Learning-by-Doing and the Optimal Solar Policy in California

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ABSTRACT

Much policy attention has been given to promote fledgling energy technologies that promise to reduce our reliance on fossil fuels. These policies often aim to correct market failures, such as environmental externalities and learning-by-doing (LBD). We examine the implications of the assumption that LBD exists, quantifying the market failure due to LBD. We develop a model of technological advancement based on LBD and environmental market failures to examine the economically efficient level of subsidies in California's solar photovoltaic market. Under central-case parameter estimates, including nonappropriable LBD, we find that maximizing net social benefits implies a solar subsidy schedule similar in magnitude to the recently implemented California Solar Initiative. This result holds for a wide range of LBD parameters. However, with no LBD, the subsidies cannot be justified by the environmental externality alone.

KEY WORDS: market failures, solar, learning-by-doing, diffusion, induced technological change, optimal policy, California Solar Initiative

1. INTRODUCTION

In light of the increasing scientific consensus on global climate change and the desire for greater energy security, many governments have recently set ambitious targets to increase the share of renewable energy in the total energy mix. To meet these targets, policymakers are deploying a variety of policy instruments, including technology subsidies. Along with wind, solar energy has been one of the largest beneficiaries of these policies, particularly in Germany, Japan and California. Appropriately assessing the economic efficiency of such policies is important as many other governments are planning on following suit.

This paper models the optimal photovoltaic (PV) solar subsidy policy in California, and compares this policy to one of the largest PV energy incentive programs in the world, the recently implemented California Solar Initiative (CSI).

Economic arguments for policies to promote renewable energy often include an assertion that the renewable energy technology will substitute for fossil fuel technologies that have important environmental externalities, in particular externalities associated with the atmospheric release of carbon dioxide. Although this argument is qualitatively correct, as will be discussed at a later point, it is not quantitatively correct for PVs: the externality appears to be far smaller than the proposed subsidy. Thus the current externality alone cannot justify large subsidies for renewable energy, including for PVs.

A second argument is based on an appropriability market failure if the production of the new technology may have spillover benefits from learning by doing (LBD). Learning by doing characterizes technical progress for a technology as related to the cumulative experience with the technology: costs may decrease as cumulative experience increases. With LBD, a positive externality occurs because increased output (e.g., of solar panels) by one firm today contributes to a lower production cost in the future, benefiting that firm as well as other firms or consumers in the market. As firms cannot appropriate this entire spillover effect, the private market under-provides the product of interest.

Such a LBD externality could provide an economic justification for a subsidy. The individually optimal production level of a firm would take into account the impact on future cost reductions for that firm alone. The socially optimal production level of that firm would take into account the impact on future cost reductions for all firms together, an amount that could be expected to be many times higher in a competitive industry characterized by substantial LBD. The question, however, remains whether such an externality is quantitatively consistent with the proposed subsidies.

Weighing the benefits of fostering a fledgling technology against the costs of the policy is complicated by difficulties of modeling the technology policy in inducing technological change. There is an extensive literature on the modeling of induced technological change in energy technologies, which tends to fall into the following camps: direct-price induced technological change, research and development (R&D)-based technological change, and learning-by-doing. Modeling technological change as directly price-induced assumes that price increases of an input, such as energy, induce technological change that economizes use of that input. Modeling technological change as R&D-based assumes a specified relationship between R&D investment and improved technology (Clark and Weyant, 2002; Edmonds, et al., 2000; Loschel, 2002).

The literature on technological change in solar energy primary focuses on learning-by-doing, with numerous studies empirically estimating the learning rate (LR), or the percent decrease in costs with a doubling of cumulative experience, where experience is often modeled simply as the capacity installed. Williams and Terizen (1993) estimate that solar photovoltaic (PV) module (i.e., solar panel) prices on the global market followed a learning rate of 18% between 1976 and 1992. Watanabe (1999) finds a 20% learning rate in installation costs in the Japanese market between 1981 and 1995. IEA (2000) and van der Zwaan and Rabl (2004) update the global learning rate with more recent data and both find a learning rate of around 20%.

McDonald and Schrattenholzer (2001) bring together estimates in the literature of learning rates in a wide range of energy technologies, including solar. Not surprisingly, they find that solar technology has had a relatively high rate of learning, especially when compared to mature fossil energy technologies. This result corresponds with Jamasb (2007), who finds that mature technologies such as coal-fired electricity generation and large hydropower have had much lower learning rates than “evolving” technologies such as nuclear power, waste to electricity, and wind power. Solar photovoltaics in California are arguably also an “evolving” technology.

Of course, such characterizations of LBD summarize all of factors associated with cost reductions into one simple functional relationship between the capacity installed and unit cost. This simple characterization leads to a common criticism: the lack of a "natural law" forcing such a relationship or theory explaining it (Junginger, et al., 2005). The intuition for learning described in the seminal paper on LBD by Arrow (1962) is that knowledge can be gained by hands-on experience with a problem and that learning occurs through action. But while the functional relationship between experience and costs may be an empirical observation, attributing all of the cost reductions to learning neglects any other sources of cost reduction (Clark and Weyant, 2002).

This criticism can also be expected to apply to the global solar PV module market. Nemet (2006) examines learning in the global PV market and finds that learning only weakly explains cost reductions in the most important factors in the cost of solar PV modules. Papineau (2004) finds that the effect of cumulative experience on total solar PV cost reductions is highly significant, but becomes insignificant when a time trend is added. However, the effect of R&D on total solar PV cost reductions is less significant than the effect of experience.

