66.80%	83.72%	89.42%
Overall	66.23%	66.83%	83.75%	89.46%
Total Installations ('000)				
PGE	63.5	34.2	69.6	107
SCE	21.7	10.5	21.7	33.9
SDGE	49	21	42.8	65.9
Overall	134	66	134	207
Subsidy	$1.1/W	$1.1/W	$1.83/W	$2.28/W
Change in CS ($ per system)				
PGE	$705.5	$695	$889.5	$972.1
SCE	$696.2	$689.4	$873.8	$945
SDGE	$710.2	$694.4	$887.8	$969.2
Overall	$705.7	$693.9	$886.4	$966.7
Electricity production	26 GWh	8.3 GWh	16.9 GWh	26 GWh
Lifetime CO_2 abatement (MMt)				
PGE	2.9	1.1	2.7	4.4
SCE	1.1	0.33	0.84	1.4
SDGE	2.4	0.65	1.7	2.7
Overall	6.3	2	5.2	8.6
Implied CO_2 price				
PGE	$64.91	$95.77	$134.4	$161.2
SCE	$60.65	$95.33	$133.7	$160.1
SDGE	$60.86	$95.72	$134.3	$161.1
Overall	$62.68	$95.68	$134.2	$161

MMt refers to million metric tons

	Baseline "Factual World Solar Radiation"	Frankfurt irradiation	Frankfurt irradiation/ same num. installations	Frankfurt irradiation/ same electricity prod.
△ num. adoptions				
PGE	51.43%	52.72%	87.86%	92.22%
SCE	51.92%	52.70%	87.83%	92.18%
SDGE	50.81%	52.48%	87.45%	91.78%
Overall	51.28%	52.62%	87.69%	92.04%
Total Installations ('000)				
PGE	82.8	18.2	7080.00%	110
SCE	33	10.9	4240.00%	65.9
SDGE	70.6	19.4	7330.00%	112
Overall	186	48	186.6	288
Subsidy	\$1.1/W	\$1.1/W	\$3.14/W	\$3.83/W
Change in CS (\$ per system)				
PGE	\$828.3	\$803.4	\$1380	\$1483
SCE	\$818.9	\$803.8	\$1383	\$1489
SDGE	\$840.4	\$808	\$1416	\$1545
Overall	\$831.2	\$805.3	\$1395	\$1509
Electricity production	36.2 GWh	6.1 GWh	23.4 GWh	36.2 GWh
Lifetime CO_2 abatement (MMt)				
PGE	2.9	0.44	2.9	4.7
SCE	1.3	0.27	1.7	2.8
SDGE	2.6	4.70E-01	3.00E+00	4.8
Overall	6.8	1.2	7.6	12
Implied CO_2 price				
PGE	\$80.22	\$116.6	\$223.4	\$266.1
SCE	\$74.85	\$116.6	\$223.6	\$266.3
SDGE	\$75.97	\$117.1	\$225	\$268.4
Overall	\$77.59	\$116.8	\$224.1	\$267

Table A2.12: Counterfactual analysis with solar irradiation for Frankfurt, Germany (Tier 4)

MMt refers to million metric tons

Table A2.13: Counterfactual analysis with solar irradiation for Frankfurt, Germany (Combined Tiered Pricing)

