Demand subsidies versus R&D:

Comparing the uncertain impacts of policy on a pre-commercial low-carbon energy technology

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Abstract

We combine an expert elicitation and a bottom-up manufacturing cost model to compare the effects of R&D and demand subsidies. We model their effects on the future costs of a low-carbon energy technology that is not currently commercially available, purely organic photovoltaics (PV). We find that: (1) successful R&D enables PV to achieve a cost target of 4c/kWh, (2) the cost of PV does not reach the target when only subsidies, and not R&D, are implemented, and (3) production-related effects on technological advance—learning-by-doing and economies of scale—are not as critical to the long-term potential for cost reduction in organic PV than is the investment in and success of R&D. These results are insensitive to two levels of policy intensity, the level of a carbon price, the availability of storage technology, and uncertainty in the main parameters used in the model. However, a case can still be made for subsidies: comparisons of stochastic dominance show that subsidies provide a hedge against failure in the R&D program.

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1 Introduction

Meaningfully addressing the problem of global climate change, while affordably meeting the world's growing demand for energy, will require the deployment of several terawatts of low-carbon energy generation technologies over the next several decades. The scale of the changes required imply that the societal consequences of the associated policy decisions are likely to be pervasive—and mistakes costly. Decisions involving energy technology policy, and more specifically, policies intended to accelerate the development and deployment of low-carbon energy technologies, lie at the center of climate policy debates. The existence of multiple market failures implies that private actors will under-invest in climate change-related technology improvements, even if measures that internalize environmental externalities are successfully implemented (Jaffe et al., 2005). As a result, policy makers must consider a variety of interventions that have the potential to stimulate improvements in, and adoption of, low-carbon energy technologies.

Integrated assessment models of climate change have shown that assumptions about technical change may be the most important driver of the costs of addressing climate change (Sue Wing, 2006; Popp, 2006; Edenhofer et al., 2006). Moreover, attempts to determine optimal policy design result in vastly different normative conclusions depending on assumptions about the expected rate of technical change and the extent to which government actions can affect that process. Ongoing debates reveal wide disagreement over the anticipated efficacy of various government policies for inducing welfare-increasing technical change. A notable division has emerged between those who emphasize the need for "technology push" policies, such as R&D investment (Hoffert et al., 2002; Nemet and Kammen, 2007; Prins and Rayner, 2007), and those who support mainly "demand pull" policies, such as a carbon price or an adoption subsidy (O'Neill et al., 2003; Pacala and Socolow, 2004; Yang and Oppenheimer, 2007). This distinction is echoed in the integrated assessment literature, with some analysts modeling endogenous technical change as resulting primarily as a result of learning-by-doing (Grubb, 1996; Manne and Richels, 2004), while others model it as predominantly a function of R&D (Goulder and Schneider, 1999; Popp, 2004, 2006).[3]

The literature on the economics of innovation makes clear that *both* R&D and demand side support are needed: demand-pull and technology-push are "necessary, but not sufficient, for innovation to result;

[3]For surveys of the literature that discuss this distinction see: Clarke, Weyant and Birky (2006); Clarke et al. (2008); Clarke and Weyant (2002); Gillingham et al. (2007); Grubb et al. (2002); Jaffe et al. (2002); Loschel (2004); and Sue Wing (2006).

both must exist simultaneously" (Mowery and Rosenberg, 1979). Successful innovations show the ability to connect, or "couple" a technical opportunity with a market opportunity (Freeman, 1974). An important observation for this study is that technology push dominates the early-stages of the innovation process, while demand pull is more important in the later stages (Freeman and Perez, 1988; Dosi, 1988) Studies of the effectiveness of technology policy specifically for energy reach a similar consensus that both are needed (Grübler et al., 1999; Norberg-Bohm, 1999; Requate, 2005; Horbach, 2007). The well-established claim that both are needed provides only limited normative guidance on the *allocation* of public funds between the two broad categories of support.

Attempts to econometrically identify the effects of demand-pull and technology-push, e.g. Kouvaritakis et al. (2000); Watanabe et al. (2000); Miketa and Schrattenholzer (2004); Klaassen et al. (2005), have so far provided limited claims because of their sensitivity to assumptions about the depreciation of R&D as a knowledge stock and about the lags between policy signals and decisions to innovate; both of these parameters have proven difficult to estimate empirically. Using the observation that most technologies tend to decline in cost over time, the notion of the "experience curve" has been widely used to simulate the cost reductions that can be expected from programs that subsidize demand (Duke and Kammen, 1999; Wene, 2000; IEA, 2008). However, observed discontinuities in learning rates, perhaps resulting from omitted variable bias, limit their reliability. We make use of a methodology that shows that bottom-up cost models provide an alternative means to model the interaction between demand and cost reductions (Nemet, 2006).

The relationship between R&D investments and technical change is even more difficult to model in part due to the inherent stochasticity of the R&D process. In such cases, common to R&D management, decision analytic techniques are often used to obtain the necessarily subjective judgment of experts who are most familiar with the specific technologies (Peerenboom et al., 1989; Sharpe and Keelin, 1998; Clemen and Kwit, 2001). A report by the National Research Council (2007) recommends that the U.S. Dept. of Energy adopt a process including expert elicitations; and they provided prototype elicitations for carbon sequestration, vehicle technologies program, and four other programs. We will draw on the results of Baker et al. (Forthcoming), who have performed expert elicitations on solar photovoltaic technologies with respect to climate change.

In this paper we combine expert elicitations with a bottom-up manufacturing cost model to simulate the cost reductions that result from R&D and demand subsidies for organic PV. In addition, we consider the effects of carbon prices, the availability of supporting technologies, and alternative assumptions about model parameters. We first discuss the role that technology policy may play in reducing the cost of PV so that it can play a meaningful role in addressing climate change. In Section 3, we describe a model used to evaluate the impacts of demand subsidies and R&D. Section 4 reports the results of simulations of policy interventions, including a sensitivity analysis. In Section 5 we consider the risk tradeoffs between the policy types and conclude in Section 6 with initial policy implications and research directions.

2 Climate change, photovoltaics and technology policy

Low-carbon energy technologies, such as solar photovoltaics, will need to be much less expensive if they are to make a meaningful contribution to reducing greenhouse gas emissions. Policy choices will almost certainly affect this outcome.

2.1 Organic solar PV

Among the wide range of technologies that offer means to address climate change—including nuclear fission, carbon capture and sequestration (CCS), efficiency improvements, and renewables—solar is particularly appealing because it consumes no fuel, has near-zero operations and maintenance costs, and accesses a massive resource; more energy from sunlight hits the earth in one hour than annual human consumption (Lewis, 2007). Additionally, full-life cycle accounting and ecological concerns are modest, especially relative to those of biofuels, CCS, and nuclear (Fthenakis et al., 2008). Solar photovoltaic (PV) cells use semiconductor materials that convert sunlight directly into electricity by transferring the energy of the light to electrons in the cell. While PV's current contribution to energy supply is trivial, it is of interest because costs have come down rapidly. Still, PV is far from being cost competitive in non-niche electricity markets and requires substantial future cost reductions for it to be affordably employed on a large scale.

Purely organic PV, which is the focus of this paper, is particularly intriguing because of characteristics that distinguish it from the current generation of PV, which consists of cells made from crystallized silicon. Purely organic PVs use a thin film of organic semi-conductor material for photon conversion. Because they don't require a glass substrate, organic PV cells can be manufactured on highly flexible material, leaving open the possibility of a much wider ranges of applications. These manufacturing techniques are more amenable to automation and high throughput because they involve chemical rather than mechanical production processes. That they also require only a thin layer of light-absorbing photovoltaic material, rather than a crystal structure, means that the amount of input materials needed is very low. The combination of highly automated "reel-to-reel" manufacturing processes and small materials consumption gives organic PV its most appealing distinguishing characteristics—the potential for very low manufacturing costs (Brabec, 2004). However, organic PVs are not currently manufactured on a commercial scale. Moreover, the current models have very low efficiency, with the highest being around 5% in laboratory conditions (Ginley, 2007); this compares to about 15% efficiency for silicon-based solar cells. Finally, organic materials are susceptible to degradation in sunlight, leading to concerns about the lifetimes of these cells.

How inexpensive does PV need to become? The residential PV industry focuses on reaching an electricity cost that that is competitive with retail electricity prices, around 10–15 cents/kWh (SEIA, 2004). Indeed, making PV competitive with retail electricity would create a massive market opportunity for the industry, perhaps in the hundreds of billions of dollars. However, in order to make a significant impact on climate change, solar will need to be deployed at a larger scale still, on the order of multiple terawatts of capacity. This magnitude of demand for PV, combined with urbanization of the world's population, mean that local solar radiation will be insufficient for on-site generation. The resulting need for transmission means that PV will need to compete with wholesale prices. And even if carbon constraints raise prices for fossil fuel generated electricity, PV will still need to compete with the expected wholesale price of nuclear power, 4 to 6 cents/kWh (Deutch et al., 2003). To be conservative, we use 4 c/kWh as our target price for large scale PV.

