Subsidies, Tariffs and Investments
in the Solar Power Market

Chrystie Burr*
University of Colorado at Boulder

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Abstract

Over the last 10 years, the solar photovoltaic (PV) market has grown rapidly due in part to government incentive programs. We estimate a dynamic model to evaluate the effects of actual and counterfactual policies on residential solar installations. Our results indicate that with a \$120 social cost of carbon, the total subsidies in California would be welfare neutral. When comparing the two most frequently-used incentive schemes and in particular when the planner and agents have different discount rates, we find that the upfront capacity-based subsidies result in lower welfare costs and more solar adoptions than production-based subsidies. Overall, we find that the welfare cost of encouraging prolific solar adoptions in a suboptimal location is extremely high.

JEL codes: C23, D12, D61, H23, Q41, Q42, Q48.

Key words and phrases: optimal policy choice, renewable energy, solar subsidy, feed-in tariffs, household choice, technology adoption.

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 photovaltaic (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[3] and the net welfare costs associated with the subsidy programs remain unclear. 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 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's important to address these issues because interests in renewable energy sources continues. By 2014, at least 144 countries had renewable energy targets and 139 countries had renewable energy support policies in place (REN21, 2014).

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[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 o 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 6 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.

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. The advantages of any subsidy policy must be weighed against costs, or it will be doomed to failure.

This paper develops a dynamic consumer demand model for rooftop solar power systems. 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. We use a nested fixed-point maximum likelihood estimation on a unique 5¼-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 decision, a production-based subsidy is equivalent to dollar for dollar decrease in the price of electricity.[4] The variation in solar irradiation across California and the changes in solar power system prices, capacity-based subsidies, tax credits, and electricity rates through time enable us to identify the impact of each variable.

We use this estimated model to answer questions concerning the economic value of various solar incentive programs. We find that the capacity-based subsidy encourages more solar investments on the per dollar basis. Liquidity constraints, consumer's hyperbolic discounting and the uncertainties into the future may explain this result. In terms of 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). 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 future revenue is higher compared to a less sunny location. Second, most CO_2 is mitigated by the greater amount of solar electricity production which drives the implied CO_2 price lower. If, however, the social planner uses a discount rate that is lower than the individual's discount rate, we find that the (upfront) capacity-based subsidy not only more effective but also more efficient than the production-based subsidy. In another words, when there is uncertainties in the private discount rate, using a production-based subsidy whose present value depends on

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[4]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.

this rate is more costly than the upfront subsidies.

We 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 the subsidy) matches the social cost of carbon[5] suggested by the Office of Budget and Management (2013). The equivalent CO_2 price of aggregate subsidies in California at the end of the sampling period is \$95/ton to \$118/ton. This amount is higher when the private and public discount rates are misaligned. If the subsidies were to decrease to \$38/ton (Interagency Working Group, 2013), the social cost of carbon, then we could expect an 18% reduction in installations. The unique declining subsidy design also calls into the question on whether it is indeed better than the more commonly-used flat rate design. We find that the Californian subsidy design does encourage more investments in the initial stage. However, a (total spending equivalent) flat-rate subsidy would have encouraged more solar investments overall.

A significant pending policy change for the solar power market in the U.S. are antidumping and countervailing duties on imported Chinese solar modules. In 2012, the U.S. Department of Commerce (DoC) levied a 22.5%-255.4% duty on imported Chinese solar cells.[6] This has led to nonsubstantial changes in solar module prices since the scope of this ruling is very limited, and firms have been able to avoid the duties. However, DoC has opened a new investigation intended to expand the scope in 2014. These duties split the U.S. solar industry between domestic manufacturers and the solar power system installers who rely on the inexpensive Chinese solar products. The latter group is concerned that the increase in solar power system costs will hurt the growth of the solar power market. Despite the grave concerns, we find that an 30% increase in the module costs leads to a 6% increase in the final system cost which leads to a relatively minor 6% to 11% reduction in demand.[7]

Finally, we use our model's ability to perform counterfactual analysis to consider the welfare loss in encouraging solar in less sunny locations. We find that the implied CO_2 price is effectively doubled when we introduce the solar radiation of Frankfurt, Germany into the estimated model. This is simply because of the solar radiation in California is twice as high as in Germany. We, however, observe a nonlinear relationship between the welfare cost and the number of solar investments made. For example, the implied CO_2

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[5]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.

[6]The supply chain of the solar power systems starts with wafer manufacturing, and then solar cell production before the cells are assembled into modules. The solar power system is completed by combining modules with DC-AC inverter and wiring.

[7]The 30% increase is the worst-case business as usual scenario estimated by Greentech Media. Firms can mitigate this large increase by simply moving the cell production back to China and pay the 2012 tariff instead.

price will quadruple if there are the same amount of households investing in solar as in the factual world with the Frankfurt solar radiation.

The 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 estimation routine and the model are based on the single agent optimal stopping model as in Rust (1987). We further expand on the model to include multiple agents with observations at the aggregate market level, similar to Berry, Levisohn and Pakes (2007). In contrast to Fischer and Newell (2008) or Goulder and Parry (2008) who examines a comprehensive set of instruments using various evaluation criteria including the distributional effect and induced technology innovation, we focus on a widely-adopted subset of the incentive-based instruments- subsidies for pollution abatement. 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. 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 of the demand side responses in the solar power market. Unlike Baker, et al. (2013) and Borenstei(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 (2014) 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%.

The following section builds the structural model, and section 3 describes the data used in this study. Section 4 presents the results. We 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.

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

2   The Structural Model

Next, the household's dynamic discrete choice model is developed. In each time period, households observe the price[9] 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 credit (τ). 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 a medium-sized 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,

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

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. $\epsilon(0)$ is the unobserved 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. We 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

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

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, we 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[10]

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

and the choice specific value function as[11]

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

or explicitly as

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

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[10]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" (Aquirregabiria and Mira, 2010) 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", we denote it as $\mathcal{F}_\theta(\mathbf{X})$ instead.

[11]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.

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.[12]

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

Rust (1988) and Rust et al. (2002) showed (2.9) is a contraction mapping using Blackwell's sufficient conditions. Appendix A3 shows a direct proof of contraction mapping in the present setting. In addition, the conditional choice probability 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. Notice that it is equivalent to the market share definition as in Berry et al. (1995) and therefore 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:

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

The second term is zero under the perfect foresight assumption.

In Rust's nested fixed point algorithm, we optimize over (2.13) to find the deep struc-

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[12]See Appendix 3.1.3 for a derivation or see Anderson et al. (1992).

tural parameters $\boldsymbol{\theta}$. Formally,

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

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 ζth iteration. At $\zeta = 0$, we make an initial guess of $\mathcal{F}_\theta^0(\mathbf{X}) = 0$. At $\zeta = 1$, we can calculate $\mathcal{F}_\theta^1(\mathbf{X})$ based on (2.9) and $\mathcal{F}_\theta^0(\mathbf{X})$, such that

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

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

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

where ξ needs to be very small so that we 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, we set $\xi = 1e - 6$. If (2.16) is satisfied then we 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 we repeat the iteration, with $\zeta = 2, 3...$, until the convergence criterion (2.16) is satisfied.

3 Data

The rooftop PV adoption pattern in California displays significant spatial discontinuity as shown in Figure A7.4. 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. The geometric spread of the adoption pattern remains about the same during the period of interest. We 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) service area, two in the Southern Califonia Edison (SCE) service area, and 6 in the Pacific Gas and Electric (PG&E) service territory (Figure A7.5). Half of the zip codes and households are located in northern California and half are in southern California. The finest geographic resolution we observe in the data is at the

zip code level which defines the market in this study.[13] We 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. We discuss each one of these variables in detail in this section.

California Solar Initiative Incentives

The California Solar Initiative (CSI) is a solar incentive program, part of the 10-year, 3 billion dollar statewide Go Solar California Initiative that started on 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 Watts (W) and the subsidy rate at the time of the application. The incentive starts at \$2.50/W and gradually reduces to \$0.20 at the end of the sampling period, by a prescribed schedule (See Table A2.1 and Table A2.2 shows the pre-allocated target for each of the three investor-owned utilities, IOUs). For instance, at the start of the program, households in the SDG&E district receive \$2.50/W incentive payment; once there are a total of 2.4 megawatts of systems installed, the next applicant receives \$2.20/W. Therefore the total incentive that an owner of a 5kW system in the above example receives \$12,500 at the beginning, compared to \$1000 at the end of the program. This unique design provides a perfect environment for a dynamic analysis. 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 lower system cost in the future and encourage adoptions to occur sooner, rather than later.[15]

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

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[13]Figure A7.6 shows the selected entries from the dataset (http://www.californiasolarstatistics.ca.gov)

[14]30% of the 2GW goal is designated for the residential sector while the remaining portion is satisfied for 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 that it's not clear whether firms decide not to install or decide to install but couldn't secure the CSI rebate and subsequently give up on installing.

[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]We used the "first new reservation request date", the date when the application for subsidy is receive, as the month when the households choose to invest solar. Although the "first reservation request review date", which is when the CSI subsidy application is reviewed, has less missing values. We believe that the first new reservation request date approximates the time when households make their investment decisions better. We construct the probability by utility districts using the empirical data to impute the

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[17], we are able to recover the unit price of solar power systems in the first stage regression analysis. 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).
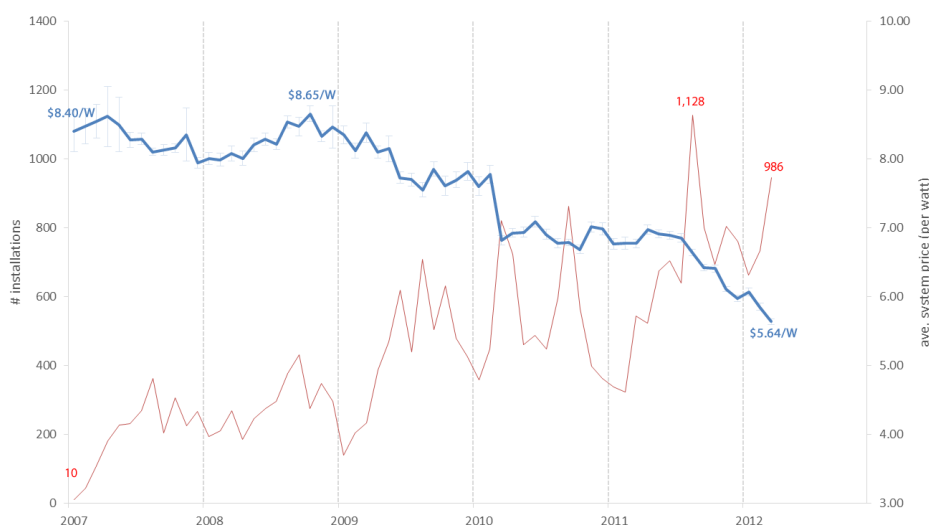
Figure 1: The average system cost versus the number of installations.

The system size varies greatly from one household to the next (Figure A7.2). However, the average system size remains relatively constant across the years (Figure A7.3). 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 the investments must be made in a product that is a homogeneous in size and in the efficiency of the module and inverter. This assumption can be relaxed by extending the binary logit model into multinomial logit (Reddix, 2014). We 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 tax.