Duke, Williams, and Payne (2005) and Duke (2002) suggest a feature of the solar PV market that may provide an explanation: learning-by-doing in solar PV module costs is a global phenomenon, but learning-by-doing in solar PV *balance-of-system* (BOS) costs is a local phenomenon. The solar PV BOS costs include all of the costs of a solar PV system installation except for the cost of the PV module (i.e., the cost of labor, the inverter, management, and marketing). Learning in the cost of PV modules is usually assumed to be based on global experience, since most modules are manufactured and sold around the world in a global market. In contrast, learning that occurs in the cost of installing solar PV systems, marketing, and managing the installations and supply chain appears to build knowledge and lower costs at a much more local level.

Just as Joskow and Rose (1985) suggest that experience appears to have lowered construction costs for building coal-burning electricity generation plants through the repetitive design of technological similar plants and repetitive management of construction, Duke (2002) suggests that in the solar PV market experience has lowered BOS costs at a local level by repetitive design of technologically similar installations and management of installations. Furthermore, in both cases, the authors suggest that some of this learning may accrue to individuals or individual firms, but at least some of it is likely to be "general" or "industry-wide" knowledge that can not appropriated by individual firms, due to employees changing firms and firms copying the best-practices of other firms.

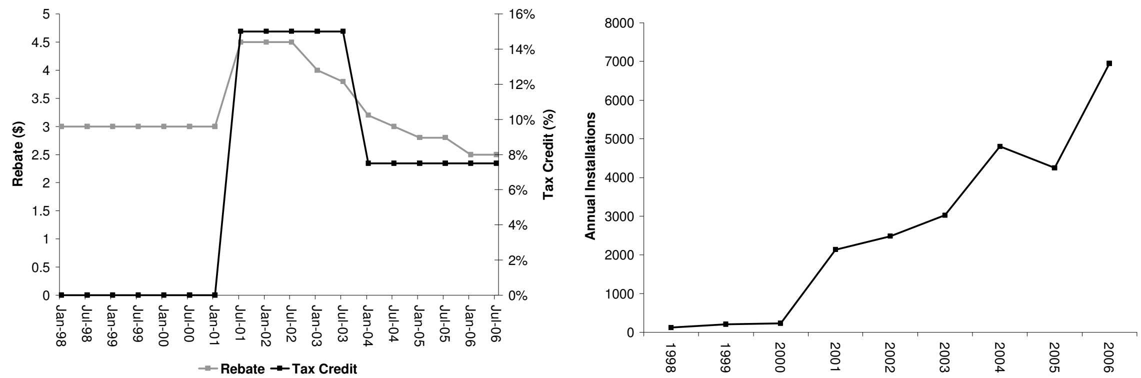
The recent evidence by Nemet (2006) and Papineau (2004) can be viewed in light of this intuition. Nemet's finding that evidence for learning in the module cost is weak can be viewed as suggesting that R&D or other factors play a larger role in solar PV module cost reductions. Papineau's finding that learning is not significant when a time trend is included may confound the lack of learning in module costs from learning in BOS costs. Duke (2002) finds that learning in the BOS cost in Japan has historically been greater than global learning in the PV module cost.

This paper examines the implications of the assumption that LBD is a reasonable model of technological change in the BOS. We develop an economic model with LBD technological change to investigate optimal subsidy policy to correct for LBD and environmental market failures. Our model has broader applicability to any renewable energy technology with strong LBD potential, but is designed and parameterized to examine the efficient level of solar subsidies in California and investigate the efficiency of the CSI. Finally, we provide a sensitivity and robustness analysis of the optimal policy, including implications of the converse assumption – that LBD is insignificant. Results indicate that if LBD at even modest rates accurately describes future cost changes, the CSI is near optimal. But if LBD is insignificant, then the CSI over-subsidizes solar relative to the social optimum.

2. BACKGROUND ON SOLAR ENERGY POLICY IN CALIFORNIA

Although solar energy makes up only 0.3% of the total electricity supply in California, solar PV has experienced rapid growth since 2000, with under 5 MW installed in 2000 and nearly 198 MW installed at the end of 2006 (CEC, 2005; CEC, 2007). This rapid growth is at least partly a result of two California government incentive programs: solar *rebates* (a dollar amount per installed Watt) and *tax credits* (a percentage of the installation cost of a solar system paid by the state).[1] Figure 1 indicates the connection between historic incentives and residential solar system installations in California.

Figure 1. Historic Incentive Levels (Left) and Residential Solar System Installations (Right) in California



In January 2004, Governor Schwarzenegger announced the "Million Solar Roofs Initiative," setting the goal of one million solar homes in California by 2015. Key elements of this vision were promulgated by a California Public Utilities Commission (CPUC) rulemaking on January 12, 2006, as the "California Solar Initiative" (CSI). CSI provides the assurance of incentives over 11 years, a serious commitment on the part of California to solar energy (CPUC, 2007b).