2.2 Policy choices and cost reductions

The availability of a diverse set of low-carbon technologies with costs around this level will depend to a large extent on policy decisions. The literature on technology policy frequently distinguishes between "demand pull" instruments—government actions that stimulate innovation by enlarging the market opportunity for new technologies—and "technology push," those that reduce the cost of innovation by increasing the supply of new knowledge (Nemet, 2008). Examples of demand pull instruments include intellectual property regulation, pollution taxes (such as a carbon price), and subsidies for demand. Technology push includes government-sponsored R&D, tax credits for R&D by private firms, and support for education.

In this case of organic PV, policy can impact future cost in multiple ways. First, technology-push policies, such as direct government-sponsored R&D, can increase the likelihood of achieving technical breakthroughs. Our model assumes that government R&D has an impact on two technical characteristics of organic solar cells: (1) their electrical conversion efficiency, and (2) their lifetime. Second, demand-pull policies, such as demand subsidies, increase demand for organic PV and thus create opportunities for cost reductions through economies of scale and learning by doing. Our model focuses on these two avenues of technical change. We note, however, another potential impact: demand-pull policies may stimulate private sector R&D through the promise of a larger, less risky market. We do not include this effect directly; the focus of our results is on a comparison of the effects of policy on technical and production improvements.

In our model, we consider the effects of two demand-pull instruments: demand subsidies and carbon prices. We model subsidies as a decision variable and treat carbon prices as an exogenous sensitivity. [4] In order to assess the effectiveness with which technology policy can induce technical change in organic PV, we need to determine how the specific policies—investment in R&D and demand subsidies—affect technology improvements. We draw on our prior work to identify and model the effects of these two policy instruments.

2.3 Combining expert elicitations and a cost model

As part of a larger project covering a number of technologies, Baker et al. (Forthcoming) performed expert elicitations on solar PVs to determine the relationship between R&D investment and technical change. They interviewed scientists and engineers with expertise on solar technology. In conjunction with the experts they defined success endpoints for each technology and funding trajectories for each project. For purely organic solar cells, success was defined in terms of efficiency, lifetime, and manufacturing cost per m^2. They then elicited probabilities of success from the experts, along with rationales for the probabilities. In these elicitations, and in others that were part of the same group (including nuclear, carbon capture, and bio-electricity), there was often a large dispersion among experts' probabilities of achieving low costs. For

[4] The reason for the focus on subsidies as the primary demand-pull decision variable in this model is that they can be designed to exclusively support organic PV, whereas carbon prices enhance demand for low-carbon technologies in general.

example, one expert reported the probability of achieving a manufacturing cost of $\$50/m^2$ as 81%, another reported it as 2.5%. The rationale for most of the low probabilities for achieving the cost endpoints was that cost reduction is a manufacturing-driven issue and that achieving desirable production costs will require much work beyond government-funded lab research. One of the experts noted "Manufacturing costs will require a significant amount of development which is much more expensive than basic research and I do not believe that $15M/year would be sufficient to meet this cost target with any reasonable probability."[5] The optimistic expert indicated that he believed that, given the right technology, the private sector was likely to get costs down to a competitive level. This wide disagreement over cost, relative to the disagreement over efficiencies, has been observed in other PV elicitation work (Curtright et al., 2007). In general, it may not be appropriate to ask scientific experts to assess the likelihood of achieving particular cost targets, since much depends on aspects outside the realm of scientific discovery, such as manufacturing processes and market demand. As a result, for the current study we use the elicitations of technical probabilities but do not use those of future manufacturing costs and instead use a cost model.

To characterize the relationship between demand and manufacturing cost, we draw on the methodology of Nemet (2006), who assembled empirical data to populate a simple engineering-based model identifying the most important factors affecting the cost of PV over the past three decades. That study found that three factors account for almost all of the observed cost reductions: (1) a two orders of magnitude increase in the size of manufacturing facilities that provided opportunities for economies of scale, (2) a doubling in the electrical conversion efficiency of commercial modules, and (3) a fall in the price of the primary input material, purified silicon. We thus model manufacturing costs as a function of economies of scale; we use the expert elicitations to model efficiency improvements; and we treat materials costs as a key sensitivity.

We developed the following methodology taking the perspective that the combination of expert elicitation with a bottom-up manufacturing cost model provides a promising avenue for more robustly understanding future technology costs. Figure 1 is a diagram representing the relationship between R&D investment and demand subsidies to the cost of electricity. In our model R&D has a stochastic impact on the efficiency and the lifetime of the solar cells. We model adoption subsidies as having an impact on cost by enabling economies of scale through increasing demand. The solid lines represent deterministic relationships; the

[5]From Baker et al. (Forthcoming).

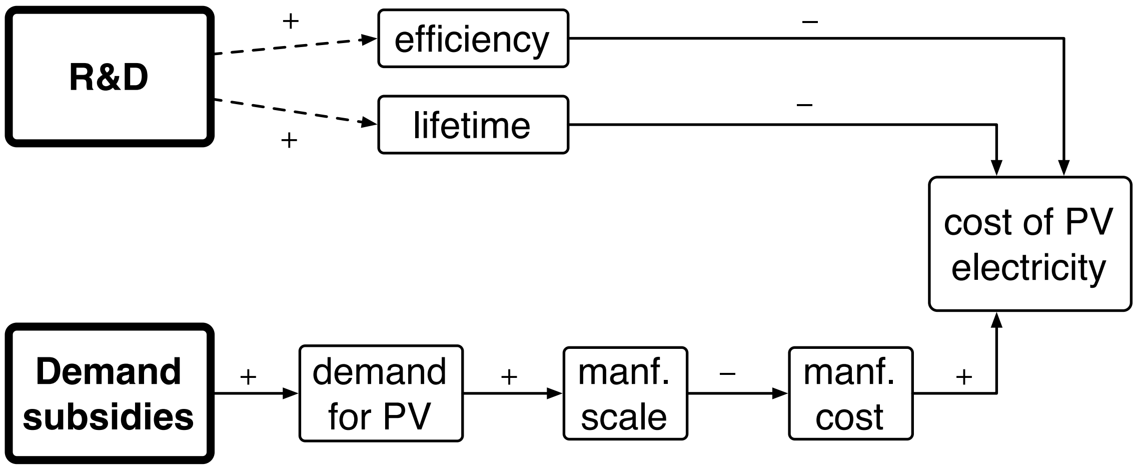

Figure 1: Influences on cost of PV electricity. Signs (+ and −) represent direction of relationship.

dashed lines represent uncertain relationships; the positive and negative signs represent the direction of the relationship; and the bold-faced nodes represent decisions. We use this schema to evaluate the uncertain impact of combinations of R&D investments and subsides on the the cost of electricity over time. The central question of this paper is how R&D investment policies interact with demand subsidy policies to impact the cost of electricity from PV.

3 A model of the effects of subsidies and R&D on PV costs

This section describes how we modeled the future cost of PV. First, we discuss the components of manufacturing cost for organic PV, including discussion of which components may decline with increasing scale and how we calculate the cost of electricity from PV. Second, we describe how we estimated future demand for PV and how changes in demand affect the components of manufacturing cost. Third, we provide details about how we simulated subsidies and, fourth, discuss the impacts of R&D.

3.1 Cost of electricity from PV

The objectives of this section are to quantify the components of cost for producing electricity from organic PV, and to identify the factors influencing these components so that costs can be dynamically modeled. For the former, we draw on detailed engineering-based studies of manufacturing costs, which we describe below.

To identify the influences, we use the results of a bottom-up model developed by Nemet (2006) to estimate how changes in the components of the PV manufacturing process have affected the cost of PV modules over time. A useful result for the current study is that certain components of cost improved with R&D investment, while others responded to increased deployment of the technology. In the case of crystalline silicon PV, almost all of the cost reductions observed over two decades are attributable to three factors, which responded to distinct influences: (1) the doubling in electrical efficiency resulted from investments in R&D, (2) economies of scale in manufacturing were driven by increased expectations about future demand, and (3) the decline in the costs of input materials, primarily purified silicon, was an exogenous spillover benefit from the information technology industry. We apply this identification of influences on PV costs to the current study and categorize changes in each of the cost components as a result of R&D, manufacturing scale, or exogenous. A central assumption in our model is that manufacturing and balance of system costs decrease with scale, and cell efficiency and lifetime increase (stochastically) with R&D. In the rest of section 3.1 we describe the levels of these components for organic PV and describe a simple cost model that we use to estimate the levelized cost of electricity from organic photovoltaics.