Revenue

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missing 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 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)

Assuming a 25-year system lifespan, we can recover the present value of the revenue, R, generated from a medium-size system by the following equation,

$$R_{zt} = \frac{1 - r^{25}}{1 - r} Q \cdot IR_z \cdot C_u^e \cdot 365$$

where Q is the system size in (kW), IR is the solar radiation measured in kWh/m²/day, and C_u^e is the annual average electricity price in time t in utility district u. Let α^D denote 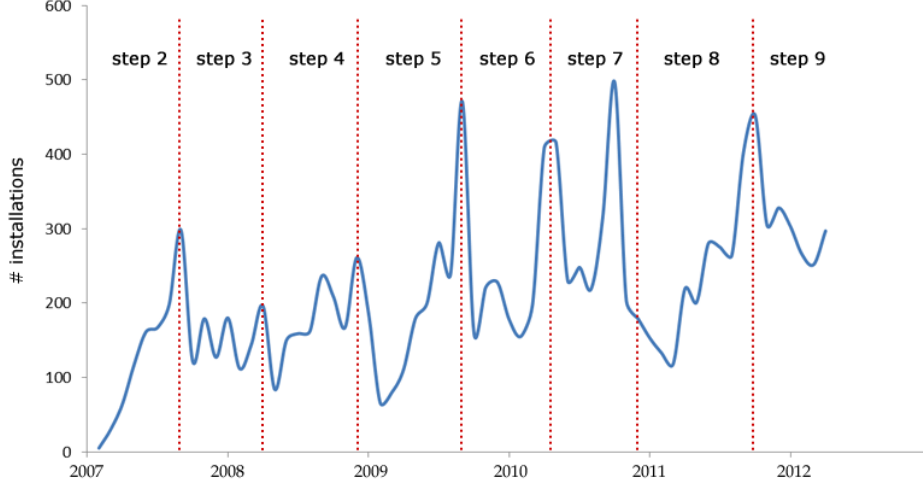the module degrade factor, α^e be the electricity escalation rate, β be the annual discount factor, and finally $r = (1 - \alpha^D)(1 + \alpha^e)\beta$. The range of the present value of the revenue stream is between \$12,000 and \$18,000 given a 10% discount rate and increases to \$20,500 and \$31,000 given a 3% discount rate (See the Appendix A5 for calibrated parameter values). The present value of the revenue varies with the geographical location and also through the years due to the annual electricity rate adjustment by the utility companies. We use the average electricity rate in this study instead of the time-of-use rate. Since solar electricity is generated when the electricity demand is the highest, this corresponds to a higher electricity rate, which would lead to a higher estimate of the revenue than what is shown here.[18] Note that we do not make an assumption about the discount rate that a household uses when making the investment decision. Instead, we calculate the present value using various discount rates ranging from 3% to 10%.

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[18]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.

Federal Residential Renewable Energy Tax Credits

The Energy Policy Act of 2005 set in place a 30% federal tax credit for 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 allowed households to claim the full 30% credit. This is a significant change from an effective 5% tax credit prior to 2009 to the full 30% afterwards.

Table 1: Summary statistics (Jan. 2007- Mar. 2012, 344 zip codes)

Variable	Mean	Std. Dev.	Min	Max	Obs.
System price[19]	43,095	5,407	30,400	49,994	21,672
Capacity-based subsidy	7,783	4,357	1,348	13,475	21,672
Present value of future revenue stream					
5%:	22,601	1,900	19,316	29,542	21,672
Present value of future O&M costs[20]					
5%:	8,946	0	8,946	8,946	21,672
Tax credit	7,661	4,566	2,000	13,688	21,672
Electricity retail rate[21]	16.06	1.02	14.8	18.68	21,672
Irradiation[22]	5.55	0.28	5.08	6.57	21,672
Weekly wage rate[23]	1,085	120	930	1253	21,672
Installed cost/watt	7.4	0.93	5.26	8.59	21,672
# installations	1.28	2.20	0	36	21,672

4   Estimation

The estimation of the primitives is carried out in the following steps: In the first stage, we 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[24] 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. This allows us to convert each installation observed in the data into a homogeneous average size system (5.39kW) and to derive the final system price in every zip code by month.

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[19]Total upfront PV system price after city and county tax

[20]Including inverter replacement cost, regular panel maintenance and increase in property insurance cost.

[21]cents/kWh

[22]Solar potential/irradiation measured by $kWh/m^2/day$

[23]Weekly wage of construction worker by county

[24]However, this individual level data contains only the zip code and not street address information.

A potential endogeneity issue 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. We should remark that 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 discussion). Since the US solar market accounts for less than 10% of the total world demand (in capacity), it is unlikely an individual utility shock can influence the solar module price. For the installation cost, the second largest component in the system cost (Figure A7.8), Friedman et al. (2011) points out that there is excess supply in the solar installation labor market during this period. It's again hard to perceive an i.i.d. shock at the household level to increase the equilibrium price for installation. As for the subsidy, we should remark that the number of households required for the subsidy to lower 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.

4.1 First Stage Estimation

The 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). We write the expression for the unit price, dollar per watt (D) as,

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

Due to increasing return to scale, the unit price is generally higher for small systems. Therefore, system size is a major determinant of system price. Let x denote the the system size (in kilo-Watts) observed in the data and x^2 be the square of x to capture nonlinearities such as economies of scale and the diminishing returns to scale observed in the data (Figure A7.7). The permit fee, inverter, and the BOS cost are not included in the regression analysis because we 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, acts as a proxy for the labor input cost. This wage stays about the same in each county during the sampling period and the 5¼ year average value is used here. We 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 unobservables such as age and types of roofs and the proximity of low cost installers. Assuming that the model is linear, the estimated result is shown in Table 2. All estimated coefficients have the expected signs and are significant at the 1 percent level. Table 1 reports reconstructed system price of an average size system. This cost is used in the second stage and also serves as the basis of the calculation of the 30% Federal tax credit.

Table 2: Regression Analysis on Installed Cost per watt

	cPw	t-stat
pre2007	-0.00093***	(-3.67)
size (kW)	-0.2576***	(-46.00)
size^2 (kW^2)	0.00566***	(29.84)
wages ($1,000)	1.683***	(10.56)
Module cost ($)	0.821***	(16.31)
Year FE	Yes	
Utility FE	Yes	
_cons	3.056***	(13.03)
N	27610	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2   Second Stage Estimation

We use three specifications in the second stage structural estimation. The first specification estimates the parameters in (2.2) separately; and the second specification combines the system price and the CSI subsidy into one term. The third specification aggregates all dollar terms into a single variable[25]. The second specification models when consumers receive a price quote that already incorporates the capacity-based subsidy. The CSI reports that some installers would charge consumers the amount of the system cost less the rebate amount. In that case the upfront cost and the CSI rebate occur simultaneously from the consumer's perspective. The third model assumes that consumers weight cost and benefit dollars equally. Therefore only net costs (i.e. net present values) enter into

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[25]This is the net present value of each system

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, we use fixed effects at the utility and year level to control for omitted variables. We also include the interaction term of the utility and the year to capture the differences in trends in each utility district. We estimate (2.13) in Matlab using the nested fixed point maximum likelihood estimation[26] In the inner loop, the fixed point algorithm finds the expected future utility (2.5) and the outer-loop search over the whole parameter space finds the parameter values that maximize the log-likelihood function. The same results are returned under both the KNITRO and the MATLAB FMINUNC optimization packages.

Table A2.4 shows the full result, and Table 3 shows selected results from the preferred models . Standard errors of the estimated coefficients are calculated by bootstrapping over the two stages. Most estimates have signs as expected except for some tax credit and revenue terms, 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 reason for the few unexpected sign is, in fact, straightforward. Since there are many more solar power investments in less sunny Northern California,[27] it appears that households respond to less revenues when utility fixed effects are excluded. This explains the negative coefficient of the revenue terms. When controlling for the year fixed effect, the residual variations in tax credits are perfectly correlated with system prices because the tax credits are 30% of the system prices by design. This means as system prices decline over time, tax credits are also lower while the number of investments increases. Therefore, the associated coefficients are negative when the year fixed effects are included.

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[26]Note that 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, we opt for a slower repeated fixed point iterations.

[27]For example, 70% of the solar installations are in the PG&E district compared with 30% from both SCE and SDG&E districts in 2007.

Table 3: Estimation Results from Maximum Likelihood Estimation

	Model Specifications with different discount rates							
	I	I	II	III	I	I	II	III
Variables	10%	10%	10%	10%	3%	3%	3%	3%
System cost	-0.31***	-0.19***			-0.30	-0.19		
	(0.02)	(0.03)						
Capacity-based subsidy	0.07***	0.13***			0.07	0.14		
	(0.02)	(0.02)						
Cost-subsidy			-0.14***				-0.14	
			(0.008)					
Revenue	0.02***	0.02	0.03*		0.01	0.01	0.02	
	(0.05)	(0.02)	(0.02)					
Tax Credit	0.47***	-0.11*	-0.32***		0.47	-0.11	-0.29	
	(0.10)	(0.13)	(0.08)					
Net cost				-0.12***				-0.06
				(0.004)				(0.0178)
Year FE	N	Y	Y	Y	N	Y	Y	Y
Utility FE	Y	Y	Y	Y	Y	Y	Y	Y
Utility×Year	N	Y	Y	Y	N	Y	Y	Y
Constant	-2.17***	-1.04	-0.99	-6.42*	-5.61	-1.07	-1.00	-7.63
	(0.90)	(1.10)	(0.83)					
N observations	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672
Log-likelihood	-1,074,483	-1,073,734	-1,073,739	-1,074,145	-1,074,991	-1,073,754	-1,073,763	-1,074,280
LR chi2	5844	8324	8313	7502	5809	8283	8266	7232

standard errors in parentheses

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

Other than the revenue terms, which take values depending directly on the discount factor, the differences in the estimates across discount rates are statistically insignificant. The coefficient of the system price is consistently and significantly higher than the other forms of payment in the first two models. This result verifies the anecdotal evidence that the upfront system cost is the greatest entry barrier to solar adoptions. Consumers either respond to a sticker shock from the high upfront price, reflecting hyperbolic discounting, or simply face liquidity constraints that prevent them from making such investments. Several types of creative financing strategies such as Property Assessed Clean Energy (PACE) and the solar leasing program were developed to address the last issue.[28] A

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[28]PACE program has passed in 28 states and Washington DC since 2008. Under PACE, the city offers the loan to purchase the solar power system and the household pays back the loan through property tax bills over a 15 to 20-year time-span. There are very limited number of households able to sign up for the program. Solar leasing is where consumers don't pay the upfront cost but instead pay a monthly equipment leasing fee for the next 20 years to a commercial company. Solar leasing wasn't

plausible explanation for consumers' different responses to various forms of monetary gains and losses is the timing of costs and payments. Households face the system price at the beginning of the project but receive the CSI rebate when the project is completed. This is followed by the tax credits, which comes up to a year later, and households finally receive the production revenue over the course of the next 25 years. In addition to the timing issues, households face transaction costs such as completing tax forms. All models are statistically significant compared to the model with only a intercept term.

A hypothesis test is carried out to investigate the cost-effectiveness comparison between capacity-based subsidy and production-based subsidies. Since 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. Therefore, we construct the null hypothesis that the effects of the CSI subsidy and revenue are equal ($\theta_2 = \theta_3$) and the alternative hypothesis that CSI subsidy has greater impact than the revenue on a per-dollar basis ($\theta_2 > \theta_3$). Using the likelihood ratio test, we find that the capacity-based subsidy has significantly greater impact than the (would-be) production-based subsidy.[29] In another words, for a fixed amount of funding the capacity-based subsidy such as the CSI subsidy induces more household to invest than the feed-in tariffs.

5 Counterfactual Analysis

This section uses counterfactual analysis to investigate 1) the welfare costs associated with the subsidy programs and the equivalent CO_2 prices when the public and private discount rates may be misaligned; 2) the impact of policy changes on the solar power market. All subsequent analysis is based on the estimated model III with the nest cost term. While the analysis can be made using any of estimated models, we believe this is the most robust way to address the differences in policies by taking away any behavior responses and timing issues.

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widely available in the first four years of our sample (on average 16% of households use solar leasing) and therefore we abstract away from the potential impact from this significant financial innovation.

[29]The chi^2-statistics has a p-value of 0 under the null using the likelihood ratio test.

5.1 Welfare Analysis of the Incentive Programs

To create a meaningful measure of the cost of solar incentive programs, we first clarify the purpose of such programs. Demand side subsidies are designed to offset various market failures such as switching costs, liquidity constraints, differences between the private discount rate and the public discount rate, externalities (both positive and negative), imperfect information, etc. The argument for subsidies are of basically three kinds: securing energy independence, creating new jobs, and reducing pollution. The first two arguments 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 we consider in this paper is pollution reductions. In particular, we focus on GHG emission reductions because natural gas peaker plants, the most flexible and expensive power generating source, are the marginal units, the benefit from reduction in sulfuric dioxide and mercury compounds is negligible (EIA website).[30] We convert the various greenhouse gasses emissions into a unifying CO_2 equivalent measure. We 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 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. Program costs calculated using this method is provided in Table A2.8. We 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 systems, the loss in surplus is the difference between total program spending and the gain in consumer surplus.[31] 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. Yet since part of utility remains unobserved to the econometrician, the best we can do is to find the expected consumer surplus (for each individual) over all possible values of ϵ.