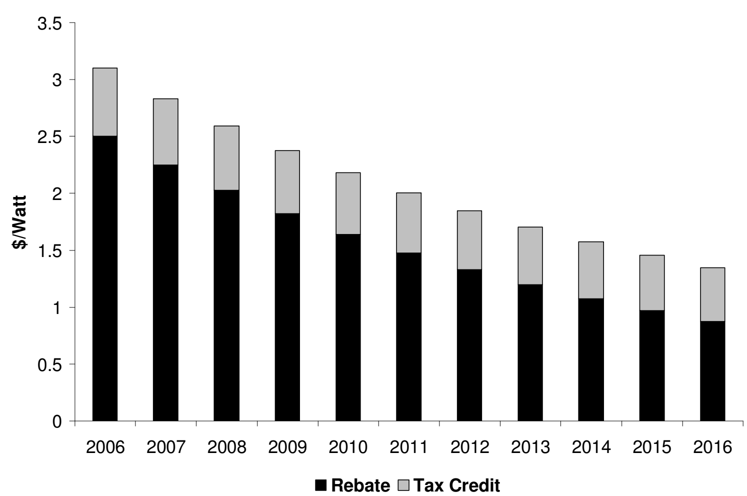
Most of California incentives are focused on residential and commercial PVs, rather than central generation solar, so our analysis follows suit. The largest market segment, PV *Residential Retrofit*, involves the installation of solar panels on rooftops of existing homes and small commercial buildings. The PV *Residential New Construction* segment installs solar systems during the construction of new homes. California has a strong commercial solar market, boosted by the Self-Generation Incentive Program. Since this program was merged with the CSI early 2007, we do not model it explicitly,

[1] From January 1, 2006 to December 31, 2007, there is also a Federal tax credit for residential installations of 30% of the installation's cost (up to $2,000). We do not model this credit due to its short-lived nature.

but instead include it in the PV *Residential Retrofit* category. Most commercial solar systems tend to be small and have similar economics to residential systems.

The CPUC does not specify an exact incentive schedule for the CSI, but the program began at $2.50/Watt in 2006, with the incentives slated to be reduced by an average of approximately 10 percent annually (nominal dollars), and fully phased out by 2017 (CPUC, 2006). Figure 2 shows our interpretation of the planned incentive scheme. In August, 2006 the CPUC modified the incentive schedule so that reductions in subsidy would be a function of installed capacity rather than a pre-determined annual rate. This scheme results in subsidies very close to the incentives in Figure 2 when matched with the installed capacity of the CSI that we find in Section 5 of this paper (CPUC, 2007a). The CSI leaves the 7.5% tax credit in place until the end of the policy.

Figure 2. Incentives Over Time in CSI (Nominal Dollars)



3. A MODEL TO ANALYZE CALIFORNIA SOLAR POLICY

We develop a model to analyze the economic efficiency of solar subsidy policies in California, with the following key characteristics:

- *Consumer choice* – purchases of solar systems depend on both the net present value (NPV) of the benefits to the consumer and a diffusion process. Subsidies influence the NPV.

- *Learning-by-doing* – costs of supply depend on the cumulative past production and installations. This assumption will be varied in order to test its implications.

- *Environmental externalities* – there are externalities associated with the electricity production for which solar substitutes.

- *Economic efficiency as a policy goal* – the goal is to set a time path of subsidies which maximizes the discounted present value of net social benefits – that is, it maximizes economic efficiency.

3.1 Consumer Choice

Consumer choice is modeled by a specification in which annual demand in California, q_t, consists of a demand curve (a function of *NPV* and *t*) and diffusion. This specification involves an S-shaped demand curve, to allow for the eventual saturation of the market:

$$q_t = \frac{a_t q_{\max}}{a_t + (q_{\max} - a_t)e^{-bNPV_t}} + diff_t, \tag{3.1}$$

where a_t represents the demand curve parameter in year *t*, $diff_t$ the diffusion in year *t*, q_{max} is the maximum annual market size, NPV_t is the net present value, and *b* is a parameter. We chose this specification to capture the key drivers of solar demand and match historical evidence from solar installation data in California that demand has grown more than linearly with the NPV of a panel (This is shown more fully in Section 4, Figure 3). In Germany and Japan, although no such data are available, the growth of solar installations over time is consistent with this demand specification (IEA, 2007). Given the uncertainty involved in the specification of the demand curve, we perform a sensitivity analysis on the parameters *a* and *b* (Section 5).

The diffusion component suggests that the demand curve shifts outward over time as consumers learn about and gain confidence in residential PV technology. More specifically, it is modeled as a logistic growth function, with the following specification:

$$diff_t = \gamma q_{t-1}\left(1-\frac{q_{t-1}}{q_{\max}}\right), \tag{3.2}$$

where γ is a diffusion coefficient.

The demand curve parameter is adjusted each year by the amount of diffusion as follows:

$$a_t = a_{t-1}\left(\frac{q_{t-1}+diff_{t-1}}{q_{t-1}}\right). \tag{3.3}$$

This adjustment serves to incorporate the previous year's diffusion into the current year's "base demand" (the first term on the right-hand side of (3.1)).

Finally, a bottom-up engineering-based model is used to quantify the relationship between the subsidies and the NPV. More specifically, for each market we calculate the NPV of a "typical" system for a solar customer. The underlying premise is that investments in solar reduce the energy bill of consumers, resulting in a positive cash flow over the lifetime of the solar investment. Loan financing is assumed for solar investments,[2] and loan payments are partly offset by tax deductions of interest. The net cash flows resulting from the utility bill and tax savings combined with loan payments and maintenance costs are then used to calculate NPV. A subsidy policy reduces the initial installation costs, and thus directly increases the NPV of the investment.

3.2 Learning-by-Doing

Following the literature indicating global learning for module costs and local learning for BOS costs, we model each of these costs separately:

$$P_t = \alpha_M Q_{G,t-1}^{-\beta_M} + \alpha_{BOS} Q_{t-1}^{-\beta_{BOS}}, \tag{3.4}$$

[2] Many solar consumers do not take out loans specifically for solar, but often combine solar investments with refinancing of mortgages.

where P_t, the installation price per Watt of the PV system in year t, $Q_{G,t-1}$ is the global cumulative PV installations, Q_{t-1} is the cumulative PV installations in California, β_M and β_{BOS} are learning coefficients, and α_M and α_{BOS} are parameters. The number $2^{-\beta}$ is often referred to as the *progress ratio* of a LBD system. The progress ratio indicates the strength of the learning effect, and is defined as 1 - *LR*, where *LR* is the learning rate discussed in Section 1.