3.1.1 Manufacturing costs

This section uses the results of an analysis by Kalowekamo and Baker (2009) of the estimated costs of manufacturing purely organic PVs. Within this description we discuss which of the factors are likely to change with increases in manufacturing scale, drawing on that study as well as work on thin-film PV manufacturing (Maycock, 2003; Keshner and Arya, 2004). Table 1 summarizes the cost structure we use in our model.

Materials costs In our base case, costs for materials decline through economies of scale in production and through learning-by-doing, which enables the use of less input material per unit of output (Keshner and Arya, 2004). We also assess, in a sensitivity analysis, the case in which materials costs are static, perhaps

Table 1: Components of base case manufacturing cost and relationship between unit cost and output. Values for costs are from Kalowekamo and Baker (2009) and values for b are discussed in section 3.2.3.

Cost component	Costs ($/m^2)	Portion of total	Unit cost f(output)	b value
Materials	28.15	37%	Declining	0.2
Processes (labor costs)	8.00	11%	Declining	0.2
Processes (capital costs)	23.50	31%	Declining	0.2
Overhead (fixed)	8.18	11%	Declining	0.2
Overhead (variable)	8.18	11%	Static	0
Total	76.00			

due to scarcity offsetting scale and learning by doing.

Process costs We divide process costs into their labor and capital components and assume in our base case that both labor and capital decrease with scale, per unit of output. Labor productivity increases with scale both as a result of learning by doing (Arrow, 1962) and because higher output justifies investment in new specialized machinery that allows the substitution of capital for labor (Neuhoff et al., 2007). In addition to specialization, capital productivity improves with scale because each of the steps involved in manufacturing—substrate preparation, screen printing, vacuum evaporation, encapsulation, electrical interconnection—either exists as, or is analogous to, an industrial process that exhibits economies of scale properties. We include sensitivity analysis of the case in which these costs do not fall with scale.

Overhead costs A portion of overhead costs—rent, electricity, water, machinery maintenance, and product warranties—include fixed costs, which can be dispersed over a larger output. In addition, warranties will become less expensive as reliability improves. On the other hand, some of these costs, such as water and electricity use, are variable, providing minimal per unit savings from larger production (Fthenakis and Alsema, 2006). We assume that half of these overhead costs are fixed and half are variable, and apply a scaling factor only to the former.

Table 2: Base case values for calculating levelized electricity cost

Variable	Symbol	Baseline value (2020)	Treatment in Model	Drivers of change
Manufacturing cost	M	\$76/m^2	dynamic	Manf. scale
Yield	Y	95%	static	—
BOS cost	BOS	\$75/m^2	dynamic	Manf. scale
Efficiency	η	5%	dynamic	R&D
Peak solar radiation	S	878W/m^2	static	—
Cost at peak	C_p	\$3.53/W$_p$	dynamic	M, BOS, η
Mean solar radiation	I	4.4kWh/m^2/day	static	—
Capacity factor	F	18.3%	static	—
Lifetime	L	5 years	dynamic	R&D
Discount rate	δ	7%	static	—
O&M	OM	\$0/kWh	static	—
Levelized elec. cost	C	\$0.54/kWh	dynamic	C_p, L

3.1.2 Balance of Systems Costs

Balance of systems (BOS) costs include all of the labor and capital necessary for a PV system to produce electricity in addition to the PV panels themselves. With current technology, these costs include inverters to convert direct current to alternating current, as well as the rooftop mounting equipment, wiring, and labor involved with installing systems. Historically, the costs of inverters have declined with scale in production, although installation costs have not (Schaeffer et al., 2004; Hegedus and Okubo, 2005). In this case, we assume that total BOS costs decline with scale. The shift toward building-integrated installations and the possibility of large generating facilities, both of which obviate the need for custom installation, make large reductions in BOS costs feasible. We analyze the sensitivity of the model to the case in which these reductions are limited.

3.1.3 Levelized electricity cost

To compete in the market place, PV will need to have a levelized cost of electricity (LEC), in \$/kWh, comparable to competing means of electricity generation. Here, we calculate LEC as a function of manufacturing and BOS costs, technical characteristics of the devices (lifetimes and efficiencies), and incoming solar radiation. We provide an example using our base case and list the values in Table 2.

We begin with a panel manufacturing cost (M) of \$76 per square meter and a yield (Y) of 95%, resulting in a cost per usable device of \$80/m^2. Adding \$75/m^2 for BOS costs results in a total cost per area of \$155/m^2. Next, we make assumptions about incoming solar radiation, both at peak and on average. Based on observations from seven large urban areas around the world, we use a value for peak incoming solar radiation (S) of 878 W/m^2 (Nemet, 2007). At this level of sunlight, a PV device with 5% efficiency (η) produces 44 W/m^2. Dividing this areal cost by the peak power generated per square meter gives \$3.53 per peak watt of power output (C_p):

$$C_p = \frac{\frac{M}{Y} + BOS}{S \cdot \eta} \tag{1}$$

Costs are sensitive to the solar resource at the location installed; the full range of values for S from the work cited above produces a range of costs of \$2.80–4.98/W.

We apply a capacity factor of 18.3% to take into account that PV cells only operate at a fraction of peak power when averaged over the course of a year, due to the diurnal cycle, seasonal variation in sun angle, and cloud cover.[6] We then calculate the levelized cost of PV electricity (C) by amortizing the capital cost of a watt of PVs, C_p, at a 7% discount rate (δ) over a 5-year lifetime (L) ,and dividing the result by the energy produced in a year: F multiplied by the number of hours in a year (h), 8760 (Stavy, 2002).[7]

$$C = \frac{C_p}{F \cdot h} \cdot \frac{\delta}{\left(1 - (1+\delta)^{-L}\right)} \tag{2}$$

As a demonstration of the sensitivity of C to the main items we assess in this study, Table 3 shows the effects of manufacturing costs and combinations of efficiency and lifetime. As we discuss in the following sections, successful R&D will move the technical characteristics of PVs to the right—to higher efficiencies and lifetimes. Increased demand has the effect of moving the technology downward on the table, to lower manufacturing costs.

[6]See the Appendix for our calculation of an 18.3% capacity factor.

[7]We assume maintenance costs (OM) to be zero. The discount rate of 7% is also used in a recent analysis of solar subsidies (Benthem et al., 2008). Other studies advise using a lower rate for public policy analysis, such as 4.5%, even if using a private rather than a social discount rate (Moore et al., 2004).

Table 3: Sensitivity of levelized cost (C), in \$/kWh, to manufacturing costs and combinations of technical characteristics of PVs.

Efficiency (η):	5%	15%	31%
Lifetime (L):	5y	30y	15y
Manf. cost (M):			
\$100/m^2	0.61	0.08	0.04
\$50/m^2	0.43	0.06	0.03
\$25/m^2	0.35	0.05	0.03

3.2 The effect of changes in demand on PV costs

In this section we describe our methodology for calculating the effect of changes in demand for PV on its levelized cost over time. We estimate the quantity of new PV systems demanded, and the resulting scale of manufacturing plants, using demand curves for PV electricity. We apply these changes in manufacturing scale to the cost model described in section 3.1 to estimate cost reductions that result from increasing demand for PV over time. The model operates in 5-year increments.

3.2.1 Demand for PV electricity

We derive future demand curves for PV using MiniCAM, a technologically-detailed integrated assessment model.[8] Demand for PV depends in part on its cost and in part on the characteristics of competing and supporting technologies. Assumptions for technologies other than solar PV are based on the version of MiniCAM used in the Climate Change Technology Program (CCTP) reference case (Clarke, Wise, Placet, Izaurralde, Lurz, Kim, Smith and Thomson, 2006). In particular, nuclear power is assumed to be widely available but the cost of CCS is assumed to be prohibitively high. We consider climate policy as an exogenous feature and take into account carbon prices, whether through a tax or a cap-and-trade scheme, of \$0, \$10, \$100, and \$1000 per ton of carbon.

To account for the effects of PV's intermittence, the analysis here was conducted under two possible regimes. In the base case, which we call "backup generation", we assume that natural gas power plants are required as backup generation to ensure grid reliability. As PV's share of electricity generation increases, the amount of back up generation required per PV installation increases such that once PV deployment reaches

[8] See Brenkert et al. (2003) and Edmonds et al. (2004) for more discussion of the model.