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

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[30]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

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

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.[32] Given the error specification of the multivariate extreme value distribution, Appendix A6 shows that the expected consumer surplus has a closed form expression:

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

We then sum over (5.2) for each household in each zip code. Since 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. In order to match this long-term change in consumer surplus, we aggregate the government spending over the next 100 years and discount it by 10%, 5% and 3%.[33] The welfare cost of the program is

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

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 change in the number of installations from 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 A4.[34]

Table A2.7 shows the welfare cost or the implied welfare-neutral CO_2 price. With a 10% discount rate, the CO_2 prices are \$137.5/ton in SCE territory, \$114.9/ton in PG&E territory and \$110.4/ton in SDG&E territory. The higher CO_2 price in SCE is associated with its higher upfront subsidy at the end of the sampling period.[35] The difference between PG&E and SDG&E, however, comes from solar intensity and consumers' preferences. More electricity produced means more CO_2 abated, which lowers the program cost per unit of CO_2.[36] The overall CO_2 price across the three utility districts ranges

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[32] $\theta = \frac{\partial U}{\partial Y} \implies \frac{1}{\theta} = \frac{\partial Y}{\partial U}$

[33] Discounting in itself is a subfield of environmental economics. There are many discussions on the proper discount rate that should be used based on positive and normative arguments. See Arrow et al. (2013) for the latest summary. The broad discount rate range adopted here provides a upper and lower bound for the impact.

[34] We use the average CO_2 emission rate of 0.348ton/MWh or 767lb/MWh published by the California Air Resources Board to calculate γ.

[35] At the end of the sample period (March 2012), CSI upfront subsidy level is still in step 7 in SCE and compared to step 9 in the other two districts.

[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. The change in γ would be insignificant for most of the years considered here.

from \$94 to \$118, corresponding to a discount rate of 3% to 10% (diagonal entries in Table 4). We find that it's critical to include the consumer surplus when evaluating the program costs. Without considering the consumer surplus, program costs would appear to be 3 to 4 times more expensive. This CO_2 price is important in designing the optimal subsidy level because efficiency requires that the marginal abatement cost (MAC) equal the marginal benefit (MB). The CO_2 price in this context is equivalent to the MAC while the SCC is equivalent to MB.[37]

The calculation above assumes that the private discount rate is equal to the public discount rate. Table 4 shows the implied CO_2 price when the public and private discount rates are the same and when the public and private discount rates differ. In the unlikely situation that society discounts the future more than private individuals, the welfare cost of the program is negative. This means that the overall gain in consumer surplus exceeds the government spending on subsidies. This result may seem surprising at first, but it is quite straightforward because the costs are discounted at a higher rate than the consumer surplus. In a more plausible scenario when the public discount rate is lower than the private discount rate, the implied CO_2 prices can be twice as high than the baseline case when the public and private rates equals.

Table 4: The implied CO_2 price of the subsidy program under various discount rates

public discount rate private discount rate	10%	5%	3%
10%	\$118.10	\$228.00	\$257.10
5%	-\$269.80	\$109.90	\$206.00
3%	-\$853.20	-\$94.85	\$94.56

<u>Feed-in Tariffs vs. Upfront Subsidies</u> (Production-based vs. Capacity-based Subsidies)

To compare the efficiency of a production-based subsidy and a capacity-based subsidy, we run a counterfactual analysis by investing the same amount of money in a production subsidy (in present value terms) as in a capacity-based subsidy and observe the change in implied welfare-neutral CO_2 prices.[38] We maintain the assumption that a rational

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[37]This comparison requires further clarification since it's difficult to precisely define each additional ton of CO_2 when our model at best addresses the cost associated with each additional unit of solar power system being installed. Therefore, we use the "average" CO_2 price to proxy for the "marginal" cost. Since cost function remain relatively flat in a small region, we argue that the average cost here is an acceptable proxy for the marginal cost.

[38]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, we use a market-independent, fixed feed-in tariff design which is independent of the retail electricity rates. This design is in use in Germany, for example.

consumer will keep the solar power systems in the optimal electricity production condition throughout the paper.[39] Intuitively, a production subsidy encourages more adoptions in sunny locations and results in a lower CO_2 price. This is indeed what we observe in the counterfactual simulations across all discount rates, but the difference between the capacity-based and the production-based subsidy is very small (less than \$0.25). This is because of the relatively small difference in solar radiation between Northern and Southern California, the preference of Northern Californians for solar power, the disutility that a consumer derives from installing solar power systems in the SCE service area, and the very simple (and nonoptimal[40]) design of the FIT used in this exercise.

To make a meaningful comparison between the two types of subsidies, we use a fixed capacity-based subsidy rate of \$1.1/W while keeping the 30% tax credit. Then, we calibrate the feed-in-tariff rate such that the present value of government spending matches that in the capacity-based subsidy. We find that if Northern California were as sunny as Newark, New Jersey, then this difference would increase to almost one dollar. This gap increases to \$2 if the solar radiation in Northern California is equivalent to that in Juneau, Alaska and the solar radiation in Southern California is equivalent to that in Phoenix, Arizona. This is still a small difference relative to the widely varying estimates of SSC prices[41] calculated using different discount rates.

However, if the public and private discount rate differs, in particular when the private discount rate is higher than the public discount rate, then the simulations show that it is more efficient to use the upfront capacity-based subsidy. As shown in Table 5 and 6, the upfront capacity-based subsidy is about 10% less costly than the production-based subsidy when the private discount rate is higher than the public rate. If the social planner mistakenly believe households are using a low discount rate, the same as the public discount rate, and subsequently sets a low FIT rate, this leads to significant drop in the investments made by households while the present value of the government spending is only slightly lower as shown in Table A2.11.

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[39]Despite this assumption may lead to biased preference towards capacity-based subsidies, we 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 lead to biased preference towards production-based subsidies.

[40]The optimal design of the feed-in-tariff is to set the rate equal to the SSC.

[41]SSC estimates range from \$5 to \$3000. As Greenstone puts it, "You feed a bunch of assumptions into a machine, and out goes a number".

Table 5: The implied CO_2 price of the subsidy program under various discount rates
(using a fixed upfront, capacity-based subsidy of \$1.1/W with 30% tax credits)

private discount rate \ public discount rate	10%	5%	3%
10%	\$169.30	\$280.60	\$310.80
5%	-\$227.20	\$155.00	\$252.80
3%	-\$816.80	-\$54.88	\$136.80

Table 6: The implied CO_2 price of the subsidy program under various discount rates
(using feed-in-tariff with 30% tax credits)

private discount rate \ public discount rate	10%	5%	3%
10%	\$169.10	\$305.90	\$347.10
5%	-\$273.60	\$154.80	\$273.40
3%	-\$911.90	-\$84.82	\$136.70

5.2 Deadweightloss resulting from suboptimal siting

To address the question raised by Der Spiegel magazine, we conduct a counterfactual analysis on the estimated model with the German solar irradiation data. Suppose that the whole California is endowed with the solar irradiation for Frankfurt, Germany which is 50% less than the CA solar resources. In this case, we find the equivalent CO_2 price under the current subsidy program would be doubled to \$236.6 (Table A2.9). In the case of having the same number of installations as in the factual world (current point extends to the future), the government would have to double the upfront subsidy which leads to the welfare neutral CO_2 price at \$418/ton in the 10% discount rate scenario. Furthermore, in order to have the same level of production as in the factual world, the government has to increase the subsidy amount to three times the current level. The welfare neutral CO_2 price increases to an astonishing \$730/ton under this scenario. The nonlinearity of the cost is driven by the fact that the consumer preference is assumed to follow a type I extreme value distribution. To offset the reduced electricity production in Germany, the policy goal would require households whose utility would decrease unless receiving a large amount of subsidy to compensate the loss. The result provides the first look into the 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 attitudes and the amount of CO_2 produced during electricity generation.[42]

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

5.3 Impacts from Policy Changes

The next series of counterfactual policies are conducted in order to find out the impact of varying policy level and policy design has on the equilibrium demand.

Pending Tariffs on Imported Chinese Solar Modules

The US is in the midst of the second solar tariff ruling on imported Chinese manufactured 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 30% to 265% of duties on imported solar panels containing Chinese manufactured solar cell. However, most Chinese companies were able to avoid duties by shifting the cell manufacturing activities 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 to close the loophole. It is a case that splits the US solar industry between domestic manufacturers and solar installers; the first group have been squeezed to bankruptcy by the cheaper Chinese solar panels, whereas the latter group have been benefited by the increase in demand due to the cheaper Chinese solar products and concern that the increase in solar system costs will have a detrimental effect on the growth of the solar power market. Using the estimated model and the average panel cost of \$0.75/W in 2014, we predict the system price from the first stage regression equation given a 30% increase in module price and use this predicted price in the second stage structural model to simulate demand. This increase leads to a relatively minor 6% increase in system price, which results in a 6% to 11% of reduction in demand (Table 7). This is the worst case scenario when firms do nothing to avoid the new tariff according to the GreenTech Media report. Meanwhile if Chinese manufacturers move the cell production back to China and pay the 2012 tariff instead, the report estimates that this will leads to a 14% increase in module prices. Given this increase, our analysis indicates we can expect a 3% increase in the system price and 3 to 5% reduction in demand. The more impatient the consumer are, the less the impact of the new tariff is (See Table A2.12).

Table 7: 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	2.6% to 3.0%	5.6% to 6.4%
10% discount rate		
# reduction in first month	81	167
% change in installations	-5.3%	-11%

Matching the Social Cost of Carbon

In 2013, the interagency working group estimated the social cost of carbon to be $38/ton under a 3% discount rate.[43] It is then of interest to understand the impact of lowering the welfare neutral CO_2 price to the $38/ton level since this is the optimal level of subsidy by definition. We find that in order to lower the equivalent CO_2 price from $96 to $42 (2012 value), we need to lower the subsidy amount by 60-70% from the level in 2012 March. The result shows that we will sacrifice 20% decline in demand using a 3% discount rate or a large decrease of 40% in demand if consumers use a 10% discount rate.

Should the policy makers decide to double the amount of current installations, the current subsidy will need be doubled. The equivalent CO_2 price increases drastically to $264-$343/ton (See Table A2.13).

Subsidy Degression Design vs. Flat-Rate Design

The distinctive degression design of the CSI subsidy leads to a natural question on whether it is indeed a "better" design than the common flat-rate subsidy. To address this question, we study the number of adopters under the CSI degression subsidy (following the observed schedule) and a spending-equivalent $1.1/W flat-rate subsidy. We find that the degression design does encourage more adoptions in the initial periods, however the flat-rate subsidy would have lead to more adoptions overall and leads to a lower welfare cost of the program. Overall, the difference is greater when larger private discount rate is used. For the 10% discount rate, the flat-rate design would encourage 7% more installations. This difference lowers to 1% when a 3% discount rate is assumed. This result is based on the assumption that the solar power system prices are exogenous. By providing a higher amount of subsidy when the prices are lower creates higher demand and less welfare loss (See Table A2.14). Figure 3 illustrate this difference in the adoption under different capacity-based subsidy design.

We should remark that the model assumes heterogeneous households due to the specified random shock, ϵ. Therefore, the values derived from the counterfactual analysis such as the welfare costs in section 5.2 doesn't increase linearly. In practice, this means the government need to spend a lot more money in order to make the "low-valued" households to invest in solar power systems. These are the households who receive small positive to negative shocks to their utility functions from investing.