The cumulative installations in California (Q_{t-1}) are determined by consumer choice, as discussed above. The cumulative global installations ($Q_{G,t-1}$) are determined exogenously, through an assumed growth rate – effectively implying that module costs are exogenously determined.

3.3 Environmental Externalities

We incorporate benefits from the avoided cost of environmental externalities directly included in the objective function, as described in the next section. We recognize that the production of a solar panel requires some energy itself. The energy payback time of solar panels with current technology is estimated to be three years over a total lifetime of 30 years, and one year for anticipated technology (Alsema, 1998; Kato, et al., 1997; Palz and Zibetta, 1991). Thus, using estimates from the literature of the size of the environmental externalities may slightly overestimate the benefits of solar. However, we believe that this is well within the range of the uncertainty of the size of the environmental externalities.

3.4 Economic Efficiency as a Policy Goal

Subsidies increase the NPV for the consumer, resulting in increased demand and cumulative installed capacity Q_t. Increased installed capacity provides both environmental benefits and, through LBD, lower future prices and hence a higher NPV for the consumer. The model is designed to solve for the time path of subsidies that maximizes the present value of these environmental and consumer benefits minus the cost of the subsidies to the people of California. This dynamic optimization problem is summarized as

$$\underset{I_t}{MAX} \quad PVSB(I_t) = \sum_{t=1}^{T} \frac{\{Xq_t(I_t) + q_t(I_t)NPV_t(I_t, Q_t, e)\} - q_t(I_t)I_t}{(1+r)^t}, \tag{3.5}$$

where *PVSB* is the present value of net social benefits, I_t the incentive (i.e., subsidy) in year t, X is the environmental externality accrued over the lifetime of an installed Watt, $q_t(\cdot)$ the installed capacity (i.e., demand) in year t, Q_t the cumulative installed capacity in year t, $NPV(\cdot)$ the net present value to the consumer per installed Watt, e the electricity price growth rate, and r the discount rate.

The total benefits in a year t are proportional to the number of units installed in that year (q_t) and include the environmental benefits plus the consumer benefits. Environmental benefits are assumed to be a fixed value X per Watt. Consumer benefits are the sum of the net value transfer to all solar customers, expressed as the product of NPV_t and q_t. The cost to taxpayers is the total cost of the subsidies ($q_t I_t$).

Rather than netting out the subsidy value, we include the subsidy in NPV and as a cost. This approach allows costs to taxpayers to be scaled by a deadweight loss factor, depending on how the incentive costs are raised. In California, the plan would impose a surcharge on electricity to fund solar subsidies. If electricity were underpriced due to a negative externality, there could be a double dividend (Goulder and Schneider, 1997).[3] However, in the tiered rate schedule of electricity pricing in California, some consumers pay *more* than the marginal social cost, implying there is a deadweight loss. We assume there are no efficiency losses or gains due to a tax to raise the subsidy revenue.

4. MODEL IMPLICATIONS FOR CALIFORNIA SOLAR POLICY

This section discusses the parameterization of our model, and then addresses the following key questions: (1) is solar currently financially attractive for consumers, (2) how economically efficient is CSI and (3) what would the "optimal" policy look like?

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[3] Raising electricity taxes also effectively decreases real income for households and acts as an implicit factor tax, lessening the double dividend (Goulder, 1995).

4.1 Parameterization

4.1.1 Optimization Model Parameters

This section provides a brief overview of the most important parameters used as baseline estimates in our model. Table 1 presents a list. The economic values are stated in terms of nominal dollars, since the incentives are determined in nominal dollars.

Table 1. Baseline Parameter Values

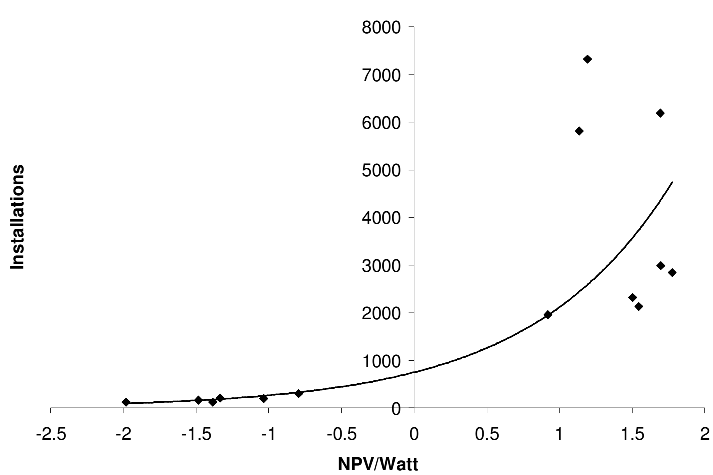
Parameter	Description	Value
X	Environmental externality benefit per installed Watt	\$0.015 per year
$2^{-\beta M}$	Progress ratio for modules	0.9
$2^{-\beta BOS}$	Progress ratio for balance of system	0.9
g_G	Long-term global solar growth rate	10%
a_{RR}	Demand curve parameter, residential retrofit	1,000
b_{RR}	Demand curve parameter, residential retrofit	1.04
$q_{max,RR}$	Maximum yearly number of installations (res. ret.)	200,000
a_{NC}	Demand curve parameter, new construction	212
b_{NC}	Demand curve parameter, new construction	1.04
$q_{max,NC}$	Maximum yearly number of installations (new cons.)	75,000
γ_{RR}	Diffusion parameter, residential retrofit	0.15
γ_{NC}	Diffusion parameter, new construction	0.15

