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Advanced solar R&D: Combining economic analysis with expert elicitations to inform climate policy

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Abstract

The relationship between R&D investments and technical change is inherently uncertain. In this paper we combine economics and decision analysis to incorporate the uncertainty of technical change into climate change policy analysis. We present the results of an expert elicitation on the prospects for technical change in advanced solar photovoltaics. We then use the results of the expert elicitations as inputs to the MiniCAM integrated assessment model, to derive probabilistic information about the impacts of R&D investments on the costs of emissions abatement.

JEL classification: D81; O32; Q54; Q55; Q58

Keywords: Climate change; Technology R&D; Uncertainty; Environmental policy

1. Introduction

In this paper we combine expert elicitations and economic modeling to analyze the potential for R&D into solar photovoltaics (PV) to impact climate change. When it comes to the question of what to do about climate change, the role of technical change is large. Estimates of the costs of

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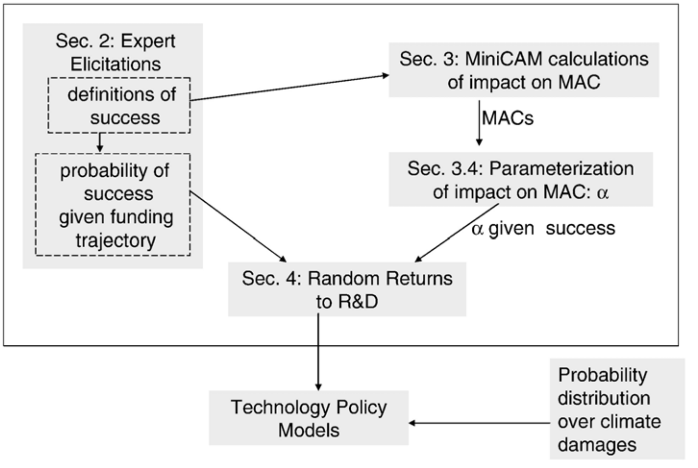

Fig. 1. A schematic representation of the flow of data in the framework. The elements inside the box are explicitly discussed in this paper.

control and of eventual damages both depend heavily on assumptions about technical change (Edenhofer et al., 2006; Popp, 2006). In order to craft good climate change policies — whether they are emissions policies or technology policies — we need to understand how technical change responds to policy, and how emissions respond to technical change. Technical change can come through two channels — investment in R&D and learning by doing. We focus primarily on R&D, but our analysis of how improvements in technology will impact costs is also relevant to learning by doing. We note that a wide variety of policies can impact investment into R&D, from policies that directly allocate government funds to R&D, to R&D-tax incentives, to carbon taxes, to adoption incentives. For this paper, we focus on R&D investment directly, and leave the analysis of the government's role in R&D investment to future research. We focus on how R&D impacts technical change, and how technical change impacts the cost of reducing carbon emissions. Specifically, we study the impacts of technical change on the entire abatement cost curve, which measures the costs of abatement, defined as a reduction in greenhouse gas emissions, at each level of abatement between zero and 100%.

We note two gaps in the current literature. First, there is very little work that directly addresses the fact that the results of investment in R&D are inherently uncertain. This topic is just starting to be studied, most notably by others in this special issue (Blanford, 2007; Bohringer and Rutherford, 2006; Bosetti and Drouet, 2005). Second, there is virtually no work that discusses how particular technologies are likely to impact the abatement cost curve. Yet, for decisions made under uncertainty, it is the shape of the whole curve, and not just a point estimate, that determines results. Thus, we need to understand the impact of technology on the abatement cost curve, for many different levels of abatement. The difficulty here is that not all technical change is alike, and not all R&D programs are alike. Different types of technologies will impact the abatement cost curve in different ways. For example, an incremental improvement in a non-carbon transportation technology may have a very small effect on the cost of abating a small amount of emissions, because of infrastructure and network effects. If climate change damages turn out to be very severe, however, then even small improvements in non-carbon transportation technologies may be very important. On the other hand, consider improvements in coal-fired electricity generation.

An incremental improvement is likely to have a large impact if damages are low and abatement is minor; but virtually no impact if damages are extreme and a no-carbon world is desirable. Another distinction between R&D programs is their levels of risk. Some programs provide a possibility of a breakthrough, but also a large chance of failure. Other programs are less risky, aiming only to improve the technology incrementally.

In Baker et al. (2007) we described a general framework for quantifying the uncertainty in climate change technology R&D programs and their associated impacts on emissions. Here, we present an implementation of that framework, focusing on advanced solar technology. Fig. 1 illustrates the flow of the data in this framework; the actions placed within the box are discussed in this paper; the actions outside the box are applications of the outputs of this paper. The first step of the project, discussed in Section 2, is collecting probabilistic data on advanced solar PV technologies through expert elicitations. The products of the elicitations include explicit definitions of success for each technology, and probabilities of success for given funding trajectories. In Section 3 we determine how the technologies would impact the abatement cost curve, if they achieve success as defined. For this step we use MiniCAM, a technologically detailed Integrated Assessment Model (IAM), to determine the impact of each technology on the Marginal Abatement Cost (MAC) Curve. In Section 3.4 we discuss the parameterization of each technology's impact on the MAC. In Section 4, we combine the probabilities with the impacts on the MAC to derive multiple representations of the probabilistic impacts of R&D. As shown in the figure, these can then be combined with probability distributions over climate damages in technology policy models. We conclude in Section 5.

2. Expert elicitations

In this section we discuss the steps in the expert elicitation, including the selection of particular technologies, and the development of definitions of success. We then discuss how we structured the probability assessments and the results of those assessments. The output from the expert elicitations are specific definitions of success for each R&D project, and probabilities of success for each of those projects, given specific funding trajectories.

2.1. Why use subjective probability assessments?

To consider the uncertain impacts on the MAC from a portfolio of candidate technologies, we must estimate the probability that, given a specified research policy, each of the technologies will meet given working definitions of success. For some technologies, there are helpful historical data and historical comparisons, e.g., Moore's law from the semiconductor industry, and manufacturing learning curves (Ruth, 1993; Yelle, 1979).

With highly innovative technologies, however, history provides only sketchy guidance. 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 (Clemen and Kwit, 2001; Peerenboom et al., 1989; Sharpe and Keelin, 1998).

We are considering breakthrough solar PV technology in particular. Basic research is needed (e.g., to find appropriate molecules that have the potential for sufficient performance that PV cells using them might be widely deployed), followed by development work to move research from the lab to production (e.g., finding the right manufacturing processes), at which point improvements would follow a more predictable path. To the extent that probability of achieving success depends on breakthroughs, what has happened with other technologies will not offer much to differentiate

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paths that are particularly promising. Experts can provide useful judgments about the likelihood that research will overcome particular hurdles, and these expert judgments can be combined to estimate overall probability of success for each technology (Howard, 1988). We have not asked the experts to provide judgments on what the overall economic benefits of the technologies will be, since these depend on economy-wide developments, such as whether a vastly improved regional or national electric grid is available to transmit electricity great distances with minimal power loss. We discuss the estimation of the economy-wide impacts of technical change in Section 3 below.

2.2. Technologies considered

Our effort is focused on how current R&D can affect abatement costs in the electricity sector forty or fifty years in the future. We identified experts recognized for expertise in solar PV technology in general, and with separate areas of specialization collectively covering much of solar PV research. The experts were asked to identify technologies with the potential for significant advances and breakthroughs. Rather than identifying and assessing prospects for very specific individual technologies, we considered the main funding areas for such research, cognizant of the fact that in each area there are numerous projects. To gain a preliminary sense of returns to R&D, we aimed to identify several such funding areas in solar energy, in parallel with efforts in other technology families such as biofuels.

A brief description of PV technology will help clarify the discussions below. PV solar cells are semiconductor devices that convert sunlight directly into electricity by absorbing and transferring the energy of the light to electrons in the atoms of the cell. The energized electrons move to a higher band in the atom, leaving behind holes in their normal positions; the electron-hole pair is called an exciton. Excitons move through the PV semiconductor material, causing electrons to go from the solar cell into an electrical circuit. This process of converting light (photons) into electricity (voltage) is called the photovoltaic effect and is done without the use of either chemical reactions or moving parts (Kalowekamo, 2007).