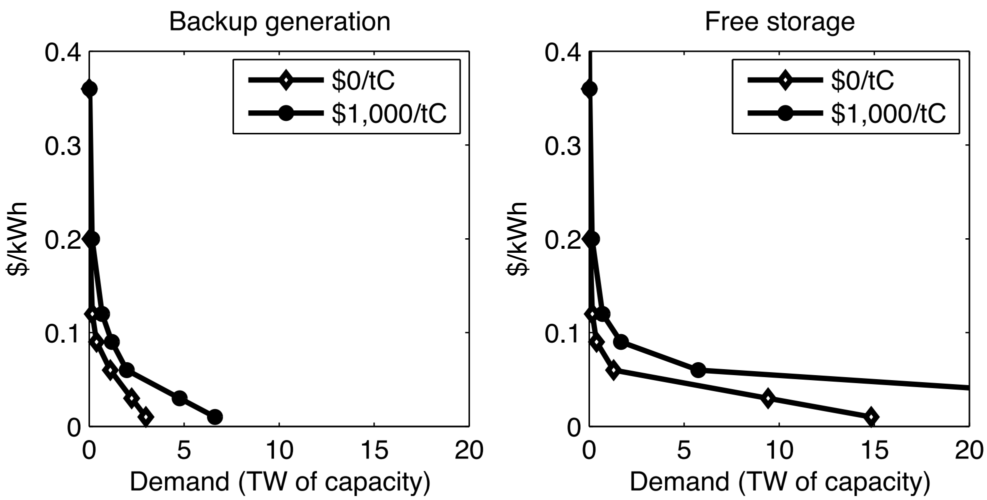

Figure 2: Demand curves for PV electricity in 2040.

20%, one MW of back up capacity is required for each additional MW of PV capacity. In the second regime, "free storage," a zero-cost electricity storage technology is available so that no additional backup is required.

As an example, Figure 2 shows demand curves for PV in 2040, which we derived from MiniCAM. The figure on the left uses the base case assumption of *backup generation*, and the figure on the right uses the assumption of *free storage*. To show the effect of a carbon price in each case, we display demand curves for the extreme cases of \$0 and \$1000/ton. Because the demand curves were originally defined in terms of energy demanded (exajoules), we convert demand into units of PV capacity needed to produce that energy (terawatts). Using the assumptions from above for capacity factor, we estimate the amount of installed PV capacity at time t required to provide the PV energy demanded:

$$K_t = \frac{E_t}{h \cdot F} \tag{3}$$

where K is total installed capacity, measured in TW, and E is total energy demand, measured in TWh. Note that the availability of free storage has little effect when the cost is high, ≥ 0.10 cents/kWh; but has a large effect at lower costs, where the constraint on backup effectively constrains the amount of solar that is deployed.

3.2.2 The effect of changes in demand on manufacturing scale

In this section we address the question: how large would manufacturing facilities become at a new level of demand? Meeting demand for PV electricity requires having a sufficient quantity of PV installed. To calculate the resulting changes in the size of manufacturing plants, we estimate the annual new capacity being manufactured in each 5-year period, k_t. We assume that manufacturers have five years to build sufficient capacity to meet a new level of demand, so demand is satisfied at the end of each 5-year period.

In each 5-year period, the quantity of PV systems manufactured is equal to the quantity of new systems necessary to meet the new level of demand, which is the sum of incremental capacity demanded and replacements of retired PV systems. Incremental capacity is the difference between the total GW of installed capacity in period t, K_t and the installed capacity in the previous period, K_{t-5}. As systems are installed, we project the date at which they will be retired based on the lifetime (L) of systems when they were installed, $t + L$. Note that the lifetime of systems can change over time as the technology improves. We describe the quantity of capacity retired at each time t as R_t.[9] The new PV capacity installed in time, t is thus:

$$k_t = K_t - K_{t-5} + R_t \tag{4}$$

3.2.3 The effect of manufacturing scale on cost

Manufacturing costs fall with increasing plant size due to economies of scale, substitution of capital for labor, and learning-by-doing. We apply scaling factors to each of the components of manufacturing cost to estimate the cost reductions that will result from larger production volumes. Each of the five manufacturing cost components described in Section 3.1.1, i has a manufacturing cost of m_i in units of \$/m^2. The total manufacturing cost, M is the sum of the five m_i values. The effect of increasing plant size on manufacturing cost M at time t is estimated using equation 5 below.

We use an overall scaling factor for M of $b = -0.18$, based on previous studies of economies of scale in PV, semi-conductors, and engineering equipment (Remer and Chai, 1990; Gruber, 1996). Because we are interested in estimating a lower bound on cost, we chose a value toward the lower end of the range of

[9] In our simulations we include retirements of legacy crystalline PV systems, which are installed through 2020, when organic PV begins to replace it.

Table 4: An example of the effect of manufacturing scale on manufacturing cost of PV modules and electricity cost of PV systems using base case assumptions from above.

Plant size MW/year	Cost ($\$/\mathrm{m}_2$) M	LEC ($/kWh) C
10	80.0	0.54
20	70.8	0.47
100	53.7	0.35
500	41.3	0.26
1,000	37.0	0.23
2,000	33.3	0.21
12,000	25.9	0.15

assumptions used in studies that calculate future cost savings for large scale PV plants, $b = -0.07$ to -0.20 (Bruton and Woodock, 1997; Ghannam et al., 1997; Maycock, 1997; Frantzis et al., 2000; Rohatgi, 2003; Frantzis et al., 2000). Because our study differentiates between manufacturing costs that decline with scale and those that do not, we set the scaling factors for the individual components, b_i such that the overall effect on M is equivalent to $b = -0.18$. Consequently, a scaling factor of $b_i = -0.20$ was applied to each of the cost components that show cost reductions with scale and of $b_i = 0$ for those costs that are static (see Table 1). Manufacturing costs are calculated in each period as follows:

$$M_t = \sum_{i=1}^{5} m_{i,t-5} \cdot \left(\frac{k_t}{k_{t-5}}\right)^{b_i} \tag{5}$$

Because we assume that the manufacturing scale of the price-setting firm is proportional to the size of demand for new PV systems k_t, the scaling factor is also proportional to changes in k.[10] Table 4 shows the effect of increasing plant size on the cost of manufacturing. The cost of PV electricity that results from this new level of M is calculated using equations 1 and 2 in section 3.1.3. In our model, costs do not rise if demand shrinks; we assume that plants last many years, so reduced demand for new PV does not result in the construction of new smaller manufacturing facilities.

[10]This assumption is consistent with industry heuristics gleaned from interviews (Taylor et al., 2007).

3.3 Simulating the effects of a subsidy

In this section we describe how we use the equations above to simulate the effects of a subsidy on the cost of PV electricity over multiple time periods. We run our model in 5-year time steps beginning in 2020 until 2050. Dropping the leading 20, we let $t \in [20, 25...50]$.

We assume that PV manufacturers make decisions about capacity expansions five years in advance. They need this lead time: (1) to secure access to long-term contracts for raw materials and component parts, (2) to integrate increasingly complex manufacturing machinery at large scales, and (3) to improve the reliability of evolving PV system designs and materials. In forecasting future demand for planning expansions, these manufacturers consider their *current* costs and subsidies. They are myopic in the sense that they do not consider the impact that an expansion will have on their manufacturing cost 5 years hence. This assumption of myopia fits with observations that PV firms are operating well below their optimal scale despite rapid growth in demand.

To begin, we assume that organic PV becomes available as a commercial product in 2020, that manufacturing output is at pilot plant scale ($k_{20} = 1$ GW), and that manufacturing and electricity costs start at the base case values described in Tables 1 and 2. Thereafter, the model proceeds as follows. In year t the firms produce new inventory equal to k_t, their currently installed capacity. They charge a price, before subsidies, equal to their costs in the previous period, C_{t-5}, as this will clear the market given their current installed capacity. Immediately following t, firms discover their new manufacturing cost, M_t and their resulting cost of electricity C_t. To determine how much manufacturing capacity k_{t+5} to have available for the next period, firms predict demand K_{t+5}, based on the expected costs that consumers will face after subsidies, $P_{t+5} = C_t - s_{t+5}$.

We assess three PV subsidy schemes (see Table 5). Producers of PV electricity receive income from the the government according to how much electricity they produce each year. Subsidies are no longer available once the subsidized cost, P_t reaches the target price, \$0.04/kWh. Firms plan capacity expansions for 2025 aware of s_{25}. They predict the price of PV electricity in 2025 to be $P_{25} = C_{20} - s_{25}$. They use demand curves for 2025 and equation 3, to determine predicted demand, K_{25}, and from that, use equation 4 to determine the required manufacturing capacity k_{25}. As an illustration of how this model works, Table 6 shows the

Table 5: Values for s ($/kWh) under three subsidy schemes.

t	20	25	30	35	40	45	50
No subsidy	-	-	-	-	-	-	-
Low subsidy	-	0.20	-	-	-	-	-
High subsidy	-	0.25	0.10	0.10	0.05	-	-

Table 6: Illustrative output using base case assumptions and a high subsidy program.