An installed Watt of PV yields environmental benefits over its lifetime. These environmental benefits are estimated based on a \$50/ton carbon externality in 2006, which makes up 70% of the total environmental benefits, with the remainder including damages from NO_x, SO_2, PM-10, and Mercury (Gillingham, et al., 2006). We assume that the carbon price increases over time but that the carbon dioxide released per marginal kilowatt hour of electricity decreases correspondingly over time, so that the nominal dollar value of the environmental externality remains constant at its year 2006 value. This approximation allows us to use an annuity formula with a 30 years lifetime and a discount rate of 7% to estimate an environmental benefit of \$15 per kilowatt of new installed capacity (\$0.015 per Watt).

Historically, the progress ratio for solar PV has been approximately 0.8 (IEA, 2000; van der Zwaan and Rabl, 2004). The degree to which learning is appropriable and will continue into the future is highly uncertain, so for one estimate, we assume a progress ratio of 0.9 in the future, the highest (i.e., least learning) value typically observed in emerging technologies. Since we are testing the implications of LBD we vary LBD between 0.75 and 0.99 with the latter figure rendering LBD nearly insignificant.

We estimate the demand curve parameters in Table 1 by fitting an S-curve from equation (3.1) through historical data from the California Energy Commission (2006) of residential retrofit solar installations and the NPV per Watt that the consumer faced at the time of purchase (Figure 3). The NPV per Watt is calculated using historical subsidies and installation costs. The data represent relatively low numbers of installations per year, so the curve looks exponential. Our PV residential new construction demand curve is a scaled down version of this demand curve.

Figure 3. Yearly Installations of Residential PV Systems Versus NPV per Watt, and the Fitted Demand Curve



For purposes of simplicity, we base diffusion only on the number of solar customers in the previous year. To estimate a value for the diffusion coefficient, we shifted the above estimated demand curve such that it passes through the most recent data point (NPV/Watt, Installations) = (1.19, 7320). Over the data collection period of seven years, this implies a yearly diffusion of approximately 15% of last year's demand. Hence, we chose $\gamma = 0.15$. A sensitivity analysis of the effect of these estimates is performed in Section 6.

4.1.2 Parameters for NPV Calculation

To calculate the consumer NPV, we use technical data from Akeena Solar (2005). Table 2 lists the most important parameter values for the residential retrofit market. New construction is very similar, but with a smaller average system size.

Table 2. Parameter Values for the NPV Spreadsheet Model (Residential Retrofit)

Parameter (technical)	Value	Parameter (economic)	Value
Average system size	5,520 DC rated Watts	Discount rate	7%
2003 net installation price per DC rated Watt	$7.28	Residential borrowing rate	5%
kWh savings per year	7,176	Marginal tax rate	32%
Inverter replacement cost	$3,600	Loan term	30 years
Maintenance cost per year	$10		
Time-of-use (TOU) factor	1.25		
Panel expected life	30 years		
Inverter expected life	10 years		

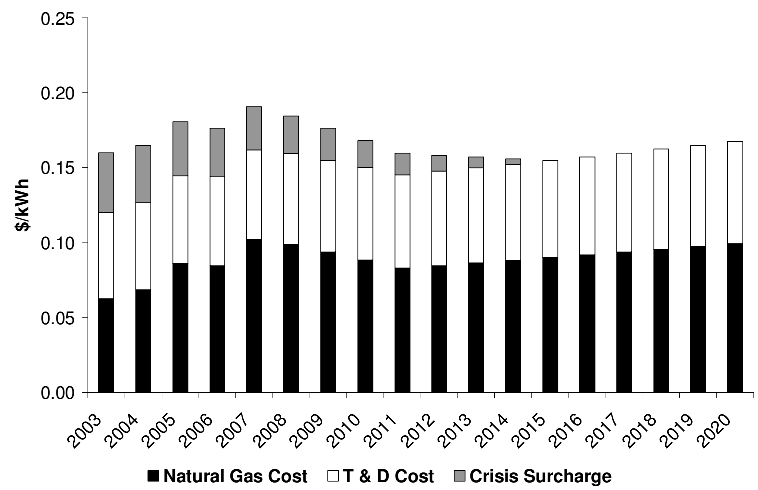
The TOU factor is included because solar systems produce much of their output during peak electricity-usage hours when the retail electricity price is higher, and sell their excess output back to the grid through net-metering.[4] This implies about 25% higher electricity bill savings (Borenstein, 2005).

An important input into model is the growth rate of nominal electricity prices, which directly influence the financial attractiveness of solar energy. The highly uncertain

[4] Net metering is a system in which the module owner receives retail credit for at least a portion of the electricity they generate.

future electricity price has three components: natural gas fuel cost, transmission and distribution costs, and a historical surcharge due to the California electricity crisis. Gas prices until 2011 are based on NYMEX futures and grow at 3% per year afterwards (NYMEX, 2006). We assume the transmission and distribution costs increase at 1% per year and that the historical surcharges are paid off linearly over 10 years. Figure 4 shows the assumed baseline evolution of the average electricity price out to 2020.