	Baseline "Factual World Solar Radiation"	Frankfurt radiation	Frankfurt irradiation/ same num. installations	Frankfurt radiation/ same electricity prod.
△ num. adoptions				
PGE	58.18%	59.22%	88.11%	92.31%
SCE	58.72%	59.34%	88.28%	92.49%
SDGE	57.65%	59.13%	87.97%	92.16%
Overall	58.07%	59.21%	88.09%	92.29%
Total Installations ('000)				
PGE	75.1	22.1	75.90	117.00
SCE	26.9	9.1	31.60	49.30
SDGE	63.9	17.2	58.5	89.7
Overall	166	48	166	256
Subsidy	$1.1/W	$1.1/W	$2.65/W	$3.22/W
Change in CS ($ per system)				
PGE	$774.4	$754.5	$1158	$1244
SCE	$764	$752.3	$1145	$1222
SDGE	$784.5	$756.3	$1169	$1263
Overall	$776.6	$754.7	$1159	$1246
Electricity production	32.2 Gwh	6.1 Gwh	20.9 GWh	32.2 GWh
Lifetime CO_2 abatement (MMt)				
PGE	3	0.61	3.1	5
SCE	1.2	2.50E-01	1.30E+00	2.10E+00
SDGE	2.7	0.47	2.4	3.8
Overall	6.9	1.3	6.8	11
Implied CO_2 price				
PGE	$72.21	$105.6	$188.2	$223.5
SCE	$67.31	$105.4	$187.7	$222.7
SDGE	$68.15	$105.8	$188.7	$224.2
Overall	$69.78	$105.7	$188.3	$223.6

MMt refers to million metric tons

A3. Calculating the equivalent CO_2 prices from deadweightloss (For Online Publication)

The deadweight loss (DL) can be derived by subtracting the increase in consumer surplus (CS) due to the increase in subsidy from the total government spending on subsidy (G).

$$DL = G - \triangle CS$$

In the logit models, consumer surplus at the specified state (S) is the logit inclusive value and θ.

$$CS(S) = \frac{1}{\theta} \log \left(e^{\beta EV(S)} + e^{\nu(S)} \right) \times M \tag{6.1}$$

Let M denote the market size, S as the current subsidy amount. Since the consumers are forward looking in the infinite horizon time span, we need to forward simulate the government spending in a very long horizon (H), take 100 years for example. The purchase probability stays constant in each period during the forward simulation process, however the market size changes due to installers exiting the market. Let n_{zt} be the number of adopters in each zip code, z at time period (month) t. The net present value of the total program spending can be expressed as

$$G = (1 \quad \beta \quad \beta^2 \cdots \beta^{12 \cdot H}) \left(\underbrace{\begin{bmatrix} n_{11} & n_{12} & \cdots & n_{1H \cdot 12} \\ \vdots & \vdots & & \vdots \\ n_{z1} & n_{z2} & \cdots & n_{zH \cdot 12} \end{bmatrix}}_{\text{zipcode} \times 12 \cdot H} \cdot \mathrm{S} \right)', \tag{6.2}$$

and the change in consumer surplus as (where S_0 is the pre-policy change subsidy amount)

$$\triangle CS = CS(S) - CS(S_0). \tag{6.3}$$

The change in the number of installations due to the change in subsidy amount is

$$\triangle Q = \sum_{h=1}^{12 \cdot H} \left[Q_h(S) - Q_h(S_0) \right]. \tag{6.4}$$

Finally the implied CO_2 price can be derived as the loss in surplus per unit of CO_2 displaced or formally as

$$P_{CO_2} = \frac{G - \triangle CS}{\gamma \times \triangle Q}. \tag{6.5}$$

γ is a constant which represents the amount of CO_2 displaced due to the avoided electricity generation from the fossil fuel based power plant. The average CO_2 emission associated with each unit of electricity production is taken from the California Air Resources Board report. Average amount of CO_2 emission associated with each MWh of electricity generation is 0.348 ton. Take San Diego vicinity for example, $\gamma = 73$ ton/unit which means by installing a solar power system with the average size of 5.59 kW, the system owner reduced the carbon dioxide emission by 73 tons over the 25 year lifetime of the system.

A4. Parameter Calibration and Data Cleaning (For Online Publication)

Table A5.1 Overall component DC-AC derate factor

Component Derate Factors	Rate
PV Module nameplate DC rating	0.95
Inverter and Transformer	0.92
Diodes and connections	0.99
DC wiring	0.98
AC wiring	0.99
Soiling	0.95
System availability	0.98
Overall DC-AC derate factor	0.78

Assumption based on 25°C, no shading

Table A5.2 Assumptions in simulating the future revenue and costs

Inflation	1.20%
Inverter Replacements	Once (70¢/W)
Utility Electric rate escalation	1.09%
Demand rate escalation	0%
Photovoltaic degradation factor (per year)	0.8%

Only residential installations are included (third party owned systems are included).