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[43]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)
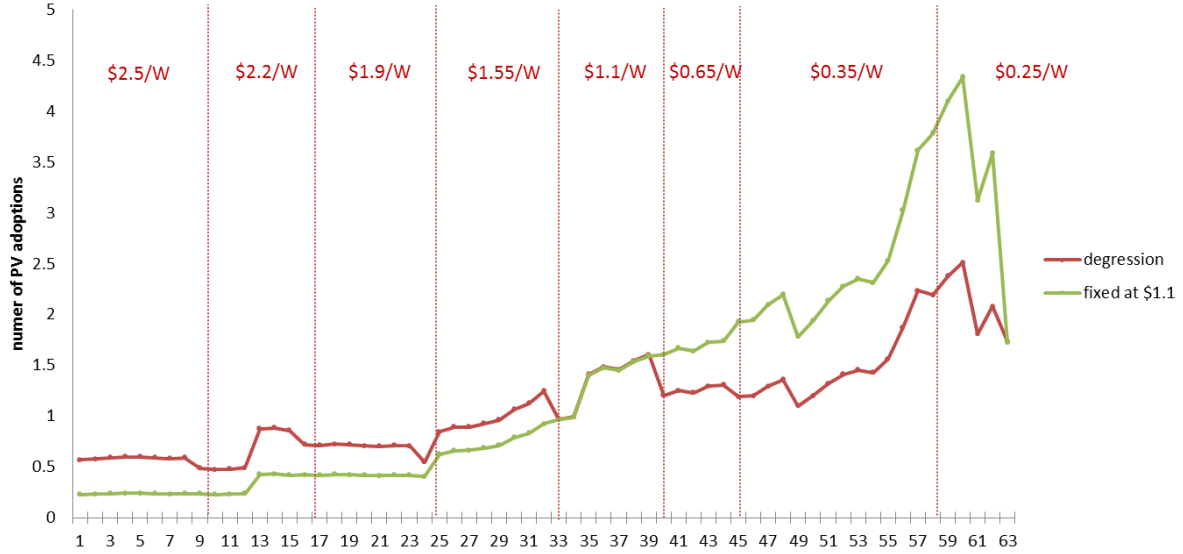
Figure 3: Number of adoptions in zip code 94610 (Oakland, Alameda)

6   Conclusion

The recent technology breakthrough that allows the exploitation of formerly unprofitable natural gas reservoirs has led to increasing uncertainties in the development of relatively expensive renewable energy technologies. Interests in renewables wax and wane as they have been since the 70's. However, the fact remains that the amount of energy received on U.S. soil in a few hours of daylight is equivalent to the annual electricity demand in the U.S. and a technology that can harvest this everlasting energy will always be pursued. In its World Energy Outlook (2012), the International Energy Agency projects renewable energy sources will become the second largest source of power generation after coal by 2015 and rival coal as the primary source of global electricity by 2035. In particular solar power technology is expected to maintain its rapid growth rate while subsidies continue to play a key role in the deployment.

This study uses the investment decision in solar power systems from a large pool of households in California during a $5\frac{1}{2}$-year period to recover the consumer demand function. It provides one of the first economic evaluation of solar incentive programs to address both normative and positive policy concerns. The result shows that overall the upfront capacity-based subsidy is a better instrument, in a robust sense, than the production based subsidies. An upfront capacity-based subsidy has greater effect than a production-based subsidy on a household's decision concerning PV system investments. 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. Despite production-based subsidies being more efficient

than capacity-based subsidies, this difference is negligible. When confronting with the issue that the private discount rate is likely to be higher than the public discount rate, the upfront capacity-based subsidy is much more efficient than production-based subsidy.

The flexibility of the structural model also allows us to assess the potential effect from the on-going solar trade war. Despite the grave concern of the negative impact from the pending tariff, we find that a 30% increase in module prices only leads to 6% increase in the overall system price which causes a minor 6-11% decrease in demand. The model shows that most of the investments in solar power systems wouldn't have been made without the CSI upfront subsidy and the residential renewable energy tax credit. However, if the CSI rebate were set at a flat-rate, up to 7% more installation would have occurred. To respond to the concern raised by *Der Spiegel*, this study also shows that the German subsidy program for solar electricity could indeed be extremely expensive due to its suboptimal solar resources. We may agree with Thomas Edison's vision of switching over to the solar power generated electricity before the exhaustion of fossil fuel resources. However, it must be conducted in a sustainable manner that balances the benefits and the costs of the programs. This paper provides the first quantitative results to address these overarching questions.

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Appendix

A1. Background Information

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.[44] 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[45] they currently do not have a cost advantage over c-Si solar cells. PV panels or PV modules are connected assemblies of multiple PV 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).

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[44]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.

[45]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.

The main disadvantage of PV technologies is that they only generate electricity when the sun is shining.[46] 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 example, 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,

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[46]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).

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.[47]

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.[48] 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[49] 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[50] 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

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[47]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.

[48]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.

[49]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.

[50]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.

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 A7.10).

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.[51] Systems larger than 30 kW[52] 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.[53] This upfront capacity-based rebate starts at \$2.50/W and declines to nil following a block schedule as shown in Figure A7.1. 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 A7.11 and A7.12), 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.

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[51]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.

[52]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.

[53]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 Utility specific capacity in each step

Step	MW in	PG&E Res	PG&E Non-Res	SCE Res	SCE Non-Res	SDG&E Res	SDG&E Non-Res
1							
2	70	10.1	20.5	10.6	21.6	2.4	4.8
3	100	14.4	29.3	15.2	30.8	3.4	6.9
4	130	18.7	38.1	19.7	40.1	4.4	9.0
5	160	23.1	46.8	24.3	49.3	5.4	11.0
6	190	27.4	55.6	28.8	58.6	6.5	13.1
7	215	31	62.9	32.6	66.3	7.3	14.8
8	250	36.1	73.2	38	77.1	8.5	17.3
9	285	41.1	83.4	43.3	87.8	9.7	19.7
10	350	50.5	102.5	53.1	107.9	11.9	24.2
	1,750	252.4	512.4	265.7	539.3	59.5	120.8

Table A2.2 Summary statistics of a medium size system (5.39kW)

Variable	Mean	Std. Dev.	Min	Max	Obs.
System price	43,095	5,407	30,400	49,994	21,672
Capacity-based subsidy	7,783	4,357	1,348	13,475	21,672
Present value of 25-year production revenue					
10%:	14,044	1,181	12,003	18,358	21,672
5%:	22,601	1,900	19,316	29,542	21,672
3%:	28,186	2,370	24,090	36,843	21,672
Present value of 25-year O&M costs					
10%:	5,190	0	5,190	5,190	21,672
5%:	8,946	0	8,946	8,946	21,672
3%:	11,302	0	11,302	11,302	21,672
Tax credits	7,661	4,566	2000	13,688	21,672
Electricity rate	16.06	1.02	14.8	18.68	21,672
Irradiation	5.55	0.28	5.08	6.57	21,672
Wage	1,085	120	930	1253	21,798
Cost per watt	7.40	0.93	5.26	8.59	21,672
# install	1.28	2.20	0	36	21,672
# households[22]	5,960	4,095	2	18,420	21,672

[22] Refer to number of owner-occupied households only.

Table A2.3: First stage regression result

	cPw	t-stat
pre2007	-0.0008***	(-3.67)
size (kW)	-0.2576***	(-46.00)
size^2 (kW^2)	0.0057***	(29.84)
wages	1.6832***	(10.56)
Module cost	0.8205***	(16.31)
2007	0.2241	(1.65)
2008	0.3698***	(2.76)
2009	0.2550**	(2.21)
2010	0.0436	(0.54)
2011	0.2850*	(5.88)
2012	– omitted –	
PG&E	– omitted –	
SCE	0.7819***	(15.97)
SDG&E	0.3212***	(9.72)
_cons	3.0557***	(13.17)
N	73787	

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

Table A2.4: Estimation Results from the Maximum Likelihood Estimation (10% Discount Rate)

Variables	null	I (1)	I (2)	I (3)	I (4)	II (1)	II (2)	II (3)	II (4)	III (1)	III (2)	III (3)	III (4)
								Model Specifications under different discount rates					
system price		-0.0552***	-0.0889***	-0.3064***	-0.1935 ***								
		()	(0.021)	(0.0231)	(0.0257)								
CSI subsidy		0.0452*	0.0460***	0.0695***	0.1307***								
		()	(0.0187)	(0.0246)	(0.0187)								
cost-subsidy						-0.0376	-0.0715	0.1209***	0.1385***				
						()	()	(0.0065)	(0.008)				
Revenue		-0.0138	0.0303	0.0237	0.0248	-0.0346	0.0215	0.0248***	0.0278				
		()	(0.0235)	(0.0468)	(0.0234)	()	()	(0.0057)	(0.0152)				
Tax credit		0.0314	0.0508	0.4719***	-0.1076*	0.0295	0.0453	-0.2586***	-0.3169***				
		()	(0.0957)	(0.0457)	(0.0627)	()	()	(0.0719)	(0.0735)				
Net cost										-0.0688	-0.0877	-0.1030	-0.1183***
										()	()	()	(0.0202)
Y2007				5.5070***	-0.3172***			-3.0056***	-2.6838***			-0.3454	0.4684**
				(0.2136)	(0.1252)			(0.6062)	(0.5880)				(0.2224)
Y2008				6.2389***	0.3939***			-2.3234***	-1.9998***			0.2874	1.0870***
				(0.1904)	(0.1444)			(0.6037)	(0.5899)				(0.2508)
Y2009				1.0705***	1.6306***			0.9326***	1.6102***			-0.3564	0.0614
				(0.1560)	(0.1683)			(0.1571)	(0.1503)				(0.0840)
Y2010				0.5978***	1.2069***			0.5622	1.2018***			-0.1488	0.3431***
				(0.1109)	(0.1383)			(0.6037)	(0.0771)				(0.1072)
Y2011				0.2080 ***	0.2087 ***			0.0118***	0.1992***			-0.0986	0.0836*
				(0.0770)	(0.0770)			(0.0001)	(0.0002)				(0.0501)
SCE			-0.3933***	-0.2676	0.0841***		-0.2393	-0.4457***	0.6840***		-0.6141	-0.6683	0.3474***
			(0.0635)	(0.0635)	(0.0908)			(0.0722)	(0.0573)				(0.0478)
SDGE			0.0493***	0.0528	0.4808***		0.2597	0.0504	0.5006***		-0.0956	-0.1301	0.2495***
				(0.0894)	(0.1193)			(0.0313)	(0.1101)				(0.0406)
constant	-8.4134	-6.6450	-5.6035***	-2.1706**	-1.0378	-6.4851	-5.3092	-1.6518	-0.9929	-7.0864	-6.6814	-6.2555	-6.4208***
		()	()	(1.1326)	(0.9945)	()	()	()	(0.7843)	()	()		(0.4020)
N observations	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672
computing time (mins)	7.63	39	74	81	–	29	63	111	532	11	30	155	608
Log Likelihood	-1,077,895	-1,075,223	-1,074,973	-1,074,483	-1,073,734	-1,075,381	-1,075,081	-1,074,596	-1,073,739	-1,076,037	-1,075,325	-1,074,894	-1,074,145
LR chi2		5,345	5,844	6,826	8,324	5,030	5,629	6,599	8,314	3,718	5,141	6,002	7,502
prob > chi2		0	0	0	0	0	0	0	0	0	0	0	0

standard errors in parentheses

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

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Table A2.5: Estimation Results from the Maximum Likelihood Estimation (5% Discount Rate)