Figure 4. Projected Nominal Average Electricity Prices for Highest Rate Tier, with Linearly Decreasing Surcharges and 3% Natural Gas Price Growth After 2011



4.2 Current Financial Attractiveness of Solar

With the above parameterization, we examine the financial attractiveness of solar in 2006 using the initial subsidy levels of the CSI: a $2.50 Watt rebate and a 7.5% solar tax credit for PV systems (Table 3). In addition, there is a third implicit federal subsidy for solar, assuming that solar panel owners finance their systems with a loan and make use of the federal tax deduction for home improvements.

Table 3. Summary of Financial Attractiveness of Solar Systems to Consumers

Market Segment	Price ($000)	Incentive ($000)	NPV no inc. ($000)	NPV with inc. ($000)	NPV/Watt with inc. ($)
PV Res Retrofit	36.9	14.3	-7.7	1.6	0.35
PV Res New	12.5	5.3	-2.1	1.4	0.78

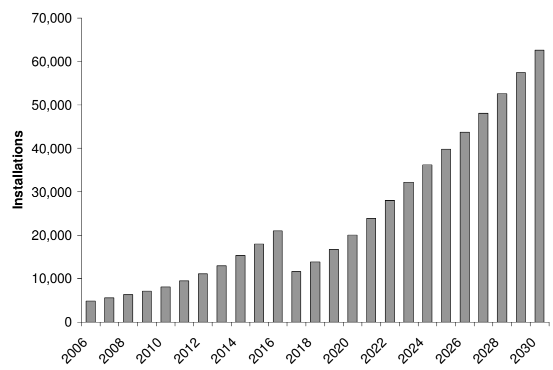
Residential PV systems have a negative NPV prior to the CSI incentives, and a slightly positive one afterwards. The size of the incentive exceeds the difference between the NPV with and without incentives because the home improvement tax deduction is larger for higher loans.

4.3 Economic Efficiency of CSI

Given the CSI incentives (Figure 2) and our baseline assumptions, including a 0.9 progress ratio, the model calculates that 145,700 PV residential retrofit solar systems are installed by 2018, representing 804 MW of capacity.[5] When combined with PV residential new construction, this implies 215,100 residential PV systems by 2018, much less than the original policy aim of one million.[6] Figure 5 presents the time path of all PV residential retrofit installations under CSI as well as the system installation costs. The LBD reduces the cost of installation over time. The price of a 5,520 Watt system equals $36,900 in 2006 and decreases to $28,100 by 2018 (decreasing further to $23,400 by 2030).

[5] Only 28,800 PV residential retrofit systems are installed if there are zero incentives.
[6] Note the original goal of one million solar systems by 2018 also included solar from other solar market segments, although cursory investigation suggests it is unlikely that the other market segments would provide nearly 0. 8 million systems without additional significant incentives

Figure 5. Total Yearly PV Residential Retrofit Installations (Left) and the Associated Installation Cost for New Systems under CSI (Right)



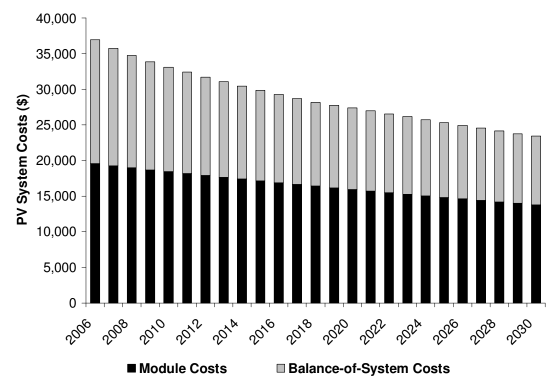


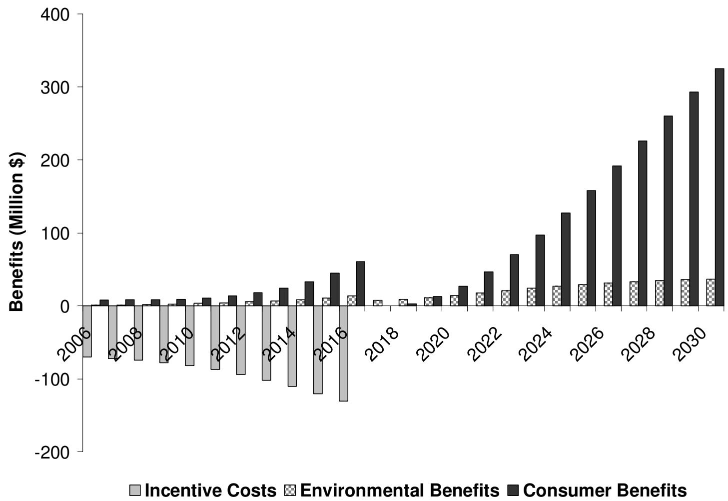
Figure 5 indicates that under our baseline assumptions, CSI is successful at fostering a self-sufficient residential PV market, albeit with a period of decline from 2017 - 2020 after the last incentives expire.

We define the "present discounted value of CSI" (*PDV*) as the difference between the present value of net social benefits of solar installations (3.5) *with* the incentives (I_{CSI}) minus the PDV of net benefits *without* any incentives (a no policy case):

$$PDV = PVSB\left(I_{CSI}\right) - PVSB\left(0\right) \tag{4.1}$$

The PDV of CSI for residential retrofit turns out to be positive and quite significant— about $1.3 billion. Residential new construction adds another $0.3 billion to the PDV of net benefits. Figure 6 illustrates the PV residential retrofit undiscounted costs and benefits of CSI over time (relative to the no policy case).