			2020	2025	2030	…	2050
Description	Definition	Units	t=20	25	30		50
Subsidy	s_t (s3.3.1)	($/kWh)	-	0.25	0.10		-
Subsidized cost	P_t=C$_{t-1}$-s$_t$	($/kWh)	0.54	0.29	0.15		0.16
Demand for PV	K_t (eq.3)	(GW)	1	21	112		104
New capacity	k_t (eq.4)	(GW)	1	30	141		183
Retirements	R_t (s3.2.2)	(GW)	-	10	50		180
Manf. cost	M_t (eq.5)	($/m^2)	80	40	32		31
B.O.S. cost	BOS_t (s3.1.2)	($/W)	75	33	24		23
Unsubsidized cost	C_t (s3.3)	($/kWh)	0.54	0.25	0.19		0.16

calculation of variables under the high subsidy case, using our base case assumptions for manufacturing cost, efficiency, and lifetime, as well as assumptions of no free storage and no carbon price.

3.4 Simulating the effects of R&D

The methodology so far describes how subsidies affect PV costs, for a given efficiency and lifetime. In this section, we incorporate the impacts of R&D on PV costs by using expert elicitation about the likelihood that R&D expenditures will lead to improvements in efficiencies and lifetimes for purely organic PVs.

Baker et al. (Forthcoming) conducted an elicitation on four key characteristics of organic PVs: efficiency, lifetime (also called 'stability'), and two hurdles related to manufacturing costs. For the purposes of this paper we will consider only the probabilities to achieve efficiency and lifetime, since we use the cost model above to assess manufacturing costs. The results of these elicitations are presented in Table 7. The two R&D programs had different definitions of success and different funding trajectories. The first program, denoted here as "Low R&D", has a goal of 15% efficiency and a 30 year lifetime. The probabilities reported here are based on assumed U.S. government funding for this program of $15M/year for 10 years.[11] The goal for the

[11] The experts did consider the impact that government funding would have on private sector funding when providing their probabilities, but did not make explicit their assumptions about the proportions of public and funding.

Table 7: Expert elicitation of the probabilities of achieving efficiency and lifetime targets under two R&D programs for purely organic PVs.

	Low R&D				High R&D			
	Ex. 1	Ex. 2	Ex. 3	Avg.	Ex. 1	Ex. 2	Ex. 3	Avg.
Probability for efficiency	0.85	0.90	0.80	0.85	0.15	0.50	0.30	0.32
Probability for lifetime	0.50	0.30	0.50	0.43	0.60	0.80	0.25	0.55
Total probability	0.43	0.27	0.40	0.37	0.09	0.40	0.08	0.19

second program, "High R&D", is to achieve 31% efficiency and a 15 year lifetime. The probabilities reported in this case are based on assumed U.S. government funding for purely organic solar cells of $80M/year for 15 years. As an additional elicitation for the purposes of this paper, we asked the experts about the relationship between the two programs. Specifically, we asked them to re-consider the High R&D program: $80M/year funding for 15 years, with an expressed goal to achieve an efficiency of 31%. We then asked for the probability that those goals would not be achieved but that the goals of the Low R&D program would. On average, the probability of achieving 15% efficiency and a 30 year life time, under the High R&D case was 39%.

For this paper we will use the simple average of the experts' overall probabilities for efficiency and lifetime, recognizing that any single measure should be treated with some caution (Keith, 1996). More sophisticated methods (Clemen and Winkler, 1999) using the same raw data will be employed in subsequent work. We use these elicitation results (see Table 8) to determine the values for η_t (efficiency) and L_t (lifetime). If R&D is successful and the goals for lifetime and efficiency are ultimately reached, we assume that the technical improvements that result from the R&D program begin to appear in 2040 and reach their full level in 2050. The lifetimes and efficiency levels in 2040 are the midpoint of the base case levels and the 2050 levels; and the 2045 levels are the midpoint of the 2040 and the 2050 levels. We examine the sensitivity of this assumption on timing in section 4.2.

Table 8: Probability of achieving three combinations of technical characteristics of organic PVs as a function of public R&D investment.

	PV characteristics		
Lifetime (L):	5y	30y	15y
Efficiency (η):	5%	15%	31%
No R&D	1.00	0.00	0.00
Low R&D	0.63	0.37	0.00
High R&D	0.42	0.39	0.19

4 Cost of PV electricity under deterministic R&D outcomes

We simulated efforts by the government to fund R&D and subsidize demand at three levels of policy intensity each. These results use the assumptions of *backup generation* and no price for carbon, the most conservative combination in that it produces the minimum level of demand for PV. The results for R&D in this section are deterministic in that they are conditional on each of the two R&D programs reaching their stated goals: $\eta = 15\%$, $L = 30$ for *Low R&D*; and $\eta = 31\%$, $L = 15$ for *High R&D*.

Table 9 shows the costs of PV electricity in 2040 and 2050 under the nine combinations of government technology programs. While both subsidies and successful R&D programs reduce costs, the effect of successful R&D on cost in 2050 is an order of magnitude larger than the effect of subsidies. Subsidies are relatively more effective in 2040 than in 2050, but the effect of successful R&D is still much larger, even though in our model only half of the benefits of R&D arrive by then. Even the highest subsidy levels do not achieve cost effective organic PV without successful R&D. The cost of PV without successful R&D never falls below 16c/kWh, far from the target level of 4c/kWh. Note also the counterintuitive result that, under successful R&D programs, the high and low subsidy programs produce costs in 2050 that are slightly higher than without the subsidy program. This result occurs because the subsidy programs shift a substantial amount of PV production to earlier years; without subsidies, almost all of the demand for PV electricity in 2050 is met by production between 2040 and 2050. Consequently, without subsidies the scale of manufacturing plants in 2050 reaches a larger more efficient scale and the cost in 2050 is lower. The curves in Fig. 3 show the path of cost reductions over time and the relationships among the policy combinations. The three subsidy curves in each Fig. 3a, b, and c are much more similar to each other than the three R&D curves in each Fig. 3d, e, and f.

Table 9: Cost of PV electricity in 2040 and 2050 ($/kWh). *Low* and *High R&D* cases are conditional on program goals for efficiency and lifetime being reached.

		Subsidy		
		None	Low	High
2040				
R&D	None	0.536	0.201	0.162
	Low	0.111	0.042	0.035
	High	0.087	0.033	0.028
2050				
R&D	None	0.536	0.200	0.162
	Low	0.014	0.016	0.016
	High	0.009	0.010	0.010

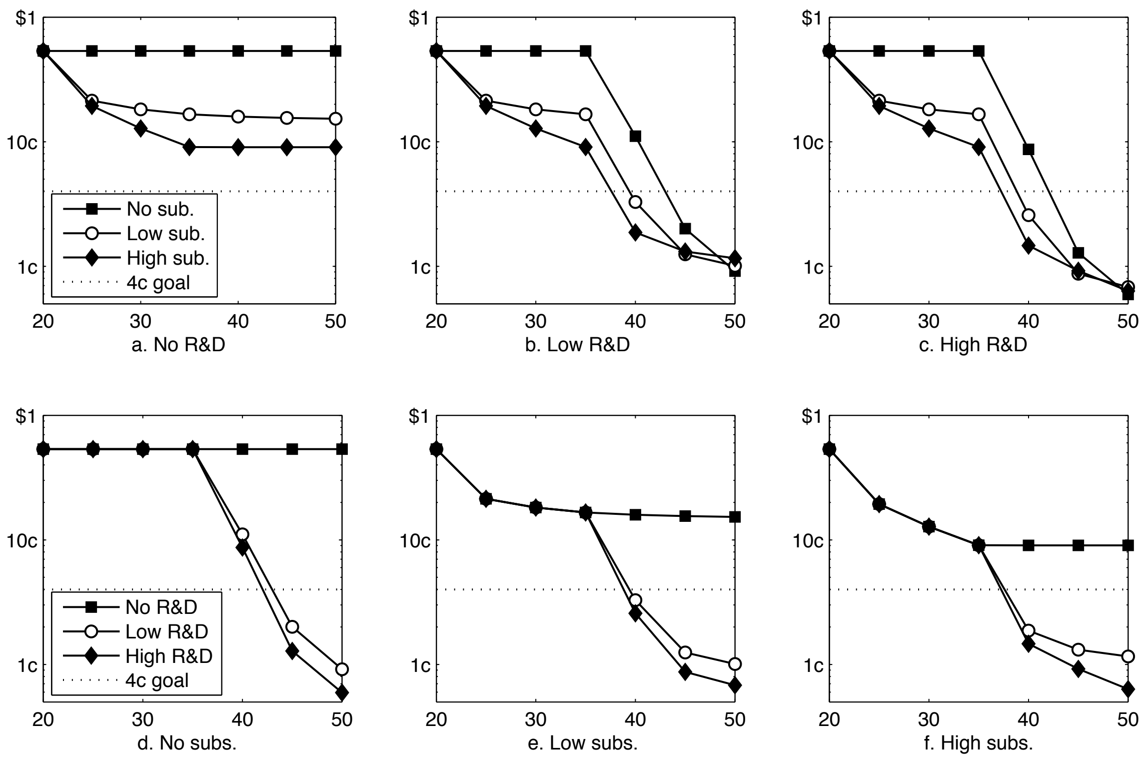

Figure 3: Impact of subsidies and R&D on cost per kWh of PV electricity. *Low* and *High R&D* cases are conditional on program goals for efficiency and lifetime being reached. Costs are on a log scale.