- Installations with zero cost per watt are counted as but not included in the first stage regression.

- There are a total of 5 relevant dates associated with each installation- first new reservation request date, first online reservation request submitted date, first reservation request review date, first reservation reserved date, first confirmed reservation date. The date that proxies the first installation decision is the first new reservation request (FNRR) date however there are 9.5% of the first new reservation request date missing. The most complete date is the first reservation request reviewed (FRRR) date with merely 1.7% of the entries missing. All installation records have either one of these two dates. The missing FNRR dates are therefore substituted by its correlation with the FRRR dates. This correlation varies by the utility district and year. For example the FRRR date could be the same month as the FNRR date or lagged by the FNRR date by a month or two. In this case, the probability of the number of lags is calculated by the data and a uniform [0,1] random variable is drawn to determined on the number of lags in the substituted data.

- The assumptions used in the lifetime solar electricity generation is based on the Department of General Services of California. In this case, the inflation rate is assumed to be 1.20%. The utility escalation rate is 1.09% (real) based on the 1982-2008 historical average. This gives a 2.29% nominal utility escalation rate. A annual PV degradation rate of 0.8% is used.

- Assume there is no technology improvement in inverter and a constant inverter cost of \$0.70/W is used. We also make the assumption that the inverter being replaced twice in the 25-year lifetime.

- We assume that there is an additional annual maintenance and operation cost (potentially including the increase in property insurance) of \$250.

A5. Figures and Charts (For Online Publication)