As a starting point, we follow a common classification of solar cells as first generation (silicon wafer), second generation (thin cells, both organic and inorganic), and third generation very high efficiency cells. Our experts felt that current efforts to extend first generation silicon cells beyond wafer-based technology could lead to improvement in cost with near term relevance, but would not lead to sufficient breakthroughs for such cells to play a large role in the more distant future. Therefore, first generation cells were not included in this study. Also excluded were cadmium-based cells, whose toxicity experts felt would preclude large scale deployment, and solar concentrators, which could augment PV cells but whose primary technical challenge is the development of the high-performing cells of the types considered below. Substantial work is occurring on second generation cells, and we divided this work into three areas, each of which has its own promises and challenges:

1. Organic cells — using thin films of purely organic semiconductors — hold the promise of low cost but have not achieved high levels of efficiency. We list this technology first among the second generation cells for purposes of exposition, though it should not be taken as the most mature of the technologies discussed.

   Beyond organic, we considered separately:
2. Other inorganic materials, beyond Cadmium Telluride and CIGS. There are a host of other possible materials that can be used for thin films, but that have not been explored in any detail.

3. CIGS (copper indium gallium selenide) cells, which have already achieved some progress but face potential cost problems due to their specific material requirements; and
   Finally, we considered:
4. Third generation cells, specifically, quantum dots and multi-junction cells, which use a qualitatively different technology. These are promising because they can theoretically generate higher efficiencies due to their ability to produce multiple excitons for each photon received.

2.3. Definitions of success

In order to meaningfully assess probabilities of success, the events constituting a successful endpoint must be defined unambiguously enough that one could say, after the fact, whether or not the event has occurred (Spetzler and Stael von Holstein, 1975). Although it is theoretically possible to fix any arbitrary set of values as an endpoint, expert input was necessary to identify reasonable endpoints — endpoints that are not so ambitious as to be practically impossible, but that require some scientific advances beyond incremental improvements. Here we detail how we defined success for an ambitious program on organic PV technology. Below we discuss more briefly the definitions of success for the other technologies.

First, we developed two separate definitions of success for purely organic PVs. With a high funding trajectory, research could aim for a very high efficiency — making rooftop PVs viable even in areas with less sunshine — while a lower funding trajectory would lead to a focus on developing PVs with a more moderate efficiency, sufficient for areas with a medium amount of sunlight. Considering two funding levels in this way, we obtain a coarse indication of returns to R&D at the technology level. We also used two funding levels, but only one definition of success, for inorganics, since the expert who provided definitions regarding this technology felt that there could be significant returns to scale. For CIGS and 3rd generation technologies, we only considered one funding level corresponding to a single target performance level. For all the technologies considered, our model separates near term R&D funding from the future abatement cost.

In defining success, it was important to find terms that experts could readily associate with particular technical hurdles, on the one hand; and that could be translated into appropriate input parameters for our IAM simulation, on the other hand. For solar PVs the critical input requirement for the IAM is the cost of electricity per kWh. We determined that this could be estimated from the cost to manufacture, the lifetime, and the efficiency (see Section 2.4 for the details of the calculation). For the ambitious, high funding trajectory program, our experts suggested we consider a technology that would provide enough electricity to power a typical house with a solar shingle roof — which, given its limited surface area, would require fairly high efficiency — and would be stable for the life of a roof for commercial viability. The experts defined success in this case as a 31% energy conversion efficiency (the ratio of usable energy produced to solar energy received). In addition, to be used on roofs, it should be stable enough to generate electricity over the physical lifetime of an installed roof. We defined stability as a requirement that efficiency drops to no less than 75% of its original level over a given lifetime, in this case 15 years. Finally, it should have a capital cost leading to an energy cost competitive with fossil-based electricity generation. Our experts focused on a manufacturing cost of $\$50/m^2$ as ambitious but plausible. This cost level is consistent with the Department of Energy's goals for PV costs (Zweibel, 1999).

Under a less ambitious program with a lower funding trajectory, success is defined similarly, but with lower efficiency (15%) offset somewhat by higher stability (a 30 year lifetime over which efficiency drops to no less than 75% of its original level), and the same manufacturing cost per unit

Table 1
Definition of success for the technologies

Technology	Definition of success	Cost (2005 ¢/kWh)
1a. Purely Organic Low	15%, 30 year, $\$50/m^2$	5.0
1b. Purely Organic High	31%, 15 year, $\$50/m^2$	3.0
2. New Inorganic	15%, 30 year, $\$50/m^2$	5.0
3. CIGS	15%, 30 year, $\$50/m^2$	5.0
4. 3rd Gen	36%, 30 year, $00/m^2$	2.9

area. The lower efficiency target allows a consideration of a much wider range of molecules that may be easier to stabilize than molecules selected primarily for having the highest efficiency.

Considerations were similar, though details differed, for the other technologies. For both CIGS and other new inorganics we use the same success endpoints as for the lower funding level definition for organics. Third generation technologies have characteristics, e.g., nano-structures, that require different production processes, but have higher theoretical limits on their effectiveness. For these, we defined success as a 30 year lifetime, along with 36% efficiency, which is theoretically possible for third generation cells in which multiple excitons may be released. These technologies, however, require very precise manufacturing, and therefore the experts set the ambitious goal of achieving a cost of $\$100/m^2$. For each technology, we specified that the endpoints would be achieved after 20 years. Table 1 summarizes the definitions of success for each technology, along with the calculated cost per kWh (discussed in Section 2.4).

2.4. From definitions of success to cost of generation

In this section we present the conversion metric we use in order to obtain a unit cost of electricity from efficiency, lifetime, and cost per unit area. We illustrate the method by describing our calculation of a baseline technology. For currently available PV technology, we chose single crystalline Silicon PV cells with 10% efficiency, 30 year lifetime, and a panel manufacturing cost of $350 per square meter. Accounting for the costs of all non-photoactive parts (such as support structure, installation, wiring, land, etc.), a $250 per square meter balance of system (BOS) cost is added to the PV cell cost itself. The total areal cost is $600 per square meter. In order to calculate the cost of electricity we need to make assumptions about insolation power (the amount of sunlight), and how much the sun will actually be shining on the cell. Assuming peak insolation power (the peak amount of solar energy received on PV cells) of 1000 W per square meter, a PV cell with 10% efficiency (W_p/W) would produce 100 peak watt (W_p) per square meter. Dividing the areal cost by the peak power per square meter gives us $6 per peak watt of power output (see Eq. (1)). We assume that PV cells operate at 20% of peak power on average (due to a diurnal cycle and cloud cover), and thus cost $30 per average watt of electric power output (W_e). Projecting this output for a $N=30$ year operating lifetime at $H=8760$ h per year, and discounting at 10% per year, results in a cost of 36 cents per kilowatt hour of electricity (kWh_e) produced by single crystalline Si PV cells (see Eq. (2), where (A/P, 10%, N) indicates the annuity conversion factor). See DOE Office of Science (2005) for details on a similar calculation.

$$\text{PV power cost}(\$/W_\mathrm{p}) = \frac{\text{module areal cost}(\$/\mathrm{m}^2) + \text{BOS areal cost}(\$/\mathrm{m}^2)}{\text{peak insolation}(1000\ \mathrm{W/m^2}) \cdot \text{effeciency}(W_\mathrm{p}/W)}$$

$$\text{PV energy cost}(\$/Wh_\mathrm{e}) = \frac{\text{PV power cost}(\$/W_p)}{\text{average elec output}(0.2W_\mathrm{e}/W_\mathrm{p})} \cdot \frac{1}{H}(A/P, 10\%, N)$$

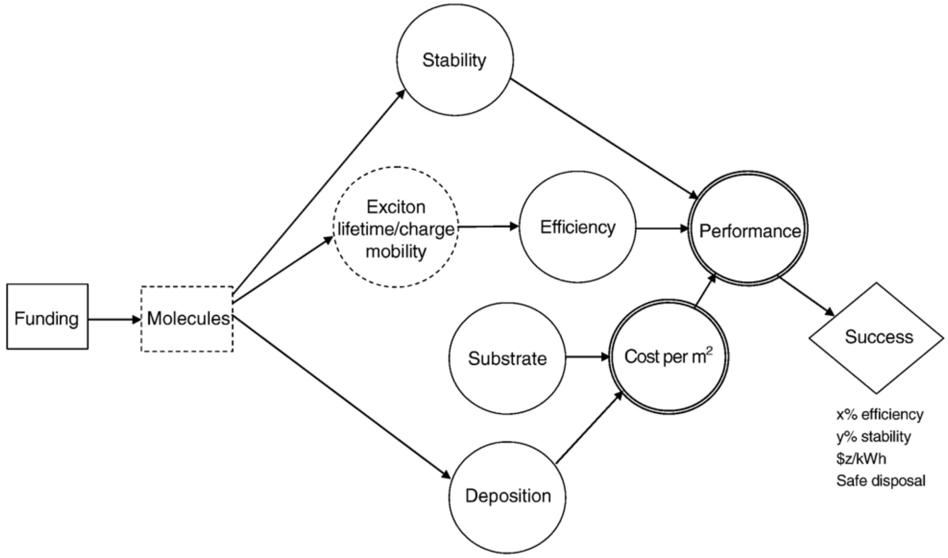

Fig. 2. An influence diagram for organic solar cells.