4.1 Scenarios for storage availability and carbon prices

We compare four scenarios here: (1) the baseline scenario of $0/ton carbon price and backup generation needed, (2) $1000/ton carbon and backup generation needed, (3) $0/ton carbon and free storage technology available, and (4) $1000/ton carbon and free storage technology available.[12] The policy combination we use to evaluate these scenarios is one with a mid-range cost outcome, High subsidies and a successful Low R&D program.

Adding the availability of "free" energy storage technology and increasing the carbon price from $0 to $1000/ton both increase the demand for PV.[13] This larger production leads to cost reductions in manufacturing and PV becomes less expensive than the baseline for all three alternative combinations of carbon prices and free storage availability (Table 10). The relative importance of the effects of a high carbon price and free storage change over time. In 2040, the carbon price is more important than free storage, although the availability of free storage does produce cost reductions if there already is a $1000 carbon price. The small effect that free storage has on its own is due to the relatively small overall demand for PV in 2040 when there is no carbon price; the benefits of free storage only become important once PV demand exceeds 20% and the need for backup capacity increases. By 2050, free storage plays the more important role. The diminished effect of a high carbon price likely results from assumptions about nuclear power, the primary alternative low-carbon technology in MiniCAM. While a high carbon price benefits both nuclear and PV, free storage only benefits PV. Because the benefits of R&D have been fully realized by 2050, demand for PV becomes very large; thus having free storage available becomes important, more important than a high carbon price.

The relative effectiveness of successful R&D and subsidies do not change under varying assumptions about storage and carbon prices; under all four scenarios, R&D success has a greater effect on cost reductions than do subsidies in 2050. High carbon prices do enhance the relative impact of subsidies and free storage increases the relative impact of R&D success, but in both cases the effects are small.

[12] The assumption that backup generation is needed implies that electricity storage is prohibitively expensive. In order to assess the impact of this assumption, we provide comparisons with the other extreme, which is that storage is free.

[13] In combination, they not only lead to even larger amounts of new PV, but shift the peak PV production much earlier, to 2035.

Table 10: Effects of carbon prices and storage availability on PV cost.

	Carbon price	Storage availability: Backup generation	Storage availability: Free storage
2040			
	\$0/ton	0.035	0.035
	\$1000/ton	0.026	0.019
2050			
	\$0/ton	0.016	0.012
	\$1000/ton	0.015	0.012

4.2 Sensitivity analysis

Sensitivity analysis shows that our two main claims are robust to uncertainty in the data used to populate the model. First, the analysis supports our claim that the base case set of assumptions represents an upper bound on the effectiveness of a subsidy program. Second, our finding, that the cost-reducing effect of successful R&D is larger than the effects of subsidies, is supported across all alternative scenarios.

We examined the sensitivity of these results to five sources of uncertainty in the choice of parameter values in our model:

1. We reduced the magnitude of the *scaling factors*, $b = -0.20$, to a more conservative estimate of $b = -0.15$.

2. Similarly, we adjusted the *scaling factor for BOS* from $b_{BOS} = -0.20$ to $b_{BOS} = 0.04$; resulting in a cost reduction of approximately one third the reduction in the base case.

3. In the base case we assumed that the cost of *input materials* for the production of PV cells decreases with increasing manufacturing scale. Here we assume that the cost of materials stays constant at the initial level, such as might occur due to increasing scarcity of the material offsetting scale effects.

4. We *delayed the subsidies* for ten years such that they begin in 2035 so that they are timed to coincide more closely with R&D effects.

5. We assumed that the outcomes of *R&D* begin to be realized ten years earlier, in 2030.

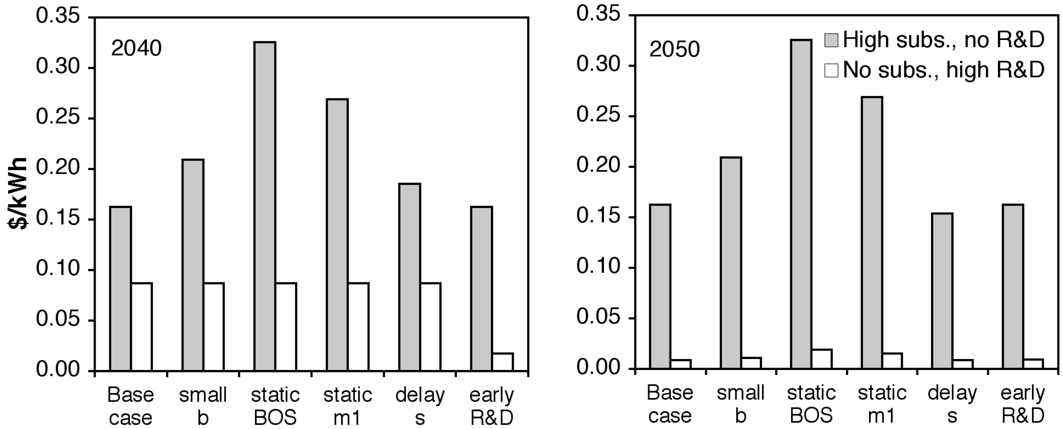

Figure 4: Sensitivity analysis: comparing cost of PV electricity in two policy scenarios for 2040 and 2050.

Of the five cases analyzed, the only alternative to the base case that results in a lower cost in 2040, is when the benefits of R&D begin 10 years earlier.[14] In every other case, costs are higher. We believe that none of the parameters analyzed here could reasonably altered in the opposite direction from the base case. The most influential changes are removing the returns to scale for material costs and BOS. Reducing the overall returns to scale parameter had a smaller effect, as did delaying the onset of subsidies for ten years.

Figure 4 compares the effects of successful R&D and subsidies under the 6 cases in both 2040 and 2050. Supporting the robustness of our results, the sensitivity analysis shows that the subsidy program never has a stronger effect than the successful R&D program. In fact, each of the alternative assumptions makes the R&D program look relatively stronger than the subsidy program compared to the base case. The base case assumptions make the strongest possible case for the effectiveness of the subsidy program. These results also show that the effectiveness of high subsidies are in no case close to the effectiveness of successful R&D.

[14] See Appendix for detail on these comparisons.

4.3 Social costs of technology policy

A consistent result across scenarios is that subsidizing a large demand for PV before the benefits of R&D arrive can be expensive. Here we calculate the net present cost of a subsidy,

$$Y_s = \sum_{t=20}^{50} \delta s_t E_t$$

where s_t is the subsidy on energy (E_t) and δ is the discount rate. Under the base case assumptions, no carbon tax and no free storage, the net present social cost of subsidies is \$5B for the low subsidy program and \$80B for the high subsidy program. These values are in line with recent estimates of the cost of subsidizing the current generation of PV (IEA, 2008). Note that they are considerably higher than the R&D amounts we have considered, which have a net present value of \$0.1B and \$0.7B. We also note that the cost of each subsidy program increases as demand for solar electricity increases. For example in the presence of a \$1000 carbon tax, the cost of the low-subsidy program rises to \$30B and the high subsidy program rises to \$3T. Given the wide range of subsidy program costs, it may be useful in future work to use this model to optimize the timing and level of subsidies—especially given various assumptions about carbon prices and storage technology.

5 Probability distributions over cost of PV electricity

In the previous section we discussed how subsidies compared with R&D, assuming the R&D outcomes were successful and known. In this section we relax the assumption of deterministic outcomes and employ the results of the expert elicitation in order to consider how policy choices affect *probability distributions* over the cost of electricity from PV. The primary intention of this section is to demonstrate the methodology. To elucidate comparison, all of the results presented in this section are costs of PV electricity in 2040, which is when both R&D effects and subsidy effects are simultaneously active.