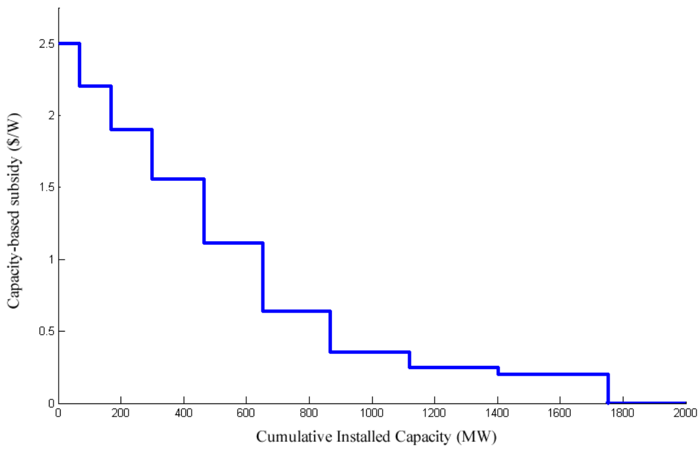


Figure A5.1: Subsidy degression in terms of cumulative installed capacity

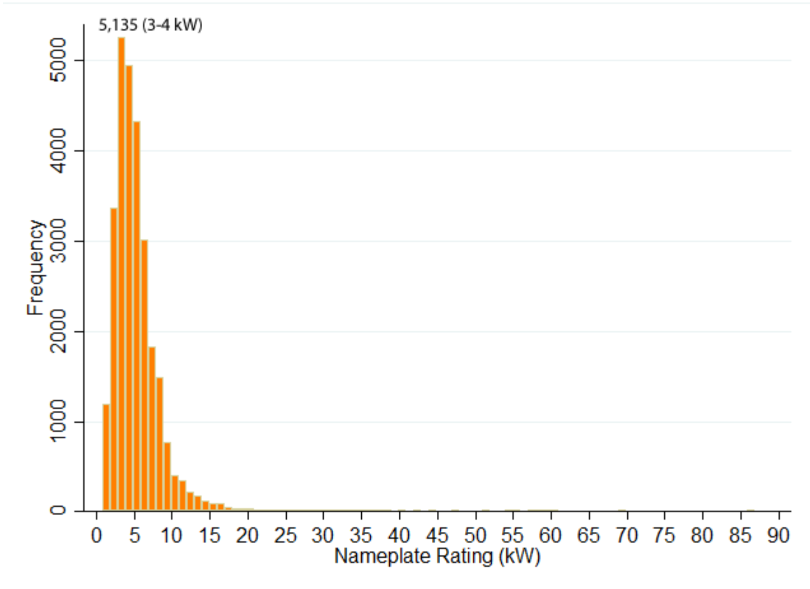


Figure A5.2: Histogram of the number of system installed by the size

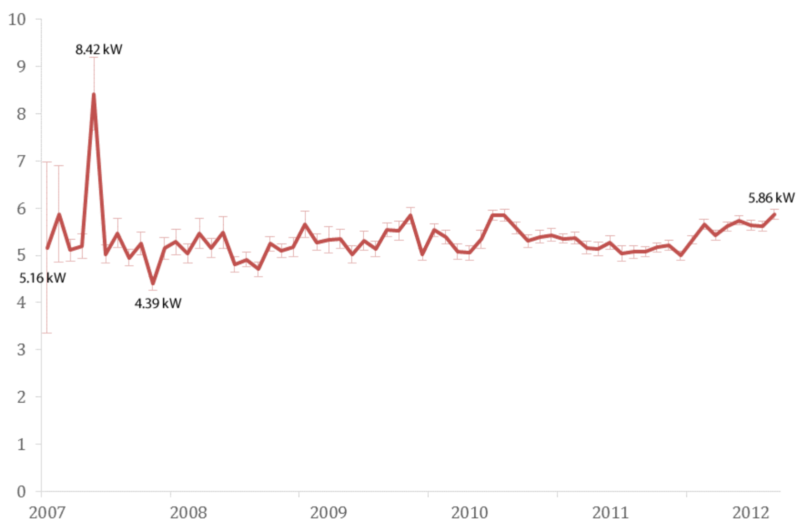
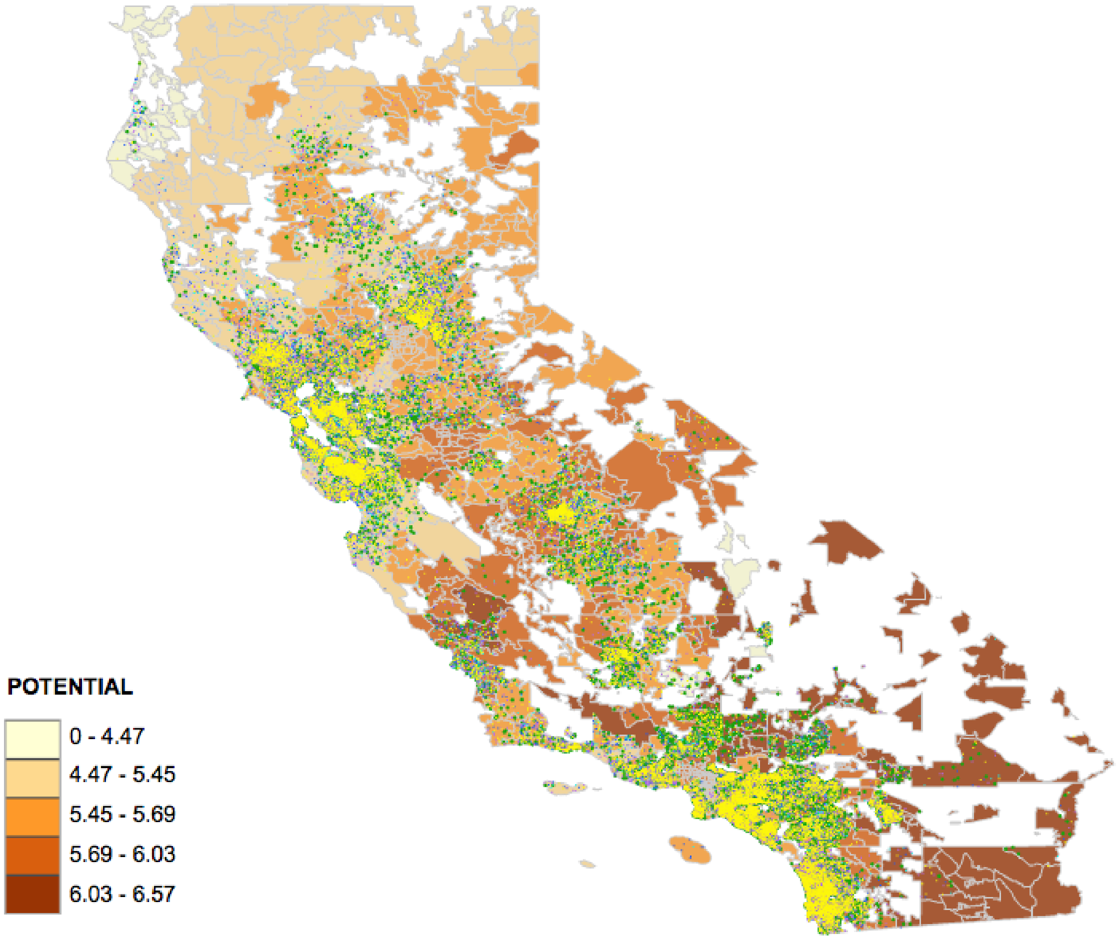