Variables	null	I				II				III			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
system price		-0.0541	-0.0868	-0.3050	-0.1947 ***								
CSI subsidy		0.0293	0.0424	0.0676	0.1347								
cost-subsidy						-0.0535	-0.0544	-0.1199	-0.1419				
Revenue		-0.0149	0.0202	0.0159	0.0157	0.0269	-0.0021	0.0175	0.0177				
Tax credit		0.0317	0.0496	0.4716	-0.1055	0.0227	0.0405	-0.2586	-0.3059				
Net cost										-0.0688	-0.0837	-0.0726	-0.0786
Y2007				5.5104	-0.3455			-3.0040	-2.5719			-0.6269	0.1005
Y2008				6.2378	0.3837			-2.3254	-1.8743			-0.0808	0.5930
Y2009				1.0736	1.6019			0.9329	1.6258			-0.4092	-0.0418
Y2010				0.5965	1.1893			0.5619	1.2269			-0.1030	0.0625
Y2011				0.0216	0.1991			0.0164	0.2342			-0.1030	0.0625*
SCE			-0.3844	-0.2836	0.6870		-0.1863	-0.4731	0.7243		-0.6690	-0.6356	0.3961
SDGE			0.0488	0.0597	0.4901		0.3078	0.0467	0.5358		-0.2864	-0.1388	0.2479
constant	-8.3808	-6.6302	-5.6065	-2.1624	-0.9664	-6.9323	-5.6830	-1.6414	-0.9444	-7.4716	-7.0718	-6.9788	-7.3094
N observations	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672
computing time (mins)	16	85	153	215	–	29	292	286	1144	40	115	254	817
Log Likelihood	-1,077,895	-1,075,236	-1,074,984	-1,074,492	-1,073,744	-1,075,443	-1,075,165	-1,074,612	-1,073,750	-1,076,131	-1,075,400	-1,074,973	-1,074,238
LR chi2		5,318	5,823	6,807	8,303	4,905	5,462	6,568	8,291	3,530	4,991	5,846	7,316
prob > chi2	0	0	0	0	0	0	0	0	0	0	0	0	0

Model Specifications under different discount rates

standard errors in parentheses

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

Table A2.6: Estimation Results from the Maximum Likelihood Estimation (3% Discount Rate)

Variables	null	I (1)	I (2)	I (3)	I (4)	II (1)	II (2)	II (3)	II (4)	III (1)	III (2)	III (3)	III (4)
						Model Specifications under different discount rates							
system price		-0.0530	-0.0852	-0.3036	-0.1912								
CSI subsidy		0.0244	0.0411	0.0656	0.1346								
cost-subsidy						-0.0149	-0.0442	-0.0477	-0.1432				
Revenue		-0.01549	0.0159	0.0136	0.0149	-0.0635	-0.0162	0.0710	0.0157				
Tax credit		0.0319	0.0500	0.4712	-0.1054	0.0256	0.0377	-0.3383	-0.2885				
Net cost										-0.0651	-0.0805	-0.0577	-0.0609
Y2007				0.4712	-0.3917			-3.9864	-0.3917			-0.7677	-0.0601
Y2008				6.2365	0.3330			-3.4673	0.3330			-0.2630	0.3749
Y2009				1.0761	1.5561			0.6854	1.5561			-0.4359	-0.0860
Y2010				0.5954	1.1591			0.4031	1.1591			-0.2207	0.2063
Y2011				0.0229	0.1937			0.0119	0.1937			-0.1072	0.0544
SCE			-0.4137	-0.2968	0.6894		-0.1670	-0.4853	0.6832		-0.7052	-0.6198	0.4514
SDGE			0.0690	0.0663	0.4915		0.3237	-0.0623	0.4859		-0.2369	-0.1229	0.2842
constant	-8.3482	-6.6271	-5.6055	-2.1606	-1.0677	-7.1868	-5.9441	-3.7597	-1.0029	-7.6892	-7.3063	-7.2518	-7.6340
N observations	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672	21,672
computing time (mins)	17	105	173	375	–	186	280	707	724	48	86	825	1305
Log Likelihood	-1,077,895	-1,075,248	-1,074,991	-1,074,501	-1,073,754	-1,075,470	-1,075,212	-1,074,750	-1,073,763	-1,076,203	-1,075,465	-1,075,013	-1,074,280
LR chi2		5,295	5,809	6,788	8,283	4,852	5,368	6,292	8,266	3,385	4,861	5,766	7,232
prob > chi2		0	0	0	0	0	0	0	0	0	0	0	0

standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.7: Welfare analysis of the end of the period incentive programs

	Without incentives	With end of the period incentives	Not counting Consumer Surplus
10%			
Purchase probability	1.5×10^{-4} - 4.4×10^{-4}	2.2×10^{-4} -5.1×10^{-4}	
# first month adopter	249	758	
Change in total number adoptions		12%-30%	
Subsidy amount		10k - 13k	
Government Spending		$812 millions	
Change in CS		$494 millions	
Implied CO_2 price (/ton)			
SCE		$137.5 (0.95)	$308.3
PG&E		$114.9 (0.37)	$305.5
SDG&E		$110.4 (0.12)	$293.1
Overall		$118.1 (0.44)	$302.0
5%			
Purchase probability	8.6×10^{-5} - 2.5×10^{-4}	2.2×10^{-4} - 5.1×10^{-4}	
# first month adopter	355	754	
Change in purchase prob.		47%	
Subsidy amount		10k - 13k	
Government Spending		$1.91 B	
Change in CS		$1.38 B	
Implied CO_2 price			
SCE		$127.2 (0.90)	$385.2
PG&E		$106.8 (0.34)	$403.4
SDG&E		$102.3 (0.11)	$389.5
Overall		$109.9 (0.42)	$394.8
3%			
Purchase probability	1.1×10^{-4} - 3×10^{-4}	$2.2 \times 10^{-4} to 5.1 \times 10^{-4}$	
# first month adopter	424	753	
Change in purchase prob.		38%	
Subsidy amount		10k - 13k	
Government Spending		$2.82 billions	
Change in CS		$2.28 billions	
Implied CO_2 price			
SCE		$110.6 (0.77)	$465.1
PG&E		$91.09 (0.29)	$507.2
SDG&E		$87.43 (0.09)	$493.7
Overall		$94.56 (0.41)	$493.0

All dollar values are in 2012 dollar. Standard errors to the prices are shown in bracket. The unit, ton, used in this paper refers to metric ton.

Table A2.8: Cost of the aggregate subsidies costs in California (traditional approach)

year \ IOU	PG&E	SCE	SDG&E
2007	276.85 (15.43)	266.20 (13.75)	274.77 (4.79)
2008	231.90 (17.87)	246.03 (17.41)	239.09 (12.88)
2009	375.72 (28.89)	413.92 (27.47)	381.29 (35.25)
2010	273.64 (32.49)	354.62 (24.48)	268.55 (26.28)
2011	211.45 (12.94)	263.84 (33.59)	203.01 (11.87)
2012	199.01 (62.39)	229.14 (70.90)	190.84 (69.75)

Table A2.9: Counterfactual analysis with solar irradiation for Frankfurt, Germany

	Baseline	Frankfurt irradiation	Frankfurt irradiation/ same num. installations	Frankfurt irradiation/ same electricity prod.
10%				
Change in total adoptions	62%	65%	81%	90%
Total Installations	725,563	398,887	725,563	1,447,732
Total electricity production	140 TWh	39 TWh	56 TWh	140 TWh
Upfront subsidy	10k - 13k	10k - 13k	$17k-20k	$28k-31k
Government spending	812 million	406 million	1.33 billion	5.78 billion
Change in CS	494 million	244 million	619 million	2.02 billion
CO_2 price (per ton)	$118.1 (0.44)	$236.6 (0.90)	$418.4 (0.98)	$730.1 (1.37)
5%				
Change in total adoptions	47%	51%	75%	87%
Total Installations	723,348	374,467	723,348	1,444,028
Total electricity production	140 TWh	36 TWh	70 TWh	140 TWh
Upfront subsidy	10k - 13k	10k - 13k	21.4k - 24.4k	29.5k - 31.5k
Government spending	$1.9 billion	$916 million	$3.9 billion	$16.8 billion
Change in CS	$1.4 billion	$647 million	$2.0 billion	$6.9 billion
CO_2 price (per ton)	$109.9 ()	$221.3 ()	$490.9 ()	$923.2 ()
3%				
Change in total adoptions	38%	43%	69%	85%
Total Installations	722,829	386,152	722,829	1,443,291
Total electricity production	140 TWh	37 TWh	70 TWh	140 TWh
Upfront subsidy	10k-13k	10k-13k	24k-27k	47.5k-50.5k
Government spending	2.8 billion	1.4 billion	6.4 billion	28.9 billion
Change in CS	2.3 billion	1.1 billion	3.9 billion	13.6 billion
CO_2 price (per ton)	$94.56 ()	$189 ()	$507.9 ()	$1053 ()

MMt refers to million metric tons

Table A2.10: Welfare comparison between capacity-based and production-based subsidies

	Capacity-based subsidy	Production-based subsidy	Capacity-based subsidy with NJ solar in N. CA	FIT with NJ solar in N. CA	Baseline with AZ solar in S. CA and AK solar in N. CA	FIT with AZ(S. CA) and AK (N. CA) solar
10%						
$\triangle$ num. adoptions	72%	72%	73%	73%	73%	73%
Total Installations	979,244	979,244	921,970	921,970	859,358	859,358
Electricity production	189 TWh	189 TWh	167 TWh	168 TWh	109 TWh	114 TWh
Per unit Subsidy	$1.1/W	+7.93 ¢/kWh	$1.1/W	8.45 ¢/kWh	$1.1/W	8.94 ¢/kWh
Government spending	1.66 billion	1.65 billion	1.53 billion	1.53 billion	1.42 billion	1.51 billion
Change in CS	873 million	872 million	801 million	802 million	746 million	780 million
Implied CO_2 price						
SCE	$167	$171.1	$167	$176.2	$158.5	$176.4
PGE	$172.8	$170.2	$201.3	$191.3	$296.7	$249.3
SDGE	$165.4	$166.5	$165.4	$171.4	$150.1	$167.2
Overall	$169.3	$169.1	$180.6	$179.9	$184.5	$182.2
5%						
$\triangle$ num. adoptions	57%	57%	58%	58%	58%	58%
Total Installations	886,954	886,954	829,270	829,270	769,716	769,716
Electricity production	171.6 TWh	171.7 TWh	151 TWh	151 TWh	137 TWh	140 TWh
Per unit Subsidy	$1.1/W	+5.18 ¢/kWh	$1.1/W	5.52 ¢/kWh	$1.1/W	5.80 ¢/kWh
Government spending	3.35 billion	3.35 billion	3.09 billion	3.10 billion	2.87 billion	2.98 billion
Change in CS	2.20 billion	2.19 billion	2.01 billion	2.02 billion	1.87 billion	1.93 billion
Implied CO_2 price						
SCE	$153.5	$157	$153.5	$161.5	$145.5	$160.7
PGE	$158.3	$156	$184.8	$175.9	$273.8	$230.7
SDGE	$151.1	$152	$151.1	$156.2	$136.7	$150.9
Overall	$155	$154.8	$165.2	$164.8	$168.7	$166.7
3%						
$\triangle$ num. adoptions	47%	47%	48%	48%	48%	48%
Total Installations	844,203	844,203	791,704	791,704	736,836	736,836
Electricity production	163 TWh	163.5 TWh	144 TWh	145 TWh	131 TWh	133 TWh
Per unit Subsidy	$1.1/W	+4.25 ¢/kWh	$1.1/W	4.52 ¢/kWh	$1.1/W	4.77 ¢/kWh
Government spending	4.63 billion	4.63 billion	4.30 billion	4.31 billion	4.01 billion	4.12 billion
Change in CS	3.47 billion	3.47 billion	3.21 billion	3.22 billion	3.07 billion	
Implied CO_2 price						
SCE	$135.4	$138.7	$135.4	$142.9	$128.3	$142.7
PGE	$139.8	$137.6	$163	$154.5	$241	$200.5
SDGE	$133.5	$134.3	$133.5	$138.3	$121	$134.5
Overall	$136.8	$136.7	$145.8	$145.5	$150.4	$148.7

Table A2.11: Welfare comparison between capacity and production-based subsidies with non-matching public and private discount rates

Public Discount / Private Discount	10%		5%		3%	
	capacity-based	production-based	capacity-based	production-based	capacity-based	production-based
10%						
# first month adopter	1,150	1,150	1,150	938	1,150	877
Subsidy amount	$5,929	+7.93 ¢/kWh	$5,929	5.18 ¢/kWh	$5,929	4.25 ¢/kWh
Government Spending	$1.7 billion	$1.7 billion	$4.9 billion	$3.1 billion	$5.5 billion	4.4 billion
Change in CS	$873 millions	$872 million	$873 millions	$670 million	$873 millions	$610 million
Implied CO_2 price (/ton)	$169.3	$169.1	$280.6	$305.8	$310.8	$347.0
5%						
# first month adopter	992	1,210	992	991	992	926
Subsidy amount	$5,929	+7.93 ¢/kWh	$5,929	5.18 ¢/kWh	$5,929	4.25 ¢/kWh
Government Spending	1.4 billion	1.7 billion	3.4 billion	3.3 billion	4.9 billion	4.6 billion
Change in CS	$2.2 billion	2.9 billion	$2.2 billion B	$2.2 billion	$2.2 billion	$2.0 billion
Implied CO_2 price	-$227.2	-$273.6	$155.0	$154.8	$252.8	$273.4
3%						
# first month adopter	925	1,180	925	984	925	925
Subsidy amount	$5,929	+7.93 ¢/kWh	$5,929	5.18 ¢/kWh	$5,929	4.25 ¢/kWh
Government Spending	$1.4 billion	$1.7 billion	$3.2 billion	$3.3 billion	$4.6 billion	$4.6 billion
Change in CS	3.5 billion	5.2 billion	3.5 billion	3.9 billion	3.5 billion	$3.5 billion
Implied CO_2 price	-$816.8	-$911.9	-$54.88	-$84.85	$136.8	$136.8

All dollar values are in 2012 dollar. Standard errors to the prices are shown in bracket. The unit, ton, used in this paper refers to metric ton.