5.1 Probability distributions comparisons

There are a total of nine possible policy combinations of *no*, *low*, and *high* subsidies with *no*, *low*, and *high* R&D. *No R&D* has a deterministic outcome, as do the three levels of subsidies. But *low* and *high R&D* have probability distributions over outcomes. Figure 5 compares the cumulative probability distributions of different policy combinations. The left panel compares three subsidy levels given high R&D; the right panel compares two R&D levels, given a low subsidy. Each bar on the graph represents the probability of achieving the electricity cost (C) on the horizontal axis, or better (lower C). For example, the probability of achieving $C_{40} \leq$ 3c/kWh given high R&D and a low subsidy is about 20%. A better program would have higher bars farthest to the left. The left panel shows that without a subsidy, there is zero probability of achieving a cost lower than 6 c/kWh; and if R&D fails completely the cost will be greater than 18 c/kWh. In contrast, with a high subsidy, there is a 60% probability of the best outcome, a cost of less than 3 cents; and even if R&D fails altogether, a cost between 12 and 15 c/kWh will be realized. The right panel shows the impact of the two R&D programs, assuming a low subsidy. The high R&D program has a probability of 20% of achieving a cost less than 3 c/kWh; and a probability of 60% of achieving a cost no higher than 6 c/kWh. The best outcome for the low R&D program is to achieve a cost between 3-6c/kWh, which has a probability of 38%. Both programs are guaranteed to achieve a cost of no more than 18 c/kWh, because of the subsidy.

5.2 Risk tradeoffs

In this section we apply the methodology of stochastic dominance in order to get a sense of how different policies may be compared in a *choice under uncertainty* framework. Stochastic dominance is frequently applied in economics and finance to identify preference orderings over uncertain options for entire groups of agents (see for example Levy (1992)). In particular, stochastic dominance can identify whether a particular option is *riskier* than another option (Rothschild and Stiglitz, 1970). Here, we identify what effects subsidies and R&D have on the risk profile of outcomes, in order to clarify the trade-offs between low-risk subsidies and risky R&D.

In order to make stochastic dominance comparisons among the policy combinations, we reverse the

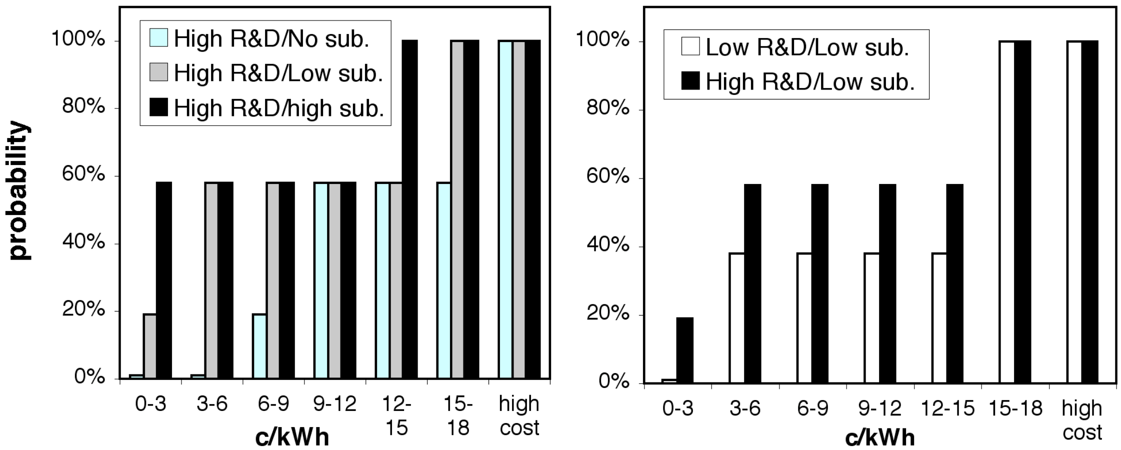

Figure 5: Cumulative probability distributions of PV electricity cost in 2040 (C_{40}) for five policy combinations.

direction of the horizontal axis of the cumulative distribution functions (CDFs) in Figures 6 and 7. The least preferred outcomes are now on the left and the most preferred are on the right. The top of the shaded area reflects the probability that the electricity cost will be equal to the value on the horizontal axis *or higher*. For example, in the left panel of Figure 6, the probability that C_{40} is 20 c/kWh or higher, given high R&D, is about 40%. We consider two classes of stochastic dominance. A probability distribution, G, First Order Stochastically Dominates (FOSD) another, H, if the CDF of G is everywhere below the CDF of H. FOSD implies that all decision makers who prefer a lower cost to a higher cost will choose the distribution that dominates the other. A probability distribution, G, Second Order Stochastically Dominates (SOSD) H if the cumulative area of the difference $H - G$ is always greater than zero. If a probability distribution SOSD another, then all *risk averters*, who also prefer a low cost to a higher one, will choose the dominant distribution. Thus, if we find a dominance relation, we can say something about the relative riskiness of multiple policies. Note, however, that we are only comparing probability distributions over the *benefits* of the policies, in terms of achieving a cost target. We will compare the social costs of the policies and welfare effects on the economy in subsequent work.

Figure 6 compares two R&D programs in the left panel, and two subsidies in the right panel. The left

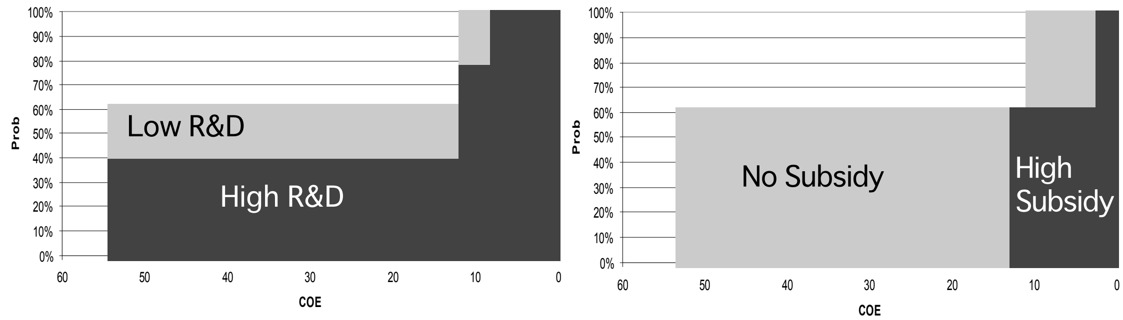

Figure 6: Cumulative distribution functions for cost of PV electricity (c/kWh) for four policy combinations. The left panel compares High and Low R&D funding, assuming no subsidy. The right panel compares no subsidy with a high subsidy, assuming low R&D funding.

panel shows that the High R&D program FOSD the Low R&D program. Moreover, it illustrates that the effect of a High R&D program is to shift the CDF down, that is, it primarily reduces the probability of bad events and increases the probability of good events. The panel on the right shows that a High subsidy FOSD no subsidy; and that a subsidy has the effect of shifting the CDF to the right. That is, it primarily reduces the cost attached to a particular probability of success: the worst event becomes less bad, the good event becomes better. While it is not surprising that the higher intensity policies FOSD the lower intensity policies, the varying effects of the policies do reveal that subsidies have a benefit in that they make the worst case much better than the case without subsidies.

Finally, we compare R&D and subsidies. Figure 7 compares a strategy of high R&D investment and no subsidy; with no R&D investment and a high subsidy. The CDF for the 2nd strategy is simply a rectangle starting at 13c/kWh and moving to the right. The CDF for the first strategy starts at 54c/kWh, and stays below the dotted line. There is no FOSD between these two policy combinations. That means that we cannot say that all decision makers would prefer one to the other. The reason is that though the *High R&D/No Subsidy* is much riskier than *No R&D/High Subsidy;* it also has the possibility of a very good payoff, thus some risk-preferring decision makers may prefer it. However, *No R&D/High Subsidy* does SOSD *High R&D/No Subsidy*. A subsidy with no R&D is “less risky”, since it avoids the worst case of a very high electricity cost, and the expected cost is lower as well. This result implies that if (1) the goal were simply to achieve as low

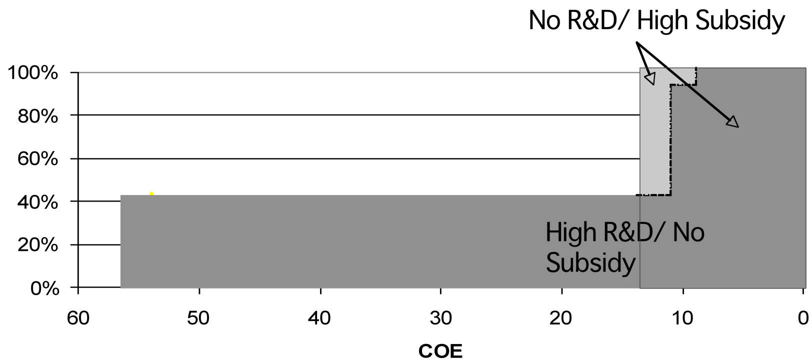

Figure 7: Comparison of cumulative distribution functions for cost of PV electricity (c/kWh) in 2040 under R&D and under subsidies.

an electricity cost as possible, and (2) the two programs had equal costs, the *No R&D/High Subsidy* program would be strictly preferred by all risk averters. We note, however, that neither of these conditions necessarily holds. These results imply that the value of subsidies is that they provide a hedge against the possibility that breakthroughs in technical change fail to take place. In a choice under uncertainty framework, subsidies provide a benefit in reducing risk.