Figure A5.3: Average system size trend



A5.4: Zip code map showing PV system adoptions in California. Yellow indicates installations occurred in 2011, green indicates installations in 2010.

Figure A5.5: Map showing the counties included in the study

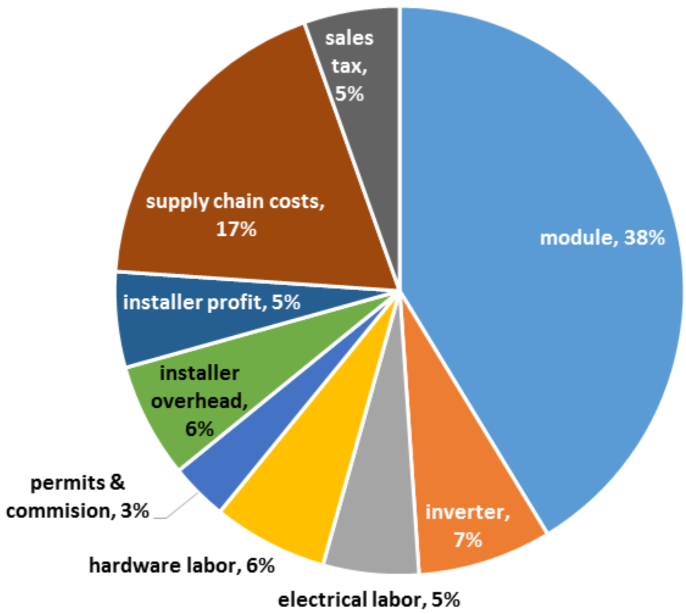


Figure A5.6: 2010 benchmark residential PV system price components in the U.S. (Goodrich et al., 2012)

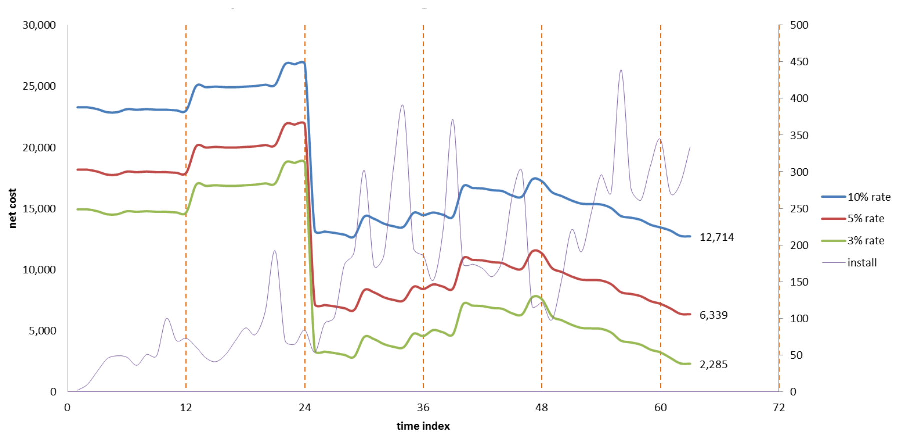


Figure A5.7: System net cost and the number of installations in La Jolla, San Diego