The 36 cents/kWh figure is set as a baseline cost[1] of PV electricity in our analysis. We use the same formula to convert each of the assessed technologies into a cost per kWh. In order to avoid imbalance between the PV cell costs and the BOS costs, we assume that the BOS cost is reduced to $75 per square meter by 2050.[2] See Table 1 for the resulting costs.

2.5. Probability elicitations

We now describe the elicitation of probability assessments for the technologies in this study, describing the process of structuring these assessments and conducting surveys to obtain judgments from multiple experts. Our method for assessing prospects of long-term R&D under varying funding scenarios is based on insights from the standard Decision Analysis literature on obtaining probability judgments from experts in ways that avoid biases due to overconfidence, motivation, anchoring, etc. (Morgan and Keith, 1995; von Winterfeldt and Edwards, 1986). In the following sections we present the raw results of these surveys and discuss how multiple probabilities may be combined.

We first asked one expert per technology to identify the key hurdles facing it, primarily in the course of defining the success endpoints discussed in Section 2.3. The experts described the specific challenges that research would have to overcome to achieve the desired level for each of the dimensions of the success endpoints. For example, while experts estimate a probability for achieving efficiency of 31%, they consider such challenges as achieving sufficient exciton lifetime, sufficient mobility (speed) of charge, having molecules that absorb across the appropriate spectrum of light given the charge mobility; and having defect free structures in the lab and then in production. Similarly, in estimating the probability of achieving a 30 year stable lifetime, experts consider the challenges of finding molecules that are stable enough to ambient air and water, and of

[1] We assume maintenance costs to be minimal, and thus we did not explicitly incorporate them for cost calculations.
[2] See page 22 of the DOE report on basic research needs for solar energy utilization (DOE Office of Science, 2005).

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resolving engineering questions about making impermeable or sealed cells of high enough quality. In estimating the probability of achieving a cost of no more than $50/m^2, experts considered the difficulty of finding a semitransparent conductor (to replace indium, which is already used but the supply of which may become constrained) as well as the costs of other materials used, e.g., polythiephene. The influence diagram we constructed in Fig. 2 was useful in clarifying the interactions between the set of molecules explored and the challenges that needed to be considered. Experts provided explicit probability estimates for the uncertainties represented in the figure by solid-line circular nodes, while they recognized but only implicitly considered the dotted-line nodes in formulating their judgments; the double-line nodes represent intermediate calculations.

We asked the experts to develop funding scenarios that were fairly realistic but sufficient to give technologies an opportunity to prove their worth. The funding levels reflect US federal funding only, while experts made their own assumptions about private industry activity. For purely organic PVs, we first defined a moderate funding trajectory of $15 M/year, corresponding to about 10 full research groups, for 10 years. The high funding trajectory (with the more aggressive definition of success) of $80 M/year for 15 years could cover about 40 four-person labs to explore a greater number of molecules, along with substantial efforts on other parts of the problem. For new inorganic PVs, we considered a baseline funding level of $10 M/year for 10 years (which we call “medium” funding below, since it is not very high compared to the high organic funding level) and a low funding scenario that simply halves this. The CIGS funding level was set the same as the baseline new inorganics. Third generation PVs (e.g., quantum dots) will require substantial basic research, therefore we set the funding at $50 M/year for 10 years.

After identifying challenges, we queried the full set of three experts about prospects for all four technology areas, with respect to each technical hurdle. The experts were provided with structured surveys (based on the structures already defined) which contained a primer on probability elicitation, relevant definitions and assumptions, definitions of success, and tree diagrams for each of the technologies. Each expert completed the same survey. In addition to the written materials of the survey, we communicated with the experts in person or electronically in order to clarify their questions and to make consistency checks along the way. Experts entered probabilities for each node and rationales for those probabilities, and repeated this for each funding scenario.

We then calculated overall probabilities of success, e.g., for organic PVs, the overall probability of the R&D successfully traversing the tree in Fig. 3 is equal to the product of the probabilities for success on each branch, i.e., $p_1{\cdot}p_2{\cdot}p_3{\cdot}p_4$.

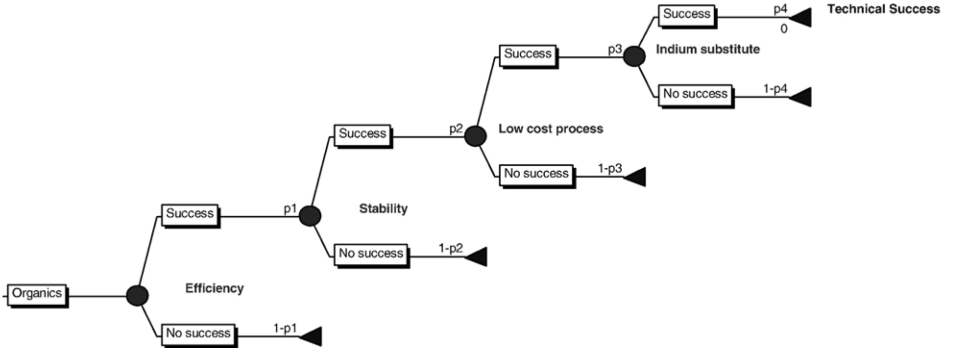

Fig. 3. Overall probability estimation tree for organic solar cells.

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Table 2
Summary Assessment Results

Technology	1a. Purely Organic Low			1b. Purely Organic High			2a. New Inorganic Low			2b. New Inorganic Medium		
	Ex 1	Ex 2	Ex 3	Ex 1	Ex 2	Ex 3	Ex 1	Ex 2	Ex 3	Ex 1	Ex 2	Ex 3
Probability of efficiency	0.85	0.90	0.80	0.15	0.50	0.30	0.80	0.90	0.10	0.93	0.95	0.25
Probability of stability	0.50	0.30	0.50	0.60	0.80	0.25	1.00	0.90	0.10	1.00	0.90	0.50
Probability of deposition cost	0.90	0.50	0.25	0.30	0.30	0.30	0.80	0.20	0.10	0.93	0.50	0.10
Probability of indium substitute	0.90	0.30	0.10	0.98	0.70	0.25	N/A	N/A	N/A	N/A	N/A	N/A
Total probability	0.34	0.04	0.01	0.03	0.08	0.01	0.64	0.16	0.001	0.86	0.43	0.01

2.6. Assessment data

Tables 2 and 3 below summarize the set of assessments, giving each expert's probability of each hurdle being achieved for each technology.

In some cases, there was substantial agreement among the experts, for example that there is a high likelihood of achieving efficiency of 15% with organic PVs. For the other PVs, the range between the pessimistic and optimistic judgments about achieving efficiency endpoints was greater. There was some disagreement about prospects for achieving stability, although only in one case was it an order of magnitude.