6 Conclusion

This paper describes a methodology to compare the effects of demand subsidies and R&D on the costs of a low-carbon energy technology that is not currently commercially available. The combination of an expert elicitation and a manufacturing cost model allows us to compare the outcomes of policy choices over a variety of scenarios. We find that (1) successful R&D enables PV to achieve a cost target of 4c/kWh, (2) the cost of PV does not reach the target when only subsidies, and not R&D, are implemented, and (3) production-related effects on technological advance—learning-by-doing and economies of scale—are not as critical to the long-term potential for cost reduction in organic PV than is the investment in and success of R&D. These results are insensitive to the intensity of either type of program, to the level of a carbon price, to the availability of storage technology, and to uncertainty in the main parameters used in the model. Sensitivity analysis also points to important influences on future cost. The central policy implication of these results is that governments must find a way to engender this R&D, whether it is funded by the government itself or by the private sector in response to changing demand conditions. In fact, one might argue that the key question policy makers face in regards to PV development is how to encourage this R&D, rather than how to support economies of scale and learning-by-doing.

We find that a case can still be made for subsidies, through our analysis of stochastic dominance. Because of the possibility of R&D failure, the benefits of subsidies second-order stochastically dominate those of R&D. In the event of R&D failure, subsidies make the costs of PV much lower than they otherwise would be, albeit not at levels close to the target. The importance of subsidies as a hedge against inherently uncertain R&D programs depends on the value that society places on the availability of a low-carbon energy source that is moderately inexpensive—that is, unlikely to be competitive with all other technologies, but perhaps inexpensive enough to be deployed at a large enough scale to diversify energy supply.

While this study makes no claims about the applicability of these results to other technologies, the methodology developed is well suited for adaptation to other cases. Historically, technologies such as wind power have improved through similarly observable combinations of directed technical breakthroughs and demand-driven manufacturing improvements (Nemet, 2008). This methodology seems especially applicable to informing policy decisions about other pre-commercial technologies, those that are not yet in production at full scale. The most troublesome technologies for policy modeling are those that if successful will have a large impact on the energy system but that are at too early a stage for simple extrapolations of historical cost reductions. Cellulosic biofuels, carbon capture and sequestration, and automotive fuel cells all fit this description and are technologies for which this methodology is likely to provide insight.

One application of this methodology in future work will be to compare the costs of these policies to the social benefits that will accrue from having low-cost carbon-free energy sources available. Stochastic optimization of the selection, timing, and levels of policy instruments can be employed to minimize the costs of meeting a technology cost goal. Although our conclusions about the relative effectiveness of policies remain valid across the full range of assumptions, the sensitivity analysis does suggest areas of further effort to understand the most important determinants of future cost—in particular, the extent to which cost components decline with increasing manufacturing scale. Further, the finding that subsidies affect the time path of investment in manufacturing capacity emphasizes the need to carefully evaluate the relative timing of subsides and

R&D. Finally, the large dispersion in outcomes that results from inherently unpredictable R&D programs suggests that simultaneous consideration of policy choices among multiple low-carbon technologies may improve the robustness of technology-oriented polices to address climate change.

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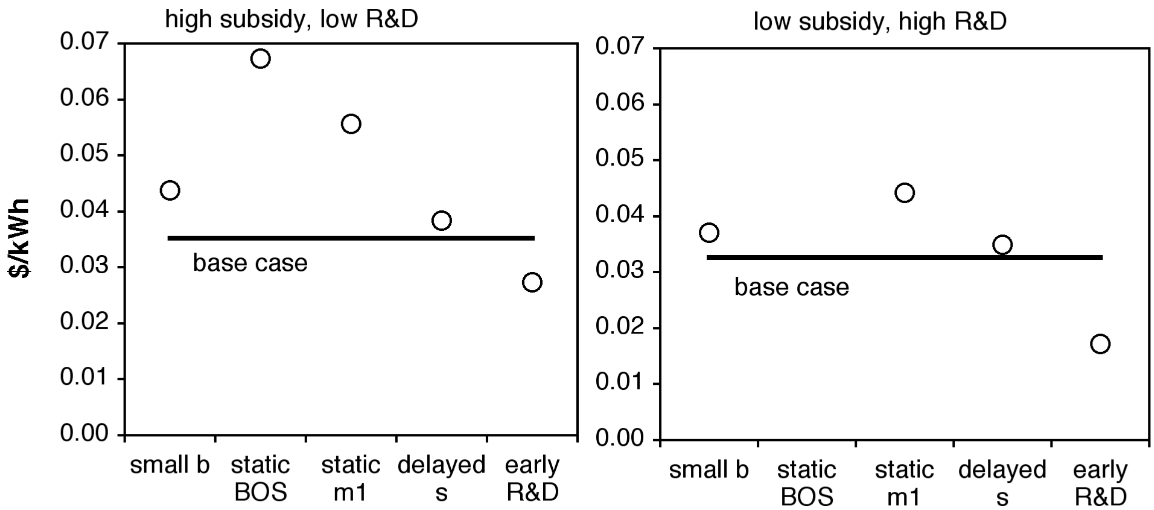

Figure 8: Sensitivity analysis: comparing PV costs in 2040 for two policy scenarios.

Appendix

The supplemental information provided in this appendix will be posted on line.

Capacity Factor

Capacity factor is the amount of energy produced in a time period divided by the energy that would have been produced during that same period if the system were operating continuously at peak capacity. Using solar radiation data from the seven major cities surveyed, we find that the daily solar insolation averaged over the course of a year (I) is 4.4 kilowatt-hours per square meter Nemet (2007). For a given system efficiency, average energy input of I to the PV system would produce 18% of the electricity that would have been produced if the the peak sunshine level, S were maintained continuously over the course of a year. We calculate capacity factor, F, where h represents the number of hours in a year, 8760.

$$F = \frac{365 \cdot I \cdot \eta}{S \cdot h \cdot \eta} = \frac{365 \cdot I}{S \cdot h}$$

Sensitivity analysis results

Figure 8 uses two policy combinations to show that the base case assumptions represent an upper bound on the effectiveness of subsidies. Table 11 shows the effects of changes in each model assumption on the cost of PV electricity in 2040. Table 12 shows the same for 2050. Table 13 shows the effect on the year at which the cost of PV electricity equals the target price, 4c/kWh.

Table 11: Sensitivity analysis: effect of changing parameter values on cost of PV electricity in 2040

	no R&D			low R&D			high R&D		
subsidy:	none	low	high	none	low	high	none	low	high
Base case	0.536	0.201	0.162	0.111	0.042	0.035	0.0869	0.033	0.028
small b	0.536	0.229	0.209	0.111	0.047	0.044	0.0869	0.037	0.034
static BOS	0.536	0.372	0.325	0.111	0.111	0.067	0.0869	0.087	0.053
static m_1	0.536	0.272	0.269	0.111	0.056	0.056	0.0869	0.044	0.044
delayed s	0.536	0.215	0.186	0.111	0.045	0.038	0.087	0.035	0.030
early R&D	0.536	0.201	0.162	0.024	0.023	0.027	0.017	0.017	0.020

Table 12: Sensitivity analysis: effect of changing parameter values on cost of PV electricity in 2050

	no R&D			low R&D			high R&D		
subsidy:	none	low	high	none	low	high	none	low	high
Base case	0.536	0.200	0.162	0.014	0.016	0.016	0.009	0.010	0.010
small b	0.536	0.227	0.209	0.016	0.018	0.018	0.011	0.012	0.012
static BOS	0.536	0.372	0.325	0.029	0.029	0.030	0.019	0.019	0.020
static m_1	0.536	0.271	0.269	0.023	0.024	0.024	0.015	0.016	0.016
delayed s	0.536	0.211	0.154	0.014	0.015	0.016	0.009	0.010	0.010
early R&D	0.536	0.200	0.162	0.018	0.017	0.014	0.009	0.009	0.010

Table 13: Sensitivity analysis: effect of changing parameter values on year at which cost of PV electricity reaches 4c/kWh target

	no R&D			low R&D			high R&D		
subsidy:	none	low	high	none	low	high	none	low	high
Base case	—	—	—	2044	2040	2040	2043	2040	2040
small b	—	—	—	2044	2042	2041	2043	2040	2040
static BOS	—	—	—	2046	2046	2045	2044	2044	2043
static m_1	—	—	—	2045	2043	2043	2044	2041	2041
delayed s	—	—	—	2044	2041	2040	2043	2040	2040
early R&D	—	—	—	2038	2036	2034	2036	2034	2034