Table A2.12: 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	2.6% to 3.0%	5.6% to 6.4%
10% discount rate		
# reduction in first month	81	167
% change in installations	-5.3%	-11%
5% discount rate		
# reduction in first month	48	100
% change in installations	3.7%	-7.8%
3% discount rate		
# reduction in first month	34	72
% change in installations	2.8%	-6.1%

All dollar values are in 2012 dollar

Table A2.13: Potential impacts from varying incentive levels

	Without incentive	End of the period incentives	Lowering subsidy match $38 SSC	Doubling num. of installations
10%				
Total Installations	275,870	725,563	410,796	1,450,862
Upfront subsidy	0	10k-13k	4k	22.5k
Government spending	0	811,530	164,994	4.6 billion
Change in CS	0	0.5 billion	0.1 billion	12.2 billion
Equivalent CO_2 price	0	$118.1 ()	$42.08 ()	$263.5 ()
5%				
Total Installations	381,120	723,348	503,954	1,446,592
Upfront subsidy	0	10k-13k	4.6k	28.5k
Government spending	0	1.9 billion	0.5 billion	12 billion
Change in CS	0	1.4 billion	0.5 billion	6.4 billion
Equivalent CO_2 price	0	$109.9 ()	$42.08 ()	$306 ()
3%				
Total Installations	446,670	722,829	583,685	1,445,616
Upfront subsidy	0	10k-13k	6k	35k
Government spending	0	2.8 billion	1.2 billion	20.7 billion
Change in CS	0	2.3 billion	1.1 billion	12.2 billion
Equivalent CO_2 price	0	$94.56 (0.41)	$42.08 ()	$342.8 ()

All dollar values are in 2012 dollar

Table A2.14: Comparison of the subsidy degression design and the flat-rate design

	Degression design	Flat-rate design	zero subsidies	actual
10%				
# installations in first 62 months	27,588	29,431	4,992	27,787
Upfront subsidy	1k-13k +tax credits	6k +tax credits	0	
Government spending[24]	$445 million	$438 million		
Change in CS	$134 million	$134 million		
Equivalent CO_2 price	$204.1 ()	$187 ()		
5%				
# installations in first 62 months	28,319	28,942	8,951	27,787
Upfront subsidy	1k-13k +tax credits	6k +tax credits	0	
Government spending	$456 million	$443 million		
Change in CS	$215 million	$216 million		
Equivalent CO_2 price	$147.9 ()	$131.6 ()		
3%				
# installations in first 62 months	28,799	29,062	11,731	27,787
Upfront subsidy	1k-13k +tax credits	6k +tax credits	0	
Government spending	$464 million	$450 million		
Change in CS	$259 million	$259 million		
Equivalent CO_2 price	$106.9 ()	$91.02 ()		

All dollar values are in 2012 dollar

A3. Proof of Contraction Mapping of the Emax function

Rust (1987, 2002) has shown that the Emax function is a contraction mapping in a general setting, here we present a different but direct proof that the contraction mapping holds for the case of this paper. In a general binary logit model, the Emax function is defined as,

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

Since we condensed all states (price, subsidy, revenue and tax credit) into a one dimension state, time, the above equation can be simplified as below (also dropping the conditional θ notation and let $A(j) = e^{\nu(\mathbf{X}',\mathbf{d},\theta)}$),

$$\mathcal{F}^{new}(k) = \sum_{j=1}^{N} P_{kj} \log\left(e^{\beta \mathcal{F}(j)} + A(j)\right) \tag{A2.1}$$

where $A(j)$ can be thought of a (different) constant associating with each state j. Adding a constant a to $\mathcal{F}$ to find,

$$\mathcal{F}^{new}(k) + a = \sum_{j=1}^{N} P_{kj} \log\left(e^{\beta(\mathcal{F}(j)+a)} + A(j)\right). \tag{A2.2}$$

To show that the function $\mathcal{F}$ is a contraction mapping, we need to show that there exists a $\bar{\beta} < 1$ such that following inequality holds,

$$\log\left(e^{\beta \mathcal{F}(j)+\beta a} + A(j)\right) \leq \log\left(e^{\beta \mathcal{F}(j)} + A(j)\right) + \bar{\beta} a$$
$$\log \frac{e^{\beta \mathcal{F}(j)+\beta a} + A(j)}{e^{\beta \mathcal{F}(j)} + A(j)} \leq \bar{\beta} a \tag{A2.3}$$

Note that the following inequality holds,

$$\sum_{j=1}^{N} P_{kj} \log \frac{e^{\beta \mathcal{F}(j)+\beta a} + A(j)}{e^{\beta \mathcal{F}(j)} + A(j)} \leq \sum P_{kj} \log \frac{\left(e^{\beta \mathcal{F}(j} + A(j)\right) e^{\beta a}}{e^{\beta \mathcal{F}(j)} + A(j)}$$
$$= \sum P_{kj} \log e^{\beta a}$$
$$= \underbrace{\sum P_{kj}}_{=1} \beta a$$
$$= \beta a \tag{A2.4}$$

Therefore, there is at least the discount factor β that is less than 1 and satisfies the inequality (A2.3). ∎

A4. Calculating the equivalent CO_2 prices from deadweightloss

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

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

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.

A5. Parameter Calibration and Data Cleaning

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%
Annual O& M and insurance cost	$250
Inverter Replacements	Twice (8th and 17th year, 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.

A6. On Deriving the Logit Inclusive Value

From (2.5), the expected future utility function is

$$\mathcal{F}_\theta(\mathbf{X}) = \int_{\mathbf{X}'} \int_{\boldsymbol{\epsilon}'} \left[\max_d [\nu(\mathbf{X}', d, \theta) + \beta \mathcal{F}_\theta(\mathbf{X}) + \epsilon(d)] \right] p_\epsilon(\boldsymbol{\epsilon}'|\mathbf{X}) d\boldsymbol{\epsilon}' \cdot p_X(\mathbf{X}'|\mathbf{X}) d\mathbf{X}'. \quad (6.6a)$$

or

$$\mathcal{F}_\theta(\mathbf{X}) = \int_{\mathbf{X}'} E_\epsilon \left[\max_d [\nu(\mathbf{X}', d, \theta) + \beta \mathcal{F}_\theta(\mathbf{X}') + \epsilon(d)] \right] p_X(\mathbf{X}'|\mathbf{X}) d\mathbf{X}'. \quad (6.6b)$$

Since $\boldsymbol{\epsilon}$ follows type I extreme value distribution,

$$G_\epsilon(y) = e^{e^{-\frac{y-b}{a}}} = e^{-ke^{-\frac{y}{a}}} \quad (6.7a)$$

and

$$g_\epsilon(y) = \frac{k}{a} e^{-\frac{y}{a}} e^{-ke^{-\frac{y}{a}}} \quad (6.7b)$$

for $k = \frac{b}{a}$. The distribution function of $\max_{d=0,1} \tilde{U}_i = \max_{d=0,1} [v_\theta(\mathbf{X}, d) + \epsilon(d)]$ is equal to

$$
\begin{aligned}
H(y) &= \prod_{d=0}^{1} F_\epsilon \left(y - v_\theta(\mathbf{X}, d) \right) \\
&= \prod_{d=\{0,1\}} e^{-ke^{-\frac{y - v_\theta(\mathbf{X}, d)}{a}}} \\
&= e^{-kLe^{-\frac{x}{a}}}.
\end{aligned}
\tag{6.8}
$$

where $L = \sum_{d=\{0,1\}} e^{\frac{v_\theta(\mathbf{X}, d)}{a}}$. The corresponding *pdf* is

$$
h(y) = \frac{kL}{a} e^{-\frac{y}{a}} e^{-kLe^{-\frac{y}{a}}}
\tag{6.9}
$$

The expected value of the maximum, i.e. $E_{\epsilon'} \left[\max_{d=\{0,1\}} v_\theta(\mathbf{X}, d) + \epsilon(d) \right]$ can be written as

$$
\begin{aligned}
&\int_{-\infty}^{\infty} y \, h(y) dy \\
&= \int_{-\infty}^{\infty} y \cdot \frac{kL}{a} e^{\frac{y}{a}} e^{-kLe^{-\frac{y}{a}}} dy.
\end{aligned}
\tag{6.10}
$$

Let $t = e^{-\frac{y}{a}}$ or $-a \ln t = y \Rightarrow dt = -\frac{1}{a} e^{-\frac{y}{a}}$, using a change of variables (6.10) can be solved by applying the Laplace transformation $\int_0^\infty e^{-st} \ln t \, dt = -\frac{\ln s + r}{s}$,

$$
\begin{aligned}
&\int_\infty^0 akL \ln t \, e^{-kLt} dt \\
&= akL \frac{\ln kL + r}{kL} \\
&= ar + a(\ln k + \ln L) \\
&= ar + a\left(\frac{b}{a}\right) + a \ln L \\
&= a \ln \sum_{d=0}^{1} e^{\frac{v_\theta(\mathbf{X}, d)}{a}}
\end{aligned}
\tag{6.11}
$$

the last equality is hold by the mean zero assumption, $ar + b = 0$. Therefore the expected future utility is

$$F(\mathbf{X}) = \int_{\mathbf{X}'} a \ln \sum_{d=0}^{1} e^{\frac{v_\theta(\mathbf{X},d)}{a}} p_X(\mathbf{X}'|\mathbf{X}) d\mathbf{X}'$$

$$= \int_{\mathbf{X}'} a \ln \sum_{d=0}^{1} e^{\frac{\nu(\mathbf{X}',d,\theta) + \beta EV(\mathbf{X}')}{a}} p_X(\mathbf{X}'|\mathbf{X}) d\mathbf{X}' \qquad (6.12)$$
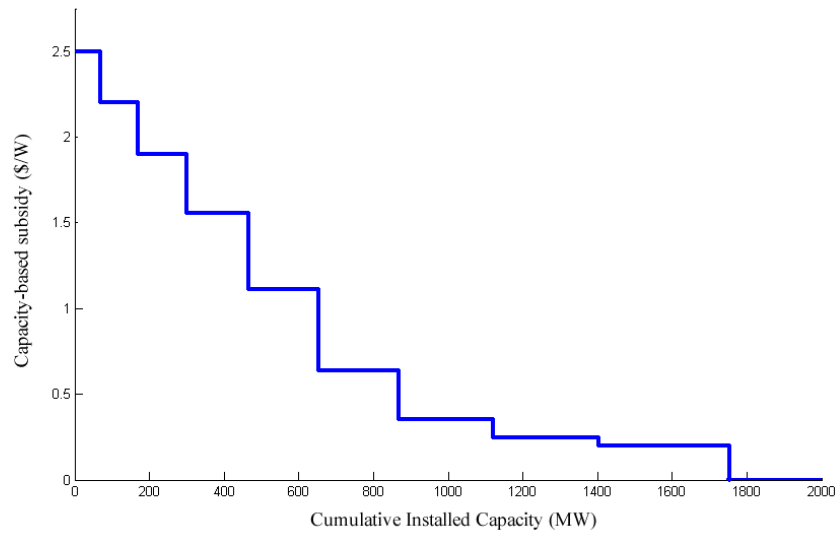
A7. Figures and Charts