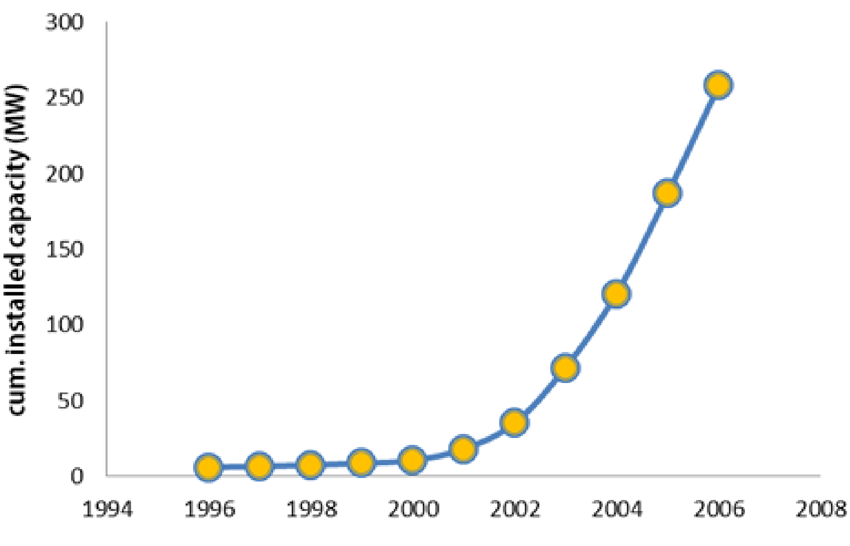


Figure A5.8: Grid-tied cumulative PV installed capacity in California, 1996-2006

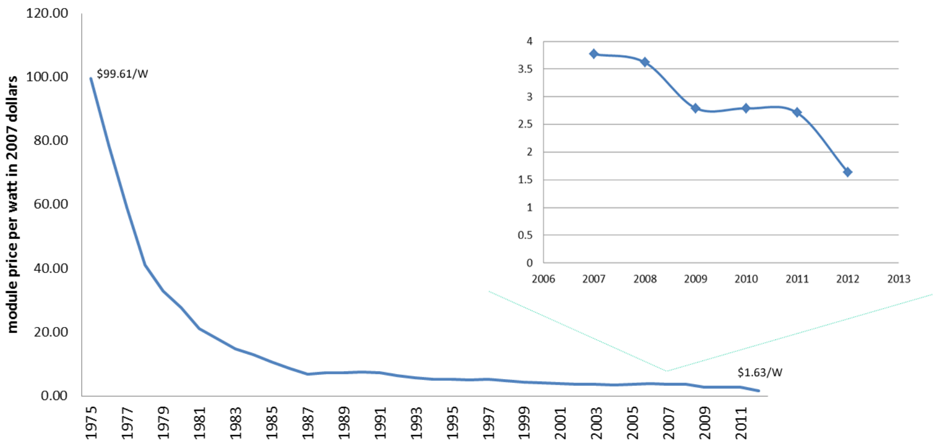


Figure A5.9: Average module cost, 1975-2012 (SolarBuzz)