Where there are substantial disagreements, the rationales are instructive. In particular, 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. Similarly, where probabilities of achieving the efficiency endpoints differed, the lower probabilities were couched in terms of the difficulty of optimizing concepts that work in the lab. Overall, the comments of experts 2 and 3 indicate that they feel the funding trajectory is simply too low, both for some of the breakthroughs (e.g., indium substitutes, in the event of scarcity of this element) and post-breakthrough development. For example 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 $15,000,000/year would be sufficient to meet this cost target with any reasonable probability.” This could reflect the fact that R&D returns curves are often thought to be S-shaped, as in Fig. 4,

Table 3
Summary of assessment results (continued)

Technology	3. CIGS			4. 3rd Gen		
	Ex 1	Ex 2	Ex 3	Ex 1	Ex 2	Ex 3
Probability of efficiency	0.99	0.90	0.30	1.00	0.10	0.80
Probability of Stability	0.80	0.90	0.80	1.00	0.30	0.90
Probability of cost of deposition	0.90	0.90	0.10	0.03	0.50	0.02
Probability of indium shortage	0.95	1.00	0.30	N/A	N/A	N/A
Total probability	0.04	0.00	0.02	0.03	0.02	0.01

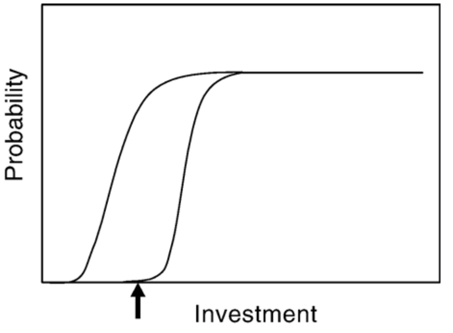

Fig. 4. S-shape of R&D return curves.

with increasing returns initially until the program is ramped up enough, followed by decreasing returns. Our data indicates that expert 1 applies the upper curve to solar technology, while experts 2 and 3 apply the lower curve, where the arrow in the figure indicates the funding levels we considered.

This point is highlighted by the disparities between experts with respect to the impact of doubling funding for new inorganic PVs, the only area in which our results give an explicit measure of returns to scale. From Table 2 we note that expert 1 sees a one third increase in the probability of success, starting from a high base, expert 2 sees a nearly three-fold increase, from a lower base, while expert 3 sees a thirteen-fold increase from a much lower base.

2.7. Combining expert judgments

The wide range of opinion within the research community is itself notable, and suggests that the connection from research to development is not yet well understood. Because the experts generally agreed about what is possible, but disagreed about the levels of difficulty, further dialog among experts could be illuminating.

For modeling purposes, we can compute returns to R&D for the technologies assuming various combinations of the elicited probabilities. Most simple is to calculate an overall probability of success for each technology, for each expert based on that expert's expressed probabilities regarding each hurdle. This can be used for sensitivity analysis, but gives quite wide ranges. To better illustrate the combined expert judgment, we use the simple average of the experts' overall probabilities (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 could further moderate the results: probabilities could be averaged for each hurdle, rather than each technology; odds could be averaged rather than probabilities; the averages could be geometric instead of arithmetic; and experts could be weighted differently depending on their relative expertise with each technology. The simple average is presented here for three reasons: this method is responsive to all judgments but is not prone to large swings based on a single opinion (von Winterfeldt and Edwards, 1986); experts used the overall probability of success as a consistency check; and, although the absolute probabilities derived from the raw data here vary depending which combination method is used, the relative ranking of success probabilities and even of expected value do not change significantly. Thus, Fig. 5 shows each of the expert's judgments together with the average

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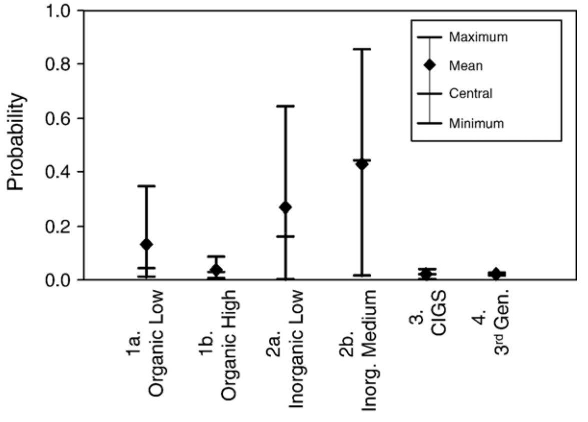

Fig. 5. Experts' assessments.

(note from the previous tables that different experts assigned the maximum probability to different technologies).

3. Impact on the MAC

The expert elicitations provide us with definitions of success for improvements in PV technology. This section describes the applied analysis of the impacts that success, as defined in the elicitations, might have on the costs of CO_2 abatement. For each definition of success above, we derive a Marginal Abatement Cost (MAC) curve.

3.1. The Marginal Abatement Cost curve

Many abstract, analytical models represent technical change in terms of its impact on the MAC. Understanding the impacts on the MAC is important because, when combined with a marginal damages curve, it determines the optimal amount of abatement, and implicitly, the optimal amounts of different technologies to be used in the economy. Fig. 6 illustrates a high level influence diagram of the climate technology R&D investment decision. The R&D

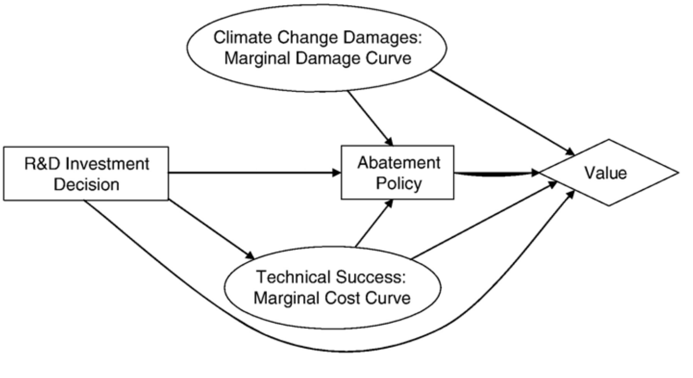

Fig. 6. Influence diagram of the R&D investment decision.

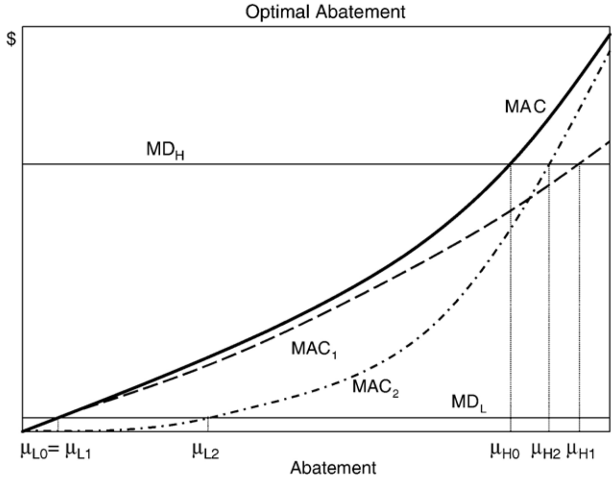

Fig. 7. Stylized representations of technical change impact on the MAC; and resulting optimal abatement levels.

portfolio impacts the MAC, but in a probabilistic way. Abatement policy is chosen to minimize the combined cost of abatement and the damages from climate change, given current knowledge about climate change and given the current state of technology. Optimal abatement is found by equating marginal costs with marginal damages. The overall goal is to minimize the expected value of total costs, including R&D, abatement, and damages in this problem of sequential decision making under uncertainty. Different technologies are likely to have a different effect on the cost curve. Fig. 7 illustrates how the impact of technical change on optimal abatement varies by technology and by the severity of marginal damages. The solid upward sloping line represents the original MAC. The two dashed lines represent different types of technical change. The horizontal lines represent two levels of marginal damages. On the horizontal axis we show the optimal level of abatement in each case, where μ_{ij} represents optimal abatement given damages $i=H$, L and MAC curve $j=0$, 1, 2. Note that the technical change embodied by MAC_1 has no effect when marginal damages are low, but a significant effect when damages are high; the impacts of MAC_2 on optimal abatement are nearly the reverse. By paying attention to the impact of technology all along the curve (rather than just a point estimate), we gain information about how optimal behavior will change with changes in marginal damages. Thus, we will investigate here the impact of technical success in the defined solar technologies on the MAC.

3.2. Methods and assumptions

For this study, we derive MACs for the year 2050 under different assumptions about technological pathways. The analysis was conducted using the MiniCAM integrated assessment model. MiniCAM is a global IAM that looks out to 2095 in 15-year timesteps. It is a partial-equilibrium model, with 14 world regions that includes detailed models of land-use and the energy sector. MiniCAM explicitly represents a range of electricity-generating technologies including various generations of nuclear power, multiple fossil generating technologies, solar and wind power, and electricity from biomass. Technology characteristics in MiniCAM are inputs to the model; the model does not include learning curves or other approaches to induced technical

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change.[3] 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 et al., 2006). The cost of Carbon Capture and Storage (CCS) is assumed to be prohibitively high.