Figure 4: Figure A7.1: Subsidy degression in terms of cumulative installed capacity
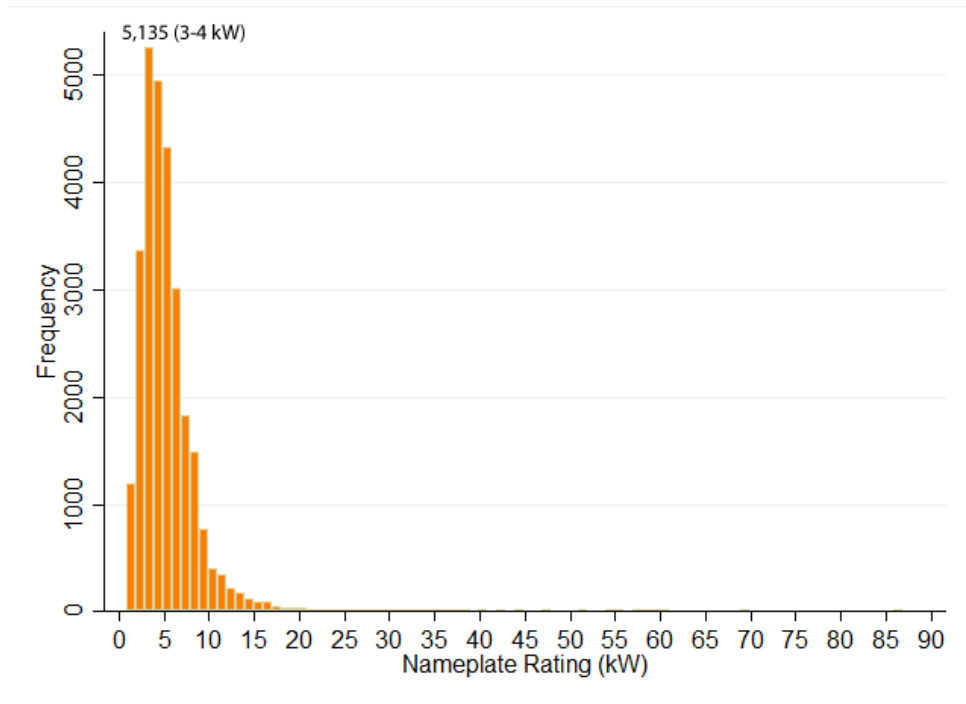
Figure A7.2: Histogram of the number of system installed by the size
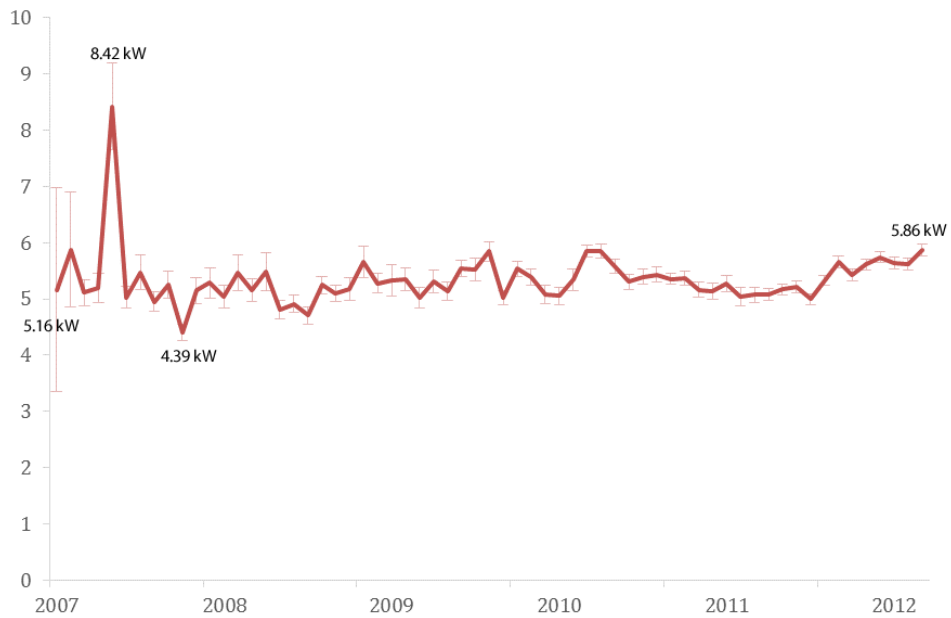
Figure A7.3: Average system size trend
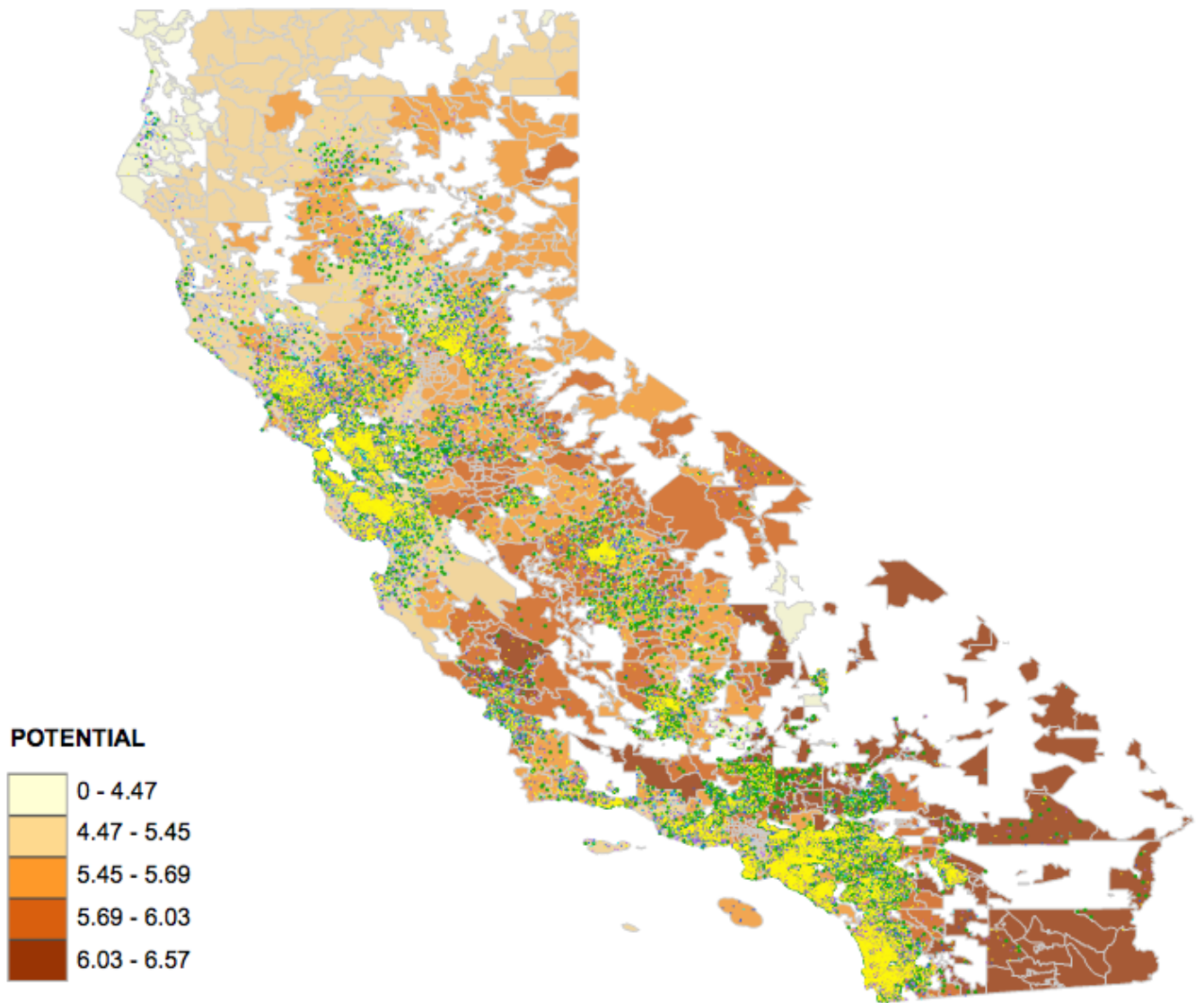
A7.4: Zip code map showing PV system adoptions in California. Yellow indicates installations occurred in 2011, green indicates installations in 2010.

Figure A7.5: Map showing the counties included in the study

Application number	Program Admin	Program	Incentive	Incentive	Incentive	Total Cost	Namplate-rating	CSI rating	Reservation	Complete Date	Host Consumer Type	3rd party Ownershi	City	County	Zip Code
SCE-CSI-06618	SCE	Small Commercial (< 10 kW) and All Residenti	Step 4	EPBB	6880	32318	4.32	3.621	6/10/2009	1/21/2010	Residential	yes	Los Angeles	Los Angeles	90002
SCE-CSI-06620	SCE	Small Commercial (< 10 kW) and All Residenti	Step 4	EPBB	6886	32318	4.32	3.624	6/10/2009	12/28/2009	Residential	no	Los Angeles	Los Angeles	90002
SCE-CSI-18725	SCE	Small Commercial (< 10 kW) and All Residenti	Step 6	EPBB	6446	43750	6.9	5.86	3/28/2011	6/15/2011	Residential	no	Los Angeles	Los Angeles	90008
SCE-CSI-06528	SCE	Small Commercial (< 10 kW) and All Residenti	Step 4	EPBB	4155	20750.4	2.475	2.187	6/3/2009	8/17/2009	Residential	no	Los Angeles	Los Angeles	90022
SCE-CSI-02275	SCE	Small Commercial (< 10 kW) and All Residenti	Step 2	EPBB	2795	17550	1.29	1.118	3/27/2008	6/6/2008	Residential	no	Los Angeles	Los Angeles	90022
PGE-CSI-29073	PG&E	Small Commercial (< 10 kW) and All Residenti	Step 7	EPBB	3432	35645	6.272	5.28	7/21/2010	12/23/2010	Residential	no	Madera	Madera	93636
PGE-CSI-19601	PG&E	Small Commercial (< 10 kW) and All Residenti	Step 6	EPBB	11201	75382	12.6	10.182	9/23/2009	11/4/2009	Residential	no	Madera	Madera	93636
PGE-CSI-24418	PG&E	Small Commercial (< 10 kW) and All Residenti	Step 6	EPBB	10865	76382.5	11.75	9.877	3/31/2010	12/29/2010	Residential	no	Madera	Madera	93636
PGE-CSI-24374	PG&E	Small Commercial (< 10 kW) and All Residenti	Step 6	EPBB	8176	54400.2	9.18	7.433	3/31/2010	8/10/2010	Residential	yes	Madera	Madera	93636
PGE-CSI-20426	PG&E	Small Commercial (< 10 kW) and All Residenti	Step 6	EPBB	5349	43987.5	6.56	4.863	10/27/2009	5/6/2010	Residential	no	Madera	Madera	93636
SD-CSI-12068	CCSE	Small Commercial (< 10 kW) and All Residenti	Step 9	EPBB	697	27055	3.29	2.789	3/9/2012		Residential	no	EL CAJON	San Diego	92019
SD-CSI-02828	CCSE	Small Commercial (< 10 kW) and All Residenti	Step 5	EPBB	1844	16632	1.512	1.19	6/17/2009	12/21/2009	Residential	no	El Cajon	San Diego	92019
SD-CSI-05467	CCSE	Small Commercial (< 10 kW) and All Residenti	Step 6	EPBB	4831	39414.5	5.16	4.392	3/8/2010	7/15/2010	Residential	no	El Cajon	San Diego	92019
SD-CSI-10311	CCSE	Small Commercial (< 10 kW) and All Residenti	Step 9	EPBB	1615	51234	7.59	6.46	9/16/2011	10/27/2011	Residential	yes	El Cajon	San Diego	92019