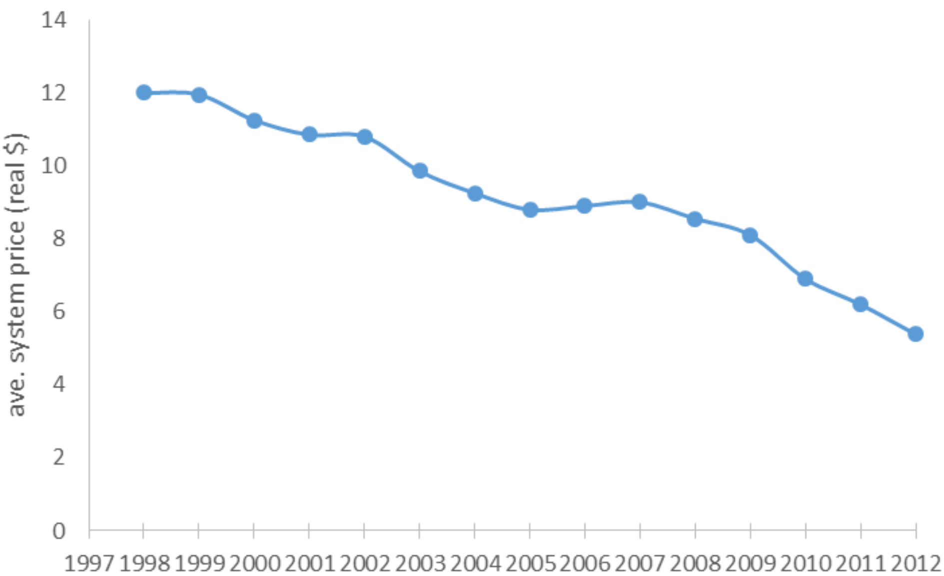


Figure A5.10: Average install system cost in the US, 1998-2012 (Barbose et al., 2013)