The objective of the analysis was to develop marginal abatement cost curves under specific assumptions about the costs of solar PVs at a particular time in the future, in this case 2050. These curves relate levels of emissions reduction to carbon prices, thus they approximate the marginal cost of emissions reductions. A range of carbon price paths were created leading up to 2050. In each path, the carbon price increases over time at the discount rate, modified by the average natural system uptake rate (i.e., consistent with a Hotelling (Hotelling, 1931) approach to resource extraction modified by Peck and Wan (1996). In order to approximate MACs, we ran a range of price paths, and then plotted abatement in 2050 on the horizontal axis against the carbon price in 2050 on the vertical axis (Fig. 9).[4] The relationship between abatement and the carbon price resulting from this analysis should be viewed not strictly as a MAC, but roughly indicative of the relationship that MACs are intended to inform. An approach similar to this was used in the U.S. Climate Change Science Program (CCSP) scenarios to explain differences in the GDP impacts of CO_2 stabilization between different modeling groups (Clarke et al., 2007).

The version of MiniCAM used in this analysis represents PVs with constant unit costs and implements them within a logit formulation, which captures regional and other factors that lead to heterogeneity in costs across applications (Clarke and Edmonds, 1993). For this reason, even if a technology such as PVs has the lowest cost on average it will not capture the entire market. This approach, although abstract, partially captures the issues of geographically varying PV electricity costs, due to solar insolation, cloud cover, etc.: The same cell would produce more electricity in a sunny sub-tropical location than it would in a cloudy temperate location; therefore a cell that cannot compete in the electricity market in general may still be deployed in niche markets.

Finally, PVs are an intermittent resource, meaning that they do not produce electricity at a constant level over time, and they are not dispatchable, meaning that they cannot be turned on when additional power is needed. These related factors could potentially provide a brake on PV deployment unless complementary technologies are developed. For example, cost-competitive electric batteries could be used to store energy from PVs for standard electric applications and could also provide a venue for PVs to support not just traditional electric loads but also an emerging transportation load. More advanced electric grid technologies, including technologies that allow effective time-of-day pricing could induce PVs to be deployed at larger scale.

To explore the important intermittency issue, the analysis here was conducted under two different possible regimes. The baseline regime assumes a need for backup electricity generation. As the percentage of electricity produced from PVs increases, backup power is required to ensure grid reliability. For this analysis, one additional unit of backup capacity is required for each additional unit of solar capacity, once electricity production capacity from PVs is 20% of the total in any region. Natural gas combined cycle power plants were assumed to provide the backup power. We will term this regime "20% limit". In the second regime, provided for comparison, PVs are assumed to be self-sufficient in terms of storage, such that no additional backup is required. This implies availability of a zero-cost storage device. There are no limits on PV deployment in the electricity sector under this regime, which we will term "free storage".

The treatment of technical change leading up to 2050 is also important. For PVs to contribute substantially to climate change mitigation, their cost must come down from what they are today.

[3] See Brenkert et al. (2003) and Edmonds et al. (2005) for more discussion of the model.

[4] We define the MAC to be non-negative, and therefore do not show negative carbon prices.

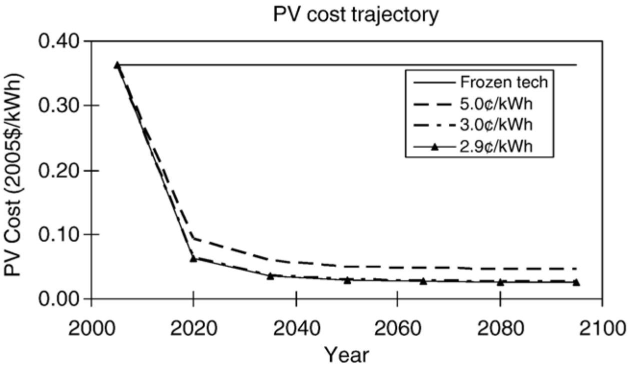

Fig. 8. PV unit cost trajectory for the technologies described in Table 1, assuming success.

In this analysis, instead of assuming an instantaneous advancement, the unit costs of PVs were assumed to decline gradually over time. The annual decline rate of unit cost is assumed to decrease as PV technology matures. Lower PV costs lead to greater PV deployment in earlier years, which also affects the emissions reductions in 2050. Fig. 8 shows the cost paths. Note that we have considered a case in which no improvements are made to PVs. Although unrealistic, this serves as a useful benchmark for evaluating benefits of PV technologies.

3.3. MiniCAM results

In this section we present the marginal abatement cost curves in 2050 generated by MiniCAM using the costs implied by the definitions of success in Table 1, and interpret the implications to CO_2 abatement.[5] Fig. 9 shows the resulting MAC curves for a baseline and two technical change cases, both with 20% limit and with free storage. (Since the results for third generation PVs, at a cost of 2.9 cents/kWh were virtually indistinguishable from the results for the ambitious organic program, at 3 cents/kWh, we have simplified the figures by only showing the results for the 3 cents/kWh technology.) Several elements of the results bear note. First, advances in PVs will lead to emissions reductions even with no carbon price. This is evidenced by the rightward shift of the abatement cost functions. For example, in the most extreme case in which free storage PVs reach 2.9 to 3 cents/kWh in 2050, global emissions are reduced by 15% absent any actions to address climate change (see the left panel in Fig. 9). In this way, PVs are different from a technology like CO_2 capture and storage which will only be implemented in the presence of a positive carbon price. Second, the development of complementary technologies is critical for the prospects of PVs. Even if PVs can reach 3 cents/kWh in 2050, the impact on the abatement cost function will be minimal if one-to-one backup is required at 20% of electricity production capacity. In contrast, if very-low cost storage could be developed, the benefits of bringing PVs down to this price would be substantially greater. Third, the benefits of PVs are highly non-linear because there are substitutes in the electricity market. In the scenarios used here, nuclear power is not constrained by issues such as waste, proliferation, and safety, and is assumed to produce electricity at between 4.8 and 5.7 cents/kWh, depending on the type of reactor (Clarke et al., 2006). Only when PVs reach this level or below do substantial benefits accrue. This is evidenced

[5] All calculations are in terms of tons of carbon and 2005 constant prices.

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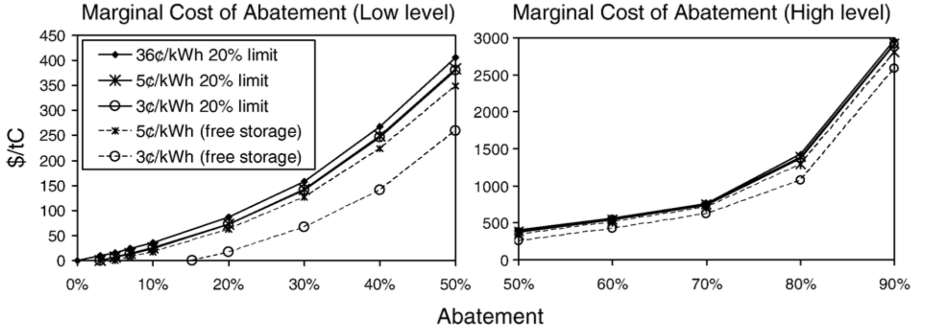

Fig. 9. MAC curves under different technology assumptions. The left and right panels show the MAC for abatement between 0%–50% and 50%–90% for emphasis.

by the dramatic shift in the abatement cost function between 5 cents/kWh and 3 cents/kWh (free storage).

Fig. 10 shows the results in two different ways to more clearly illustrate the impacts. The panel on the left shows the absolute difference between the baseline MAC and the MACs with technical change. From this figure we see that technical change is having an impact, and that the absolute level of the impact is larger at higher levels of abatement. The panel on the right shows the percentage difference between the baseline and the MACs with technical change, that is, the absolute difference of the MACs divided by the baseline MAC. This panel shows that the percentage impact on the MAC gets smaller as abatement increases. This is in contrast to the most common assumption about technical change — that it will reduce the MAC proportionately for all abatement levels, or pivot it down (Baker and Adu-Bonnah, in press; Baker et al., 2006; Downing and White, 1986; Fischer et al., 2003; Goulder and Mathai, 2000; Goulder and Schneider, 1999; Jung et al., 1996; Milliman and Prince, 1989; Montero, 2002; Parry, 1998). This assumption would lead to a straight line in the right-hand panel.

Finally, Fig. 11 shows how optimal abatement is impacted by technical change. The horizontal axis shows different levels of a carbon tax and the vertical axis represents optimal abatement given that tax. This indicates how changes in technology impact optimal behavior. Note that the impact of technology on behavior tapers off as the carbon tax gets large. Improvements in PV technologies have the greatest impact on optimal behavior for low and moderate levels of

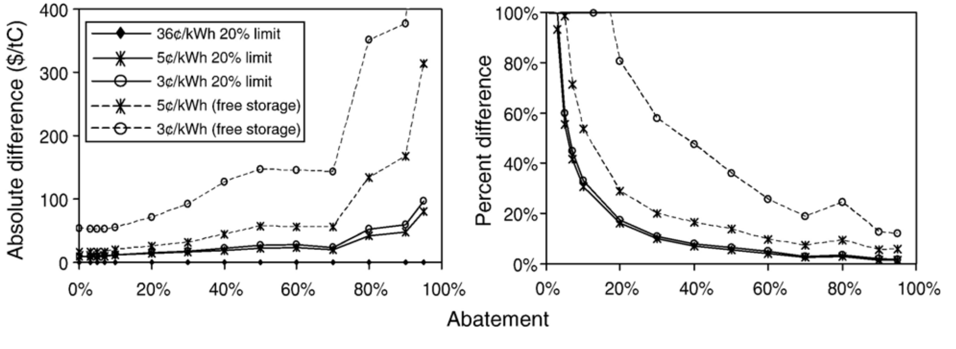

Fig. 10. The left panel represents the absolute difference between the baseline MAC and the MACs with technical change. The right panel shows the absolute difference divided by the baseline MAC.

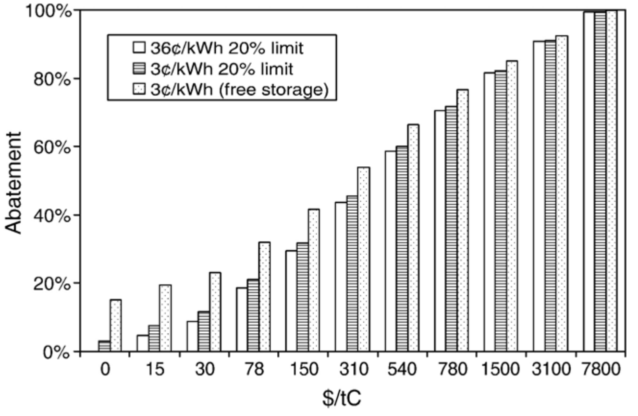

Fig. 11. Impact of technical change on optimal abatement. The horizontal axis represents a carbon tax.

abatement; the differences in abatement amount at a given tax level get smaller as the carbon tax increases.

3.4. Parameterizing the impact on the MAC

In this section we parameterize the impact of PVs on the MAC. We use the data generated above to estimate a smooth relationship between technical change and the impacts on the MAC. This has two purposes. First, it clarifies the qualitative impacts of PVs on the MAC. For example, as mentioned above, most analytical models assume that technical change will pivot the MAC down. Here we provide a similar simple relationship that better represents the data. Second, it provides a single parameter, a kind of summary statistic, to represent the impacts of various projects. This simplifies analysis and portability. We focus on the results in the absence of improvement in storage technology (20% limit case), since such improvement is itself a direction of technical change. We postpone analysis of this until we have formally assessed the potential for storage technologies.

From the panels in Fig. 10 we noted that while the absolute difference between the baseline MAC and the MACs with technical change was increasing in abatement level μ, the percentage difference was getting much smaller. In particular, we noted that the percentage difference in the right panel of Fig. 10 has an approximately logarithmic shape. Thus we hypothesize that we can estimate the empirical curves using the following equation:

$$\tilde{MC}(\mu,\alpha) = \max\left[MC(\mu)[1+\alpha \ln],0\right]$$

where MC (μ) is the baseline marginal abatement curve, assuming 36 cents/kWh; and $\tilde{MC}$ (μ,α) is the marginal cost after technical change parameterized by α. This equation implies that for low abatement levels, the technology has a larger percentage impact (larger than α); while for higher abatement levels the percentage impact is small. We used a least squares estimation method on this equation and the data to estimate a value for α for each of the cost levels shown in Table 1, plus two more levels [6] for comparison. We present the results in

[6] 26 cents/kWh is selected to illustrate the effect of cost reduction only in BOS costs. 10 cents/kWh is arbitrarily selected as an intermediate level of technical advancement.

Table 4
Statistics for selected success levels

Scenario (c//kWh)	26	10	5	3	2.9
α	0.0061	0.0493	0.1418	0.1666	0.1690

Table 4. The square root of the average mean squared error ranges from.7 to 9 (the MAC itself ranges from about 4 to about 4000).

The three panels in Fig. 12 give a visual representation of the fit of the estimated curve to the actual curve. Each figure compares the actual and estimated numbers for a cost of 5 cents/kWh. The top left panel of the figure shows the absolute difference between the advanced technology MACs and the baseline MAC. This shows that we underestimate the impact of PVs, in an absolute sense, at high levels of abatement. In fact, our estimation leads to no impact on the MAC at full abatement, while the data does not show this. The top right panel shows the abatement percentage difference, and indicates that we are underestimating the percentage difference between the baseline and the advanced technology MAC at low levels of abatement. The bottom left panel of the figure compares the MACs themselves, only up to 20% abatement. At higher abatement levels, the difference between the MACs are difficult to see. This estimate should be taken as a loose approximation that can be used to give insight in analytical models. We will use these estimates below.

Note in Table 4 that cost and α are not perfectly (negatively) correlated. In particular, the first improvement, from 26 cents/kWh to 10 cents/kWh, results in a very large impact on the MAC, increasing α by a factor of 8. Thus, while the cost per kWh provides useful information, it cannot be used as a measure of the impact on the whole MAC curve.

In this section, we have estimated the impact of technical successes on the MAC curve. In the next section, we combine the assessed probabilities of achieving such success for the given

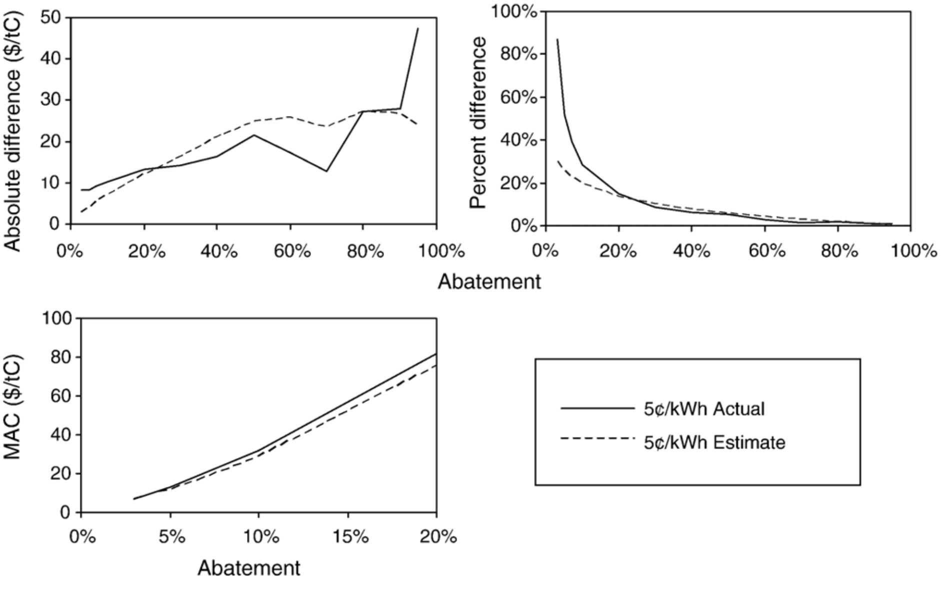

Fig. 12. Absolute and percent difference curve estimation at 5 cent/kWh.

funding levels with the calculated impact for a successful technology in order to analyze the net potential impact of R&D funding.

4. Data analysis

In this section we combine the probabilities provided by the experts in Section 2 with information on the impacts on the MAC from Section 3. We want to represent the probabilistic relationship between R&D investments and technical change, where technical change is represented by the impact on the MAC, α. In order to translate our data into information about the returns to R&D, we need to hypothesize funding orders — rules determining which project will get funded first, second, etc. Using these funding orders, we present information on the marginal impact of additional R&D investment in three different ways — on the expected value of α; on the probability of success; and on percentiles of α.

4.1. Funding orders

We would like to use our data to answer the question: what is the marginal impact of another dollar invested in R&D? In order to do that, we must make assumptions about the funding order for the projects. That is, we need to know in which project the additional dollar is being invested. This is complicated by the fact that sometimes it is optimal to fund less attractive projects in order to exhaust leftover funds. A further complication arises from the fact that some of these projects are mutually exclusive, while others are substitutes. We assume that the two purely organic projects (1a,1b) are mutually exclusive, as are the two "other inorganic" projects (2a, 2b). All other combinations of projects are feasible. If multiple projects are successful, we assume that the overall result is equal to the lowest cost per kWh achieved.

Most natural is funding in order of impact per dollar of funding. In order to determine this funding order, we simply calculate the expected impact α divided by dollars of funding, and fund projects in order from highest to lowest. This is a good heuristic that is widely used in industry, although it clearly does not always result in the optimal portfolio. One major weakness of this heuristic is that it ignores risk issues completely, only focusing on expected return. Therefore, it may be useful to consider alternate funding orders. In particular, in prior work we have suggested considering "low risk" and "high risk" funding orders (Baker et al., 2007). The "low risk" order is determined by funding projects in order of the probability of success per dollar invested. This is what an extremely risk averse decision maker might do. The high risk order is determined by funding projects in order of the potential impact per dollar invested (ignoring the probability of success). This corresponds to the behavior of an extremely risk seeking decision maker.

In order to calculate these metrics, we need a single amount to represent the dollars invested. The different projects have different yearly amounts over different numbers of years. In order to put them on an even footing, we calculated the present value of the funding trajectory, assuming a 10% interest rate. We calculate per-dollar impact using both the impact on the MAC as represented by α and the impact on costs, represented through a "cost improvement" metric. The cost improvement metric is simply the baseline cost of 36 cents/kWh divided by the cost/kWh for a given program, assuming technical success. We calculate the expected α per dollar as the probability of success times α if successful divided by the present value of the funding investment. The expected cost improvement metric per dollar is calculated similarly. Table 5 shows the metrics for each project.

It turns out that for this data there is a natural funding order. The order is the same whether we fund by expected α per dollar funding; expected cost improvement metric per dollar funding; or

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Table 5
Technology metrics

Project	1a. Organic low	1b. Organic high	2a. Inorganic low	2b. Inorganic medium	3. CIGS	4.3rd Gen
Expected α/Dollar (main funding order)	0.00031	0.000011	0.0013	0.0010	0.000032	0.000033
Expected cost improvement/Dollar (main funding order)	0.016	0.00080	0.065	0.052	0.0016	0.0024
α/Dollar (main funding order)	0.0024	0.00028	0.0047	0.0024	0.0016	0.0019
Cost improvement metric/Dollar (high-risk funding order)	0.12	0.020	0.24	0.12	0.080	0.14
Probability of success/Dollar (low-risk funding order)	0.0022	0.000067	0.0090	0.0072	0.00022	0.00019

α per dollar funding. In all cases the funding order is: to fund low cost inorganics first, then fund medium cost inorganics as a substitute, then add low cost organics, then 3rd generation and CIGS. Finally, high-cost organics would be funded last as a substitute for low cost organics, resulting in the order 2a, 2b, 1a, 4, 3, 1b. There are two exceptions. The first is if we fund by cost improvement metric per dollar funding, as shown in the 4th row of Table 5. In this "high risk" case (in terms of probability of not succeeding), 3rd generation moves up to be funded second. The order remains the same otherwise: Projects 2a, 4, 2b, 1a, 3, 1b. The second exception is if we fund by probability of success per dollar funding, as shown in the 5th row of Table 5. In this "low risk" case, CIGS and 3rd generation switch places compared to the baseline order: Projects 2a, 2b, 1a, 3, 4, 1b. Below we present representations of the returns to R&D for each of these three orders.

4.2. Returns to R&D

4.2.1. By expected value

The most straight forward way to present the results is in terms of how the expected benefit of R&D changes with the investment of R&D. In Fig. 13 we show the expected benefits in terms of α on the left and the cost improvement metric on the right, for the main, high and low risk funding

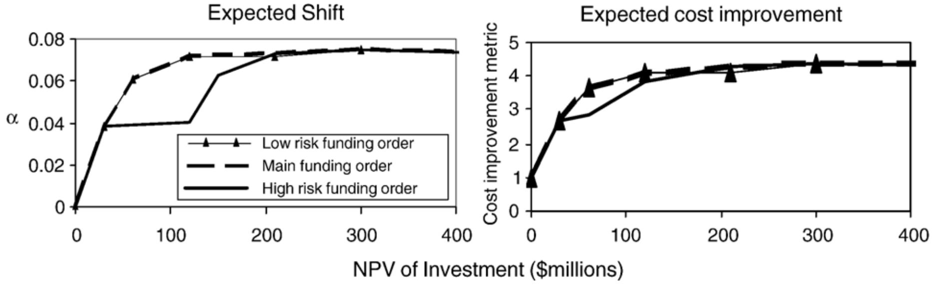

Fig. 13. R&D returns in terms of expected impact.

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orders. First we note that there is no qualitative difference between the curves for α and for the cost improvement metric. Second, note that the main funding order shows the classic shape of a returns curve, increasing and concave. Using the natural funding order of impact per dollar will always result in this shape. On the other hand, the returns curves for the high-and low-risk funding orders are increasing, but not everywhere concave. In the high-risk order we are giving up some expected return in order to have the possibility of a high payoff from 3rd generation technology. For the low-risk order, there is a small dip at the $200 M mark, where we are funding the slightly safer CIGS project before the 3rd generation project. Finally, we have not included Project 1b, the high cost organics, since this project leads to a lower expected value of α and of the cost improvement metric. Thus, if decisions were being made based on expected values, project 1b would never be funded.

These functions could be approximated and used as deterministic returns-to-R&D functions in computational models. They can be used qualitatively to think about the trade-offs between investment and increasing the efficiency of PVs. But, by focusing on expected value, we ignore the randomness inherent in the investments. If the ultimate payoffs are non-linear, then the expected payoff will depend on the probability distribution over the actual α or cost improvement metric, not the average.

4.2.2. By expert

In Fig. 14 we again show the expected α, but this time we have separated the various experts out. This is one way of assessing the variability in the estimates. One approach is to assign an equal probability to each expert. This may be particularly useful for calculating the value of better information.

We see that our experts seem to encompass an optimist, a pessimist, and a middle-ground. Nevertheless, despite the differences in the magnitude of some of the different experts' estimates, their inputs lead to almost the same investment order according to expected impact per dollar. The only exception is expert 2 — this expert's assessments lead to an investment order in which both low cost inorganics and CIGS are skipped altogether.

Note that we have included Project 1b, the "high" organic program as a substitute to Project 1a, the "low" organic program. As mentioned above, this program leads to a lower expected α: a very high investment leads to a small probability of a breakthrough. This causes some of the curves in Fig. 14 (and Fig. 15 below) to bend back down after the $200 M mark.

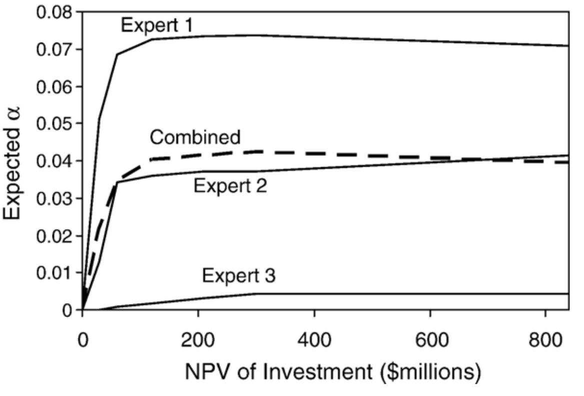

Fig. 14. Returns to Solar R&D by Expert.

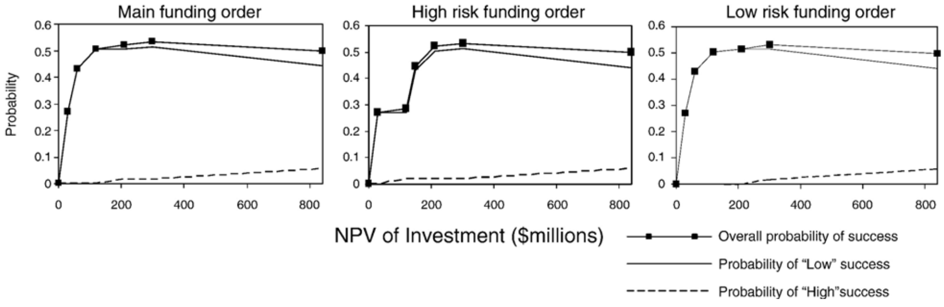

Fig. 15. Probabilities of success as a function of investment.