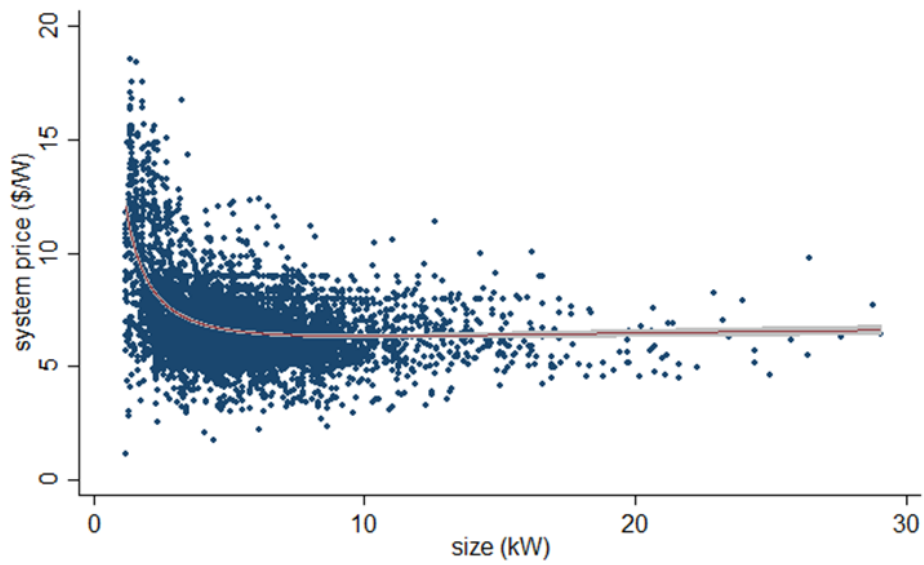*Figure A7.6: Raw CSI installation data*

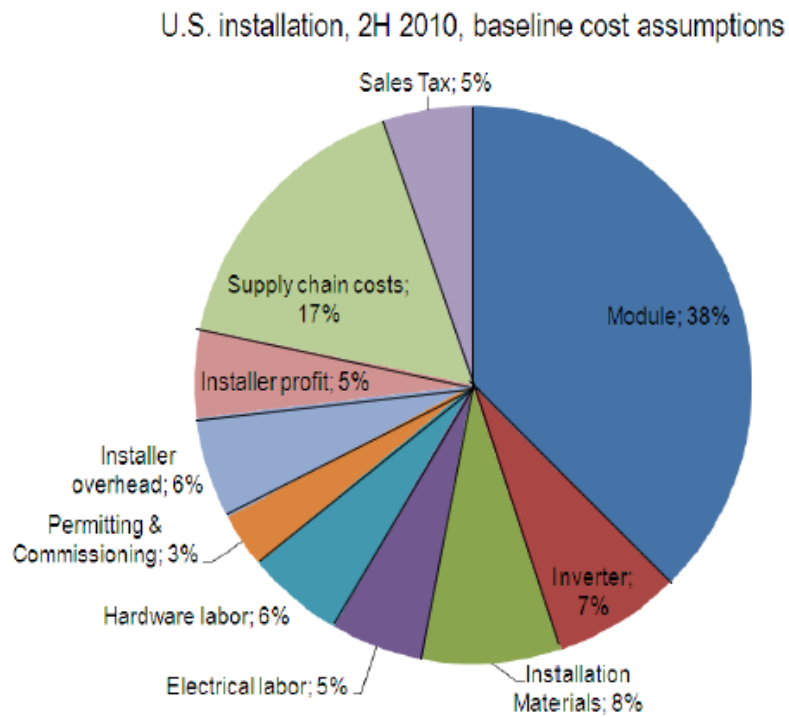*Figure A7.7: The nonlinear relationship between unit price and system size*

Figure A7.8: 2010 benchmark residential PV system price components, Goodrich et al., 2012
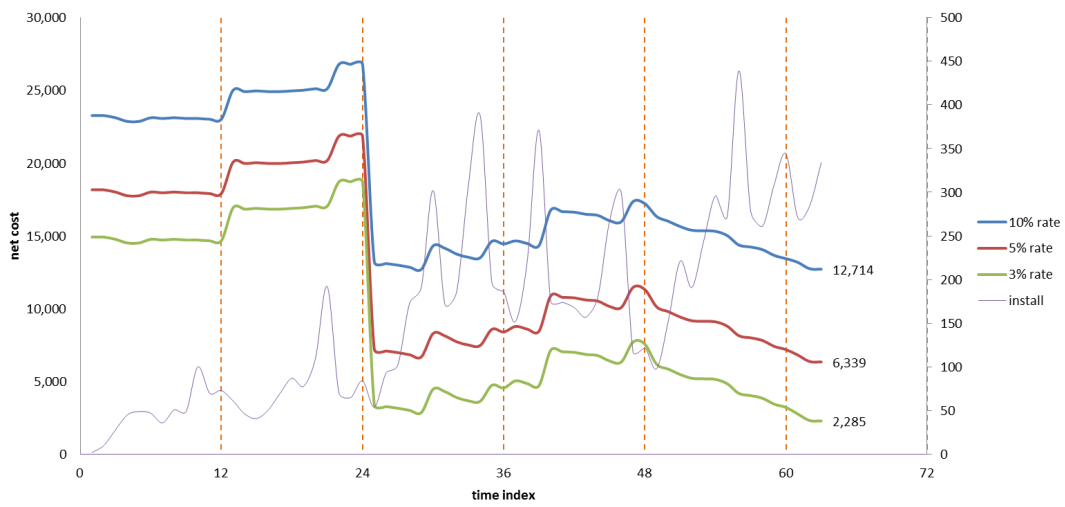
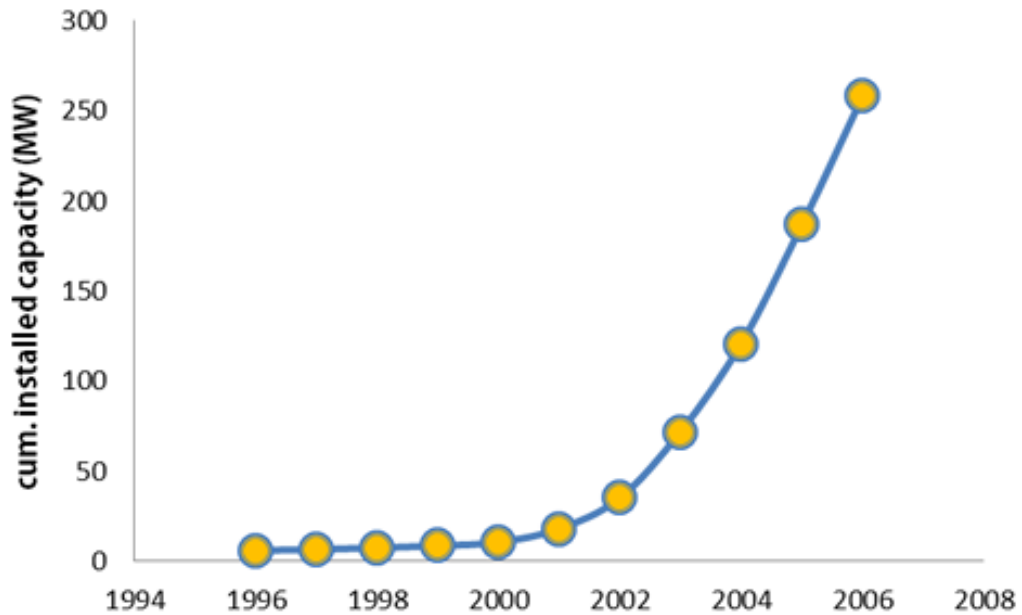*Figure A7.9: System net cost and the number of installations in La Jolla, San Diego*

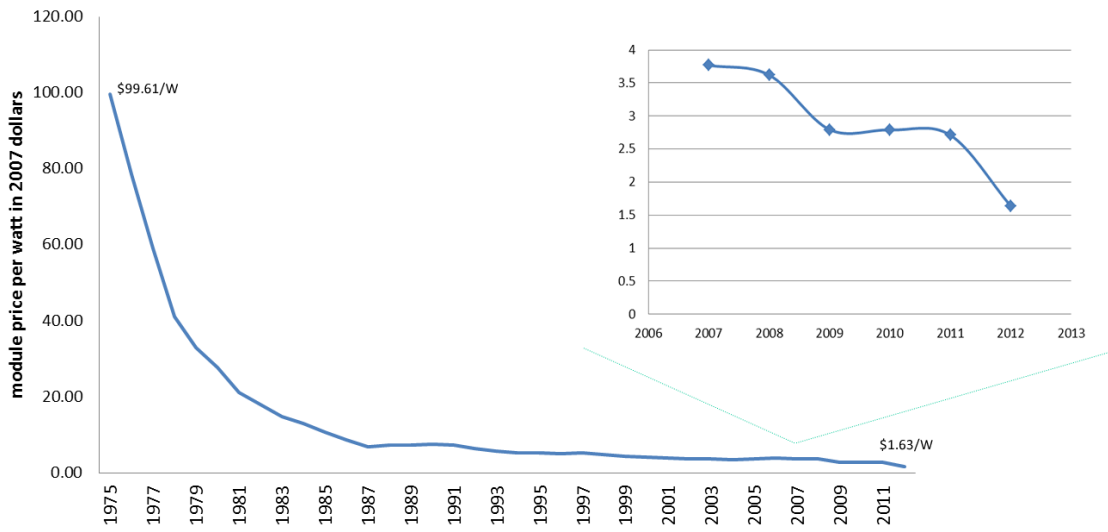*Figure A7.10: Grid-tied cumulative PV installed capacity in California, 1996-2006*
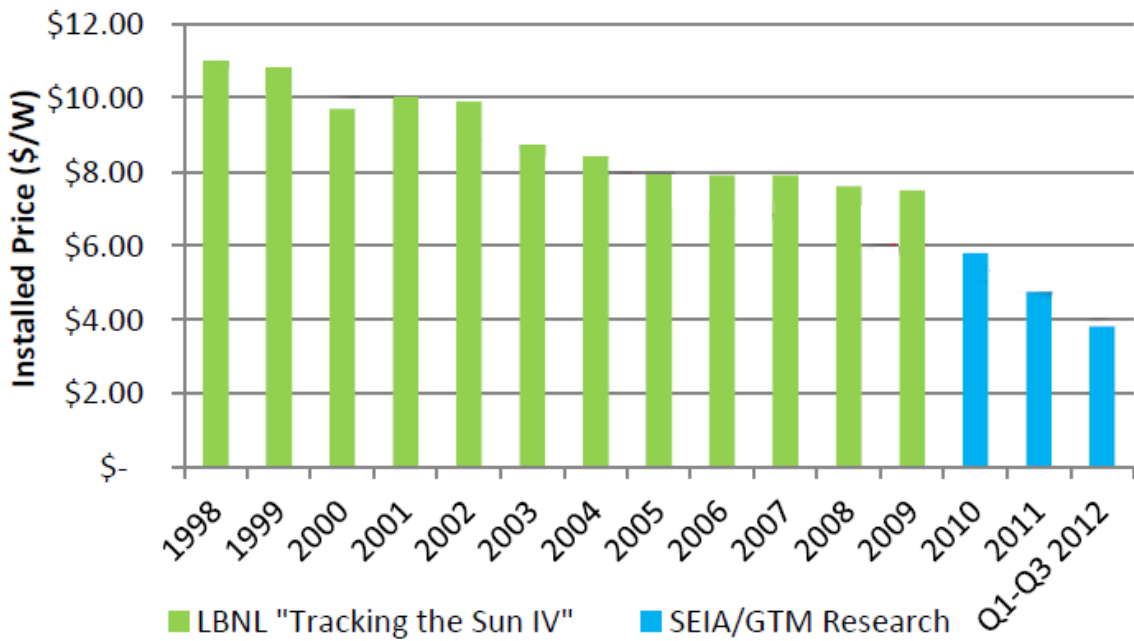
Figure A7.11: Average module cost, 1975-2012

Figure A7.12: Average install system cost in the US, 1998-2012. Source: SEIA Solar Energy Facts: Q3 2012