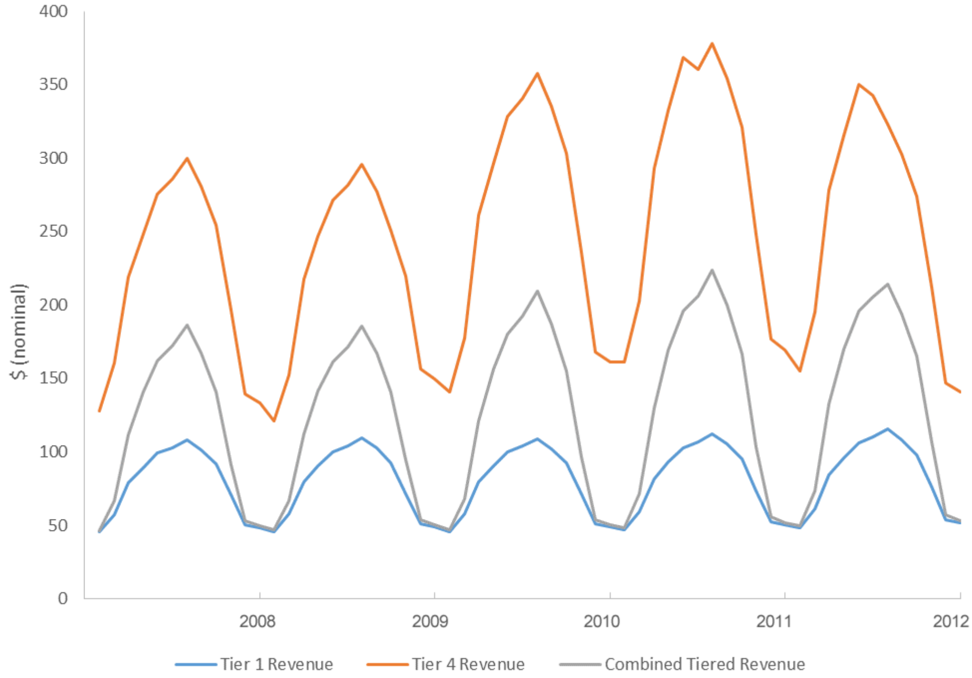


Figure A5.11: Monthly revenue for tier 1, tier 2 and tier c pricing

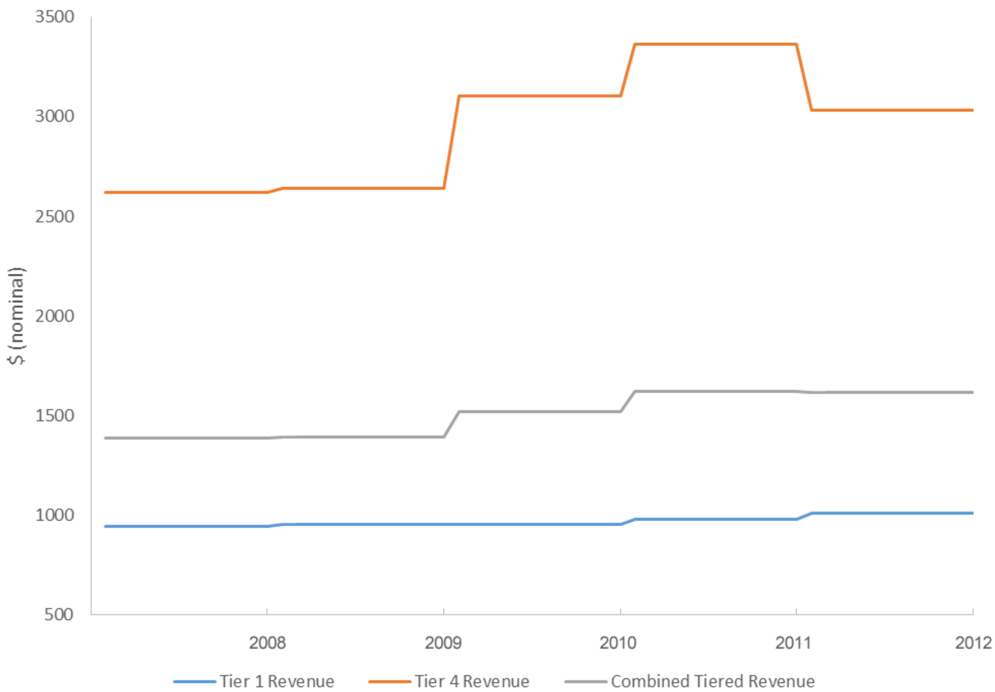


Figure A5.12: Annual revenue for tier 1, tier 2 and tier c pricing

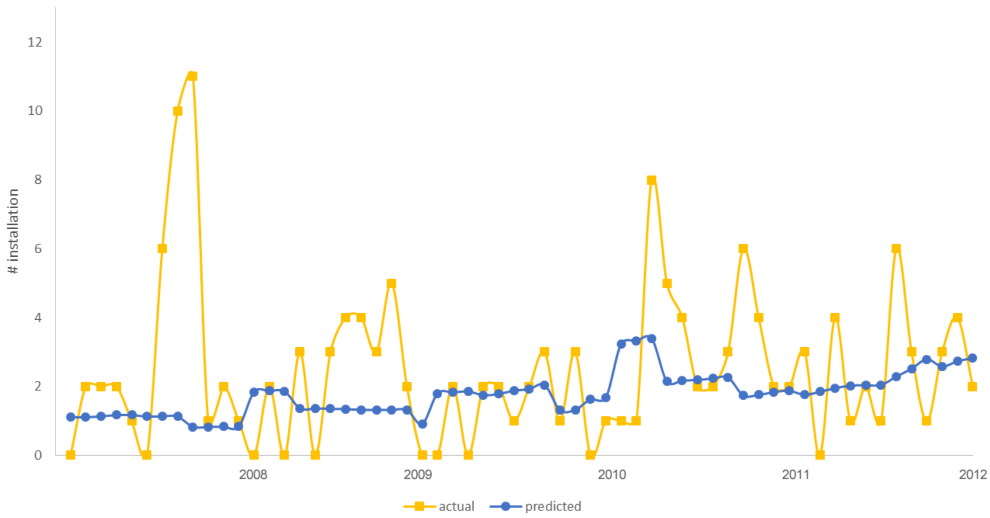


Figure A5.13: Actual and predicted number of installations in out-of-sample verification for zip code 94010