4.2.3. By probability

Another way to present the results that includes variability is to show how the probability of success changes with investment. To simplify the presentation, we have divided the projects into only two success levels. The "Low" level of success indicates achieving 5 cents/kWh, which is equivalent to an alpha of 0.1418 or cost improvement of 7.2. The "High" level indicates achieving at least 3 cents/kWh; thus it includes the slightly more successful goal of 2.9 cents/kWh. Fig. 15 shows the change in probability with increases in investment, with the main funding order on the left, the high risk funding order in the middle, and the low risk funding order on the right. We have also shown the overall probability of success: the probability of achieving at least 5 cents/kWh. If we ignore the high-cost organics investment, then the overall probability of success has the classic increasing, concave shape for the main funding order. When high-cost organics are added in, the overall probability of success goes down, since we have dropped the low cost organics project; but the probability of "High" success has been increased.[7] If the high-cost funding order is followed, then the probability of success for achieving a "High" breakthrough is concave, but the overall probability of success is non-concave. The distinction between the low risk and the main funding order is in the higher level of investment required to achieve any probability of "High" success, and a slight dip at \$200 M in the overall probability of success.

This data can be used in models that represent R&D as increasing the probability of success (for example see (Blanford, 2006; Bohringer and Rutherford, 2006)). To account for multiple levels of success, multiple functions can be used. It may be useful to run sensitivity analysis by using the high-risk funding order. This may be the most straightforward way to implement the randomness in a wide variety of models.

4.2.4. By percentiles

In this section we represent the data in a way that is analogous to the method in Section 4.2.1, in that it uses the value of α, but includes variability. Here, instead of showing the expected return as a function of investment, we show the percentiles for the actual returns. Fig. 16 shows the 10th, 50th, and 95th percentiles for the main and high-risk funding orders in terms of α. The 95th percentile line show the values of alpha for which we have a 95% chance of being below, and a 5% of being at or above, for each different investment level respectively. The low-risk funding order resulted in the same figure as the main order. The only difference between the two panels is

[7] We did not explicitly elicit the relation between the low-cost and high-cost organic programs. We have assumed that if the high-cost organics program fails, it fails completely. It is possible that a program aimed at achieving the very high efficiency levels of Program 1b might fail in that goal, but still achieve the more conservative goals of Program 1a.

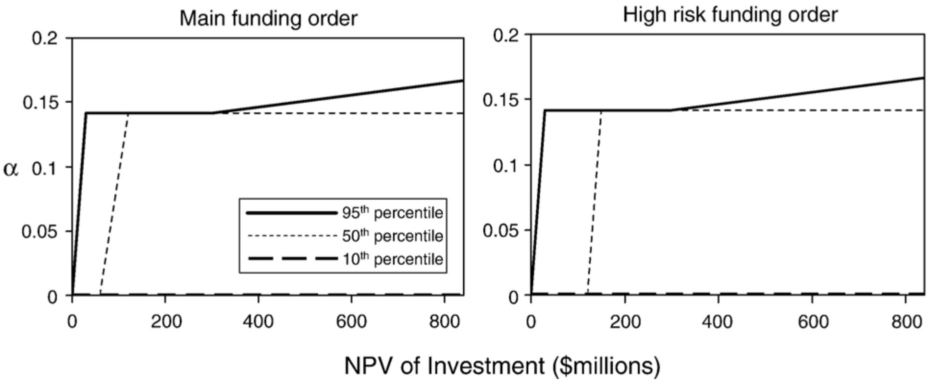

Fig. 16. R&D returns percentiles.

that the 50th percentile line jumps up later for the high-risk order. Because there is a small number of levels of success, these figures are very lumpy. This representation may be more useful when there are a number of different levels of success that might be achieved (if results were additive, rather than substitutes, for example). This information could be implemented in models by letting each line be a returns-to-R&D function, and assigning a probability to each function. In this case, we could assign a probability of 25% to the 10th percentile line; 67.5% to the 50th percentile, and 7.5% to the 95th percentile. This could be implemented in models where the level of technical change is related to the investment. The difficulty here is that the lines are not smooth and cannot be easily approximated using standard functional forms.

5. Conclusions

We have collected data on the relationship between R&D investment and technological outcomes for advanced solar PVs; and implemented a framework for understanding the probabilistic impacts of R&D funding on the cost of abatement. We have presented information on this relationship in a number of ways, and discussed how it can be implemented in a variety of models.

Subject to the limitations discussed below, this analysis leads to four conclusions. First, it appears that even very large advances in PVs will have a relatively small effect on the abatement cost curve. However, when these advances are combined with improvements in storage, the impacts are considerably more significant, and highly non-linear. That is, improvements in PVs or storage alone have little impact; a breakthrough in solar (to around 3 cents/kWh) when combined with low cost storage has considerable impact compared to a more moderate improvement to 5 cents/kWh. Even more striking, PVs with a cost of 5 cents/kWh with free storage have a larger impact than PVs with a cost of 2.9 cents/kWh but facing a capacity limit due to costly storage. This implies that capturing the interactions between technologies is crucial; and that capturing the impact on the cost of abatement goes beyond just improvements in cost.

Second, if we focus on cost reduction in PVs alone (the 20% limit case), we see that these will tend to have the most significant impact (in terms of changing optimal abatement as well as reducing costs) at moderate levels of abatement, up to about a 20% reduction below our baseline, equivalent to stabilizing at an atmospheric CO_2 level of about 550 parts per million. The reason these improvements to PVs do not have a significant impact on the MAC at high levels, is that solar is likely to be implemented up to the capacity limit at those high levels, even without the improvements. Thus, the improvements will lead to a cost reduction for the given amount of solar, but will not lead to a higher implementation of solar. All of these results depend on our assumptions about the other technologies available in the economy, most notably the availability (and acceptability) of nuclear; and the non-availability of carbon capture and storage.

Third, there is significant disagreement among experts about the efficacy of R&D expenditures, especially on reducing the costs of manufacturing. This suggests directions for future work: a) facilitated interaction between experts such as a workshop setting, allowing experts to share information and come closer to agreement about underlying assumptions; b) making explicit assumptions about industry activity and funding; c) using a longer and higher funding trajectory, making it easier to separate differences of opinion about the relative maturity of the technologies from differences over their ultimate promise; and d) a more detailed analysis that looks at technologies at a finer level, incorporating judgments from scientists working on each component of the individual technologies. Additionally, we note that our probability assessments are based on just three experts. Studies have shown that the incremental benefit of adding another expert decreases significantly after 3–4 experts (Winkler and Clemen, 2004). Nevertheless, it is possible that our sample is not representative of the population of solar scientists as a whole. Another concern is that our project descriptions, particularly in the definitions of the budgets, are too limited. Thus, these results should be seen as preliminary.

Finally, even with disagreement among the experts, some regularities appear. The order of investment is rather robust, with higher expected values for the "other inorganic" projects, followed by the lower risk organic project, with third generation somewhere in the mix. Thus, if we face a problem with a given budget, the resulting portfolio would be the same for each of the experts.

At a theoretical level, an important finding from this study is that our analytic methodology appears viable. Expert elicitation, which has been powerfully applied in R&D portfolio management in various industries, can be applied even at the industry or public policy level by deriving the impact of success in terms of economic curves, in this case the MAC. This approach requires special attention to the definitions of technical success and the way that technical success is translated to impact in the economic model. This methodology provides information about the supply of technical change. This can be combined with information on the demand for (or benefits to) technical change in models of sequential decision making under uncertainty to determine robust climate change policies.

We have generated MACs using MiniCAM, a particular integrated assessment model, with its own unique set of assumptions and foibles.[8] Beyond this, the data we have collected can be used with other IAMs, to better confirm the qualitative and quantitative impact that advances in solar are likely to have on the MAC. Additionally, this is only one part of a much larger analysis. We are performing expert elicitations on a much larger group of energy technologies. We expect that analyzing the interactions between technologies will lead to broader and more robust results. By quantifying both technical uncertainty and the impact of potential progress on the MAC, we can facilitate economic analysis of investment in energy technology to mitigate climate change.

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[8] See the CCTP (Clarke et al., 2006) for particular set of technology assumptions used in this analysis and see the CCSP (Clarke et al., 2007) for a comparison of MiniCAM with two other IAMs.

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