Figure 6. Costs and Benefits of CSI for PV Residential Retrofit



These results allow us to quantify the two externalities. The PDV of CSI for residential retrofit ($1.3 billion) can be split up into the PDV of additional environmental benefits ($0.2 billion), the PDV of additional consumer benefits due to LBD ($1.7 billion) and the PDV of incentive cost ($0.6 billion).[7] This suggests that with a progress ratio of 0.9 the environmental externality is only about 10% the size of the LBD externality, an important result indicating that the primary motivation for solar subsidies depends on assumptions about LBD, rather than environmental externalities.

This is underscored by the fact that the bulk of the benefits of the policy would occur many years after the costs of the incentive have been paid, and are predominately due to LBD raising the NPV of solar investments in these later years (consumer benefits). The discounted benefits level off around 2030, and soon afterwards decline.

We conclude that, given our baseline assumptions, CSI has a positive net benefit and appears to be an economic efficiency-improving policy.

[7] Adding in new construction brings the total cost of the CSI to just under $1 billion.

4.4 Optimal Solar Policy

Table 4 below presents the time path of incentives that maximizes net benefits and compares it to CSI under our baseline assumptions.[8]

Table 4. Optimal and CSI Incentives

Year	Optimal	CSI	Year	Optimal	CSI
2006	$3.23	$3.10	2012	$1.82	$1.85
2007	$2.96	$2.83	2013	$1.58	$1.70
2008	$2.74	$2.59	2014	$1.34	$1.57
2009	$2.52	$2.37	2015	$1.09	$1.46
2010	$2.30	$2.18	2016	$0.78	$1.35
2011	$2.06	$2.00	**Average**	$2.04	$2.09

Under our baseline assumptions, the two time paths of incentives are remarkably similar, with the optimal path being somewhat steeper. This is underscored by a nearly identical average of the incentives over the eleven years. Thus, it is not surprising CSI and the optimal subsidy lead to similar numbers of cumulative installations by 2018 (Table 5).

Table 5. Installations in 2018 for CSI, Optimal Policy and No Policy

	Systems in 2018, CSI	MW	Systems in 2018, Optimal Policy	MW	Systems in 2018, No Policy	MW
PV Res Retrofit	145,700	804	141,000	778	28,800	159
PV Res New	69,400	146	80,500	169	3,700	20
Total	215,100	950	221,500	947	32,500	179

Given similar incentives and installations, the total incentive cost of CSI subsidy ($1.2 billion) and the optimal policy ($1.1 billion) are also quite similar. Moreover, the

[8] We show results for the PV residential retrofit market because it is the largest market that is being promoted in the CSI. We allow the incentives in the new construction segment to be different from residential retrofit, However, in the optimal solution, incentives for new construction are very similar to incentives for retrofit.

time path of installations in the optimal subsidy is relatively close to that of CSI and is difficult to differentiate from Figure 5. The only notable difference between the time path of installations with the optimal subsidies and CSI is that the drop off in incentives in 2017 is lessened, due to the smoother phasing out of incentives.

Thus, under our baseline assumptions, including a progress ratio of 0.9, CSI is remarkably close to the economic efficiency-optimizing policy. The total installations in 2018 would still fall short of the initial goal of one million solar homes, without considerable contributions from other solar market segments.[9] Nevertheless, under these assumptions it appears there is an economic rationale for solar subsidies in California.

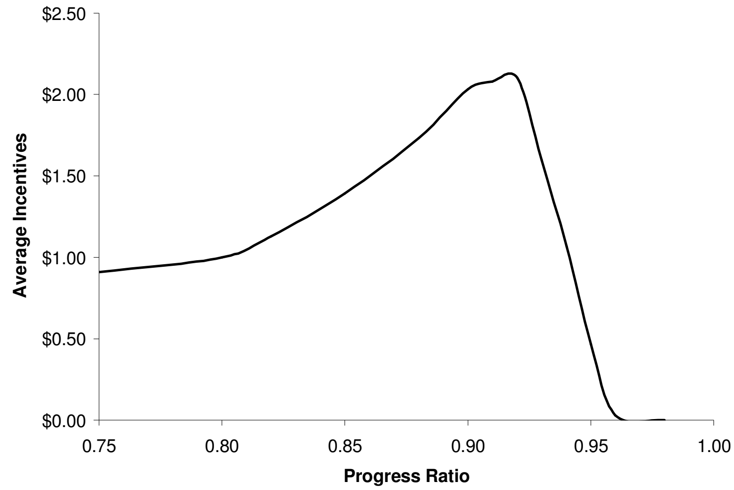
5. SENSITIVITY ANALYSIS OF THE OPTIMAL POLICY

A critical question is how *robust* this optimal policy (or CSI) is to different sets of assumptions, i.e., is the optimal policy still optimal if LBD is small or other assumptions are varied. Since the model is based on LBD-induced technological change, we first examine different assumptions about the progress ratio. The analysis above is based on a progress ratio of 0.9, which implies significant LBD (although less LBD than implied by the 0.8 value often used in the literature). Figure 7 shows that the average optimal residential retrofit incentives[10] vary between $1 and $2/Watt under reasonable assumptions of long-term LBD in the range of 0.75 to just over 0.92. Average incentives are increasing with the progress ratio over this range because increasing LBD allows the solar market to become self-sufficient with less government intervention. However, if we assume very little LBD (e.g., a progress ratio much over 0.95), installations induced by government incentives have little effect on the long-run cost of solar systems. Thus the optimal policy involves very small incentives for solar – indicating that CSI could not be justified on efficiency grounds.

[9] Interestingly enough, if we maximize the number of systems in 2018 subject to the constraint that the cumulative net benefits of the policy (until 2060) are greater than zero, we can achieve just over 725,000 residential retrofit systems by 2018.

