Advanced Solar R&D: Applying Expert Elicitations to Inform Climate Policy

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Abstract

Both climate change and technical change are 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 technological 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

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1 Introduction

In this paper we combine expert elicitations and economic modeling to analyze the potential for R&D into solar Photovoltaics 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 control and of eventual damages both depend heavily on assumptions about technical change [26]. 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 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 another paper. 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 issue is just starting to be studied, most notably by others in this special issue [6][5]. Second, there is virtually no work that discusses how particular technologies are likely to impact the abatement cost curve. This is important since the ultimate damages from climate change are uncertain. If damages were known, then a simple point estimate of the reduction in the cost of achieving a particular concentration level would suffice. But, since damages are uncertain, the optimal concentration level is uncertain. Thus, we need not a point estimate, but a curve – 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 technological 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 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 improvements in transportation technologies may be very important. On the other hand, consider improvements in coal-fired electricity generation. An incremental improvement will 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 how risky they are. 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 fact, our prior work has shown that there are interactions between uncertainty in damages, uncertainty in technical change, and the representation of technical change. In Baker & Adu-bonnah [1] we show that when technical change pivots the cost curve down, optimal R&D investment is higher in riskier programs. When technical change is modeled as decreasing the emissions-output ratio, then, qualitatively, optimal investment is higher in less-risky programs under most uncertain damage scenarios. The exception is that when the probability of a catastrophe inducing full abatement is very high, optimal investment may be twice as high in risky programs compared to programs with certain returns.

In [2] 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, focussing on advanced solar technology. We have collected probabilistic data on advanced solar PV technology, and used a technologically detailed Integrated Assessment Model (IAM) to determine how the technologies would impact the abatement cost curve. The rest of the paper is organized as follows. In Section 2 we discuss the technologies that we assessed, and how we defined success. In Section 3 we introduce the idea of using the Marginal Abatement Cost Curve (MAC) as an organizing principle in analyzing the impact of technical change in the climate change problem. In Section 4 we use an IAM to translate the definitions of success into impacts on the MAC; and parameterize the impacts. In Section 5 we discuss the probability elicitations over technical success for the different technologies. In Section 6 we provide multiple representations of the probabilistic impacts of R&D. We conclude in Section 7.

2 Structuring the Expert Elicitations

In this section we discuss the initial steps in the expert elicitation, including the selection of particular technologies, and the development of definitions of success. In Section 5, we discuss how we structured the probability assessments and the results of those assessments.

2.1 Why use subjective probability assessments?

To consider the uncertain range of impacts on the curve from a portfolio of candidate technologies, we must estimate the probability that each of the technologies will be successful. For some technologies, there are helpful historical data and historical comparisons, e.g., Moore's law from the semiconductor industry, and manufacturing learning curves [27][32]. 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 subjective judgment of experts who are most familiar with the specific technologies [10][25][28].

We are considering breakthrough solar PV technology in particular. Basic research is needed (e.g., to find appropriate molecules that have the potential for adequate performance to be deployed) followed by development work to move research from the lab to production (e.g., finding the right process for deposition), at which point improvements would follow a more predictable path. To the extent that probability of success depends on breakthroughs, what has happened with other technologies will not offer much to differentiate 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 [18].

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 subject matter 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, in parallel with efforts in other technology families such as biofuels.

As a starting point, solar cells are commonly categorized as first, second and third generation. Our experts felt that current efforts on alternatives to wafer-based silicon could lead to improvement in cost with near term relevance, but not breakthroughs with impact in the more distant future. Therefore, first generation cells were not included in this study. 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 organic semiconductors – hold the promise of low cost but have not achieved high levels of efficiency.

Beyond organic, we considered separately:

2. CIGS (copper indium gallium selenide) cells, which have already achieved some success but face potential cost problems due to their specific material requirements; and

3. Other new inorganic materials which have shown some promise but are currently far from viable for large scale electricity production for various reasons.

Finally, we considered:

4. Third generation cells, e.g., quantum dots and multi-junction cells, 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 assess probabilities of success, events must be defined unambiguously enough that one could say, after the fact, whether or not the event has occurred [29]. 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.

We developed two separate definitions of success for this technology. With a high funding trajectory, research could aim for a very high efficiency (and thus broad geographic distribution), while a lower funding trajectory would lead to a focus on developing PVs with a more moderate efficiency, sufficient for areas with a reasonable amount of sunlight. Considering two funding levels in this way, we obtain a coarse indication of returns to R&D at the technology level.

Our experts suggested that a successful organic PV technology would have an efficiency level that could provide power to a house with a solar shingle roof, and would be stable for the life of a roof for commercial viability. If the material works as well as hoped (under an ambitious program with a high funding trajectory), it will approach 31% energy conversion efficiency, the theoretical limit. In addition, to be used on roofs, it should be stable enough to generate electricity over the physical lifetime of an installed roof (with efficiency dropping to no less than 75% of its original level over a 15 year lifetime), and it should have a capital cost leading to an energy cost competitive with fossil-based electricity generation, on the order of 5 cents/kWh. In defining success, it was important to find terms that experts could readily associate with particular technical hurdles, and that could be translated into appropriate input parameters for our IAM simulation. For solar PVs the critical input requirement is the cost per kWh. We determined that this could be estimated from the cost to manufacture, the lifetime, and the efficiency (See Subsection 4.1 for the details of the calculation). Our experts focussed 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 [33].

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 area (since the film materials will still be a small portion of the cost).

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 will require different production processes but have higher theoretical limits on their effectiveness. For these, we defined success as still having a 30 year lifetime, along with 36% efficiency while 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 and an efficiency metric, discussed in Section 4 below.

Technology	Definition of success	Cost (cent/kWh)	Efficiency metric
1a. Purely Organic	15%, 30 year, $50/m^2$	5.0	7.2
1b. Purely Organic	31%, 15 year, $50/m^2$	3.0	12
2. New Inorganic	15%, 30 year, $50/m^2$	5.0	7.2
3. CIGS	15%, 30 year, $50/m^2$	5.0	7.2
4. 3rd Gen	37%, 30 year, $100/m^2$	2.9	12.4

Table 1: Definition of success for the technologies

3 The Marginal Abatement Cost Curve: An Organizing Principle

In this section we argue that the impacts of technology on the marginal abatement cost curve (MAC) can be used as an organizing principle when analyzing a number of technologies under uncertainty. In this paper we are focussing our attention on one particular technology, solar PVs. But the role that PVs will play in combatting climate change depends not only on technical success in PVs, but also on the state of other technologies and the state of the environment. Thus we need to be able to compare advances in different technologies under different damage scenarios. For example, we would like to know how a reduction in the cost per kWh of solar compares to a reduction in the cost per unit of carbon captured in CCS. Additionally, there is a need to incorporate uncertainty in technological change and in damages into environmental-economic modeling.

Representing the impacts of technological advance on the MAC is a concept that has been widely used in abstract, analytical modeling. 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. Figure 1 illustrates a high level influence diagram of the R&D investment decision. The R&D 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. Different technologies are likely to have a different effect on the cost curve. For example, electricity technologies will tend to have a larger effect at lower levels of abatement; while transportation technologies will tend to have a larger effect on higher levels of abatement. Figure 2 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.

Research to date has made assumptions about how technical change will impact the MAC, with the assumption that it will pivot it down being most common ([1][3][12][15][14][16][19][20][21][23]). One contribution of this work is to empirically estimate the impacts of improvements in PVs on the MAC, using the definitions of success provided by experts above. Understanding the *qualitative* impacts of a particular technology on the MAC can provide insights into the results of technologically detailed Integrated Assessment Models. *Quantifying* the impacts of a technology on the MAC provides a portable representation of the impacts of technology that can be used in abstract models, in computational models that use an abatement cost curve, and in technology portfolio modeling. In the next section we use the definitions of success developed in Section 2 in conjunction with a technologically-detailed IAM to generate MACs under different assumptions about technical success. In Subsection 4.3, we parameterize the impact on the MAC, in order to provide a portable representation.

4 Impact on the MAC

This section describes the applied analysis of the impacts that improvements in PV technology and manufacturing processes might have on the costs of CO_2 abatement. 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 technological change.[1]

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. 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 [17] approach to resource extraction modified by Peck and Wan [24]). After running a range of paths, abatement in 2050 was plotted against the carbon price in 2050. 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 CCSP scenarios to explain differences in the GDP impacts of CO_2 stabilization between different modeling groups [9].

The version of MiniCAM used in this analysis represents PVs with fixed marginal costs and implements them within a logit formulation, which captures regional and other factors that lead to heterogeneity in costs across applications [8]. 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 PV costs depending on the solar insolation, which varies geographically: PVs are more attractive in the sunny Mojave Desert than in rainy Seattle. PVs are also distinguished by their efficiencies. Higher efficiency cells require less area to generate a given amount of power. Although the PV resource is ostensibly large enough that gross land area is not an issue, in potentially important applications with limited area, such as roofs, efficiency could be important, not just amortized cost.

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

[1] See Brenkert et al. [7] and Edmonds et al. [13] for more discussion of the model.

effective time-of-day pricing could allow PVs to deploy at larger scale.

To explore the important intermittency issue, the analysis here was conducted under two different possible regimes. The baseline approach 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-to-one backup is required when electricity production capacity from PVs is 20 percent of total capacity in any region. Natural gas combined cycle power plants were assumed to provide the backup power. 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 using this approach.

The treatment of technological change leading up to 2050 is also important. In this analysis, for PVs to contribute substantially to climate change mitigation, they must come down in cost from where they are today. This will not happen instantaneously. PVs were assumed to improve gradually through 2095. The annual decline rate of unit cost is assumed to decrease as PV technology matures. This means that advancements before 2050 provide benefits. Lower PV costs lead to greater deployment in these earlier years, which leads to emissions reductions in 2050. Figure 3 shows the price 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 PVs benefits.

4.1 From Definitions of Success to MiniCAM parameters

The PV electricity generation technology is modeled through an efficiency parameter normalized to the baseline level. A standard conversion metric is used to obtain the baseline unit cost from efficiency, lifetime, and cost per unit area. For currently available PV technology, we chose single crystalline Si PV cells with 10% efficiency, 30 year lifetime, and a cost of \$350 per square meter. Adding the current balance of systems (BOS) cost \$250 per square meter, the total cost per square meter is \$600. A PV cell with $eff = 10\%$ efficiency (W_p/W) would produce $100W_p$ per square meter at assumed peak insolation power of $1000W$ per square meter. Dividing the cost per square meter by the peak power per square meter gives us \$6 per peak watt of power output (See equation 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 power output ($\overline{W}$). Projecting this output for a $N = 30$ year operating lifetime

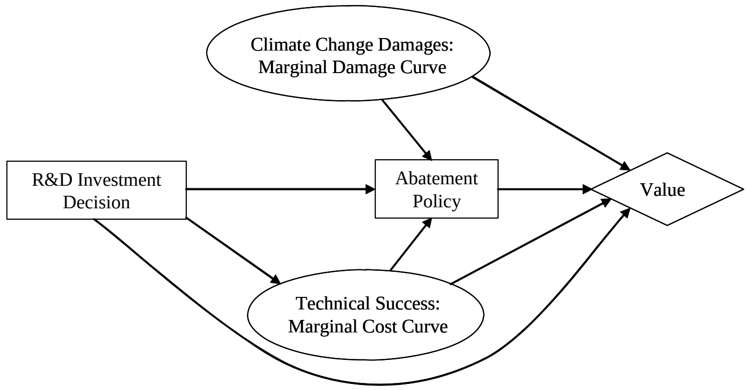

Figure 1: Influence diagram of the R&D investment decision

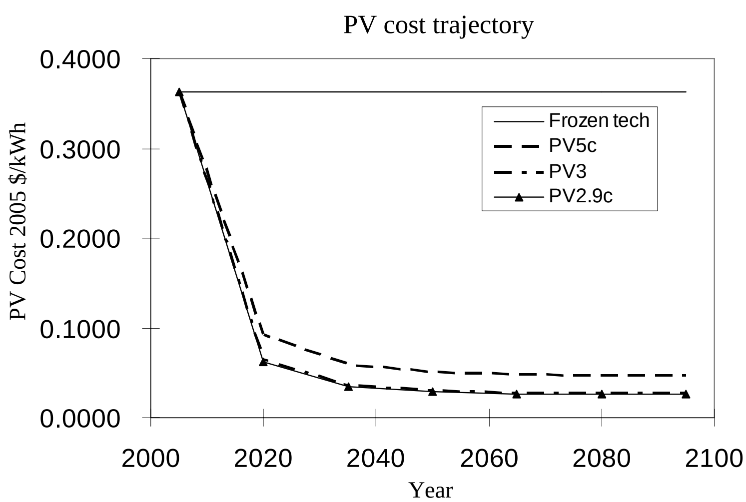

Figure 3: PV unit cost trajectory

at $H = 8760$ hours per year, and discounting at 10% per year, results in a cost of 36 cents/kWh for electricity produced by single crystalline Si PV cells (see equation 2, where $(A/P, 10\%, N)$ indicates the annuity conversion factor).

$$\frac{\$}{W_p} = \frac{\frac{\$}{m^2}}{\frac{1000W}{m^2} \cdot eff\frac{W_p}{W}} \tag{1}$$

$$\frac{\$}{kWh} = \frac{\$}{W_p} \cdot \frac{W_p}{0.2\overline{W}} \cdot \frac{1000\overline{W}}{k\overline{W}} \cdot \frac{1}{H}\,(A/P, 10\%, N) \tag{2}$$

The 36 cents/kWh figure is set as a baseline cost of PV electricity in MiniCAM. 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 and efficiency parameters.

4.2 MiniCAM Results

Figure 4 shows the resulting MAC curves for the three technical change cases and a baseline, both with and without free storage. Several elements of the results bear note. First, advances in PVs will lead to emissions reductions 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 PVs with storage reach 2.9 to 3 cents/kWh in 2050, global emissions are