[10] The results in the sensitivity analysis are analogous for new construction.

Figure 7. Average Incentives as a Function of the Progress Ratio, Holding All Other Parameters Constant



In addition to the LBD progress ratio, we also vary the values of other key parameters (Table 6). We vary each parameter individually, while keeping all other parameters at their baseline values.

Table 6. Average Optimal Incentives with Different Parameters

Discount rate	0.05	0.07	0.09
Average incentives ($)	*2.05*	*2.04*	*1.84*
Residential borrowing rate	0.03	0.05	0.07
Average incentives ($)	*0.99*	*2.04*	*2.72*
Natural gas price growth rate	0.01	0.03	0.05
Average incentives ($)	*0.00*	*2.04*	*1.16*
Diffusion coefficient	0.10	0.15	0.20
Average incentives ($)	*2.16*	*2.04*	*1.84*
Demand curve a parameter	500	1,000	1,500
Average incentives ($)	*2.23*	*2.04*	*1.89*
Demand curve b parameter	0.52	1.04	1.56
Average incentives ($)	*2.17*	*2.04*	*1.90*
Maximum annual market size	100,000	200,000	300,000
Average incentives ($)	*1.81*	*2.04*	*2.16*

An examination of Table 6 indicates that if we assume a LBD progress ratio of 0.9, the optimal policy appears to be relatively robust to nearly all of the other key parameters we examined. Of course, with different values of these other parameters, we find considerable differences in the PDV of the net benefits of the policy ($1.3 billion in the baseline optimal case). For example, raising the discount rate to 9% reduces the PDV of the policy to $0.3 billion, while a lower discount rate of 5% increases the PDV of the policy substantially to $4.1 billion. Still, the most important conclusion is that if we believe in LBD at a level around 0.9, in most cases the optimal incentives remain relatively close to those of CSI.

However, the optimal policy is the *least* robust to the natural gas price growth rate and, to a lesser degree, the residential borrowing rate. The natural gas price growth rate is one of the most uncertain parameters in the model, and it also appears have the most influence on the final results – far more even than the assumption about LBD. Our central estimate of 3% is derived from natural gas futures prices, but estimates ranging from 1% to 5% can all be considered within a reasonable range.

Low natural gas prices imply low electricity prices, lowering the energy bill savings, and correspondingly, the NPV of the solar installation. Thus, solar PV would be sufficiently unattractive as an investment that incentives would induce few new solar customers although there would still be some rebate costs. The baseline policy has a negative PDV of net benefits (-$0.2 billion), and the optimal time path has *zero* incentives. With high growth in gas prices, the optimal policy is not successful at inducing as many *additional* solar systems, so the average optimal incentives are lower than the baseline result. However, the PDV of the baseline optimal policy ($1.3 billion) does not change much with much higher natural gas prices. Thus while the baseline optimal policy may not be optimal under different values of the natural gas price growth rate from our baseline, it is still *efficiency-improving* under a relatively wide range of natural gas price growth rates.

The residential borrowing rate has varied in the recent past from 3% to 7%, depending on how consumers finance their purchase (Cinnamon, 2005). With low residential borrowing rates, solar becomes very financially attractive, both with and without a policy. Thus, the policy is not as effective at inducing *additional* solar installations above the no policy case, and the optimal incentives are lower. With high residential borrowing rates (up to a certain point), the policy is more critical for inducing additional solar installations. In both cases the baseline optimal policy is still *efficiency-improving*.

One final assumption worth noting is the time horizon of the model. We find that the optimal incentives are quite robust to extending the time frame significantly beyond 2060, for discounting implies that the net benefits from the policy after 2060 are negligible.

6. CONCLUSION

This paper develops an inter-temporal model that solves for the optimal solar subsidy policy in California. The policy internalizes externalities from avoided carbon emissions and firms' unappropriated LBD benefits in BOS costs. Under our baseline assumptions, including nonappropriable learning, we estimate that the optimal subsidies lead to a substantial increase in economic efficiency, here estimated as $1.6 billion. Interestingly, only a small fraction of the policy benefits can be allocated to environmental benefits. The majority of the benefits can be attributed to a correction of the LBD externality.

The baseline results suggests that subsidies should start out above $3 per installed Watt and drop down to $0 in 2017, a subsidy schedule very similar in magnitude to the CSI. These subsidies will lead to a self-sufficient market and approximately 200,000 residential solar systems in 2018 if natural gas prices grow as we have assumed. This amount is much less than the one million envisaged by some politicians. Still, the advantages (export, energy security, consumer benefits) of having a self-sufficient solar market at the end of the next decade are potentially high, and should be of interest to California's policy-makers.

These results are robust to most key parameters. However, large differences in the natural gas growth and residential borrowing rates would lead to an optimal policy quite different from the CSI – in most cases lower than the CSI. In addition, we find that the results do hinge on there being nonappropriable learning in the BOS cost of residential solar systems. If LBD at even modest rates accurately describes the future cost changes, then the CSI is near optimal. Over a broad range of assumed LBD, the average optimal incentives are increasing with less LBD, but when we assume very little LBD, the average optimal incentive declines sharply. If LBD is insignificant, then the CSI over-subsidizes solar relative to the social optimum and could not be justified based on environmental benefits only.

This result points to the importance of the nature of technological change in modeling solar policy. Future work to elucidate the origins of technological change in the renewable energy industries would greatly enhance our ability to accurately evaluate the economic efficiency of California's solar policy, as well as national renewable energy policy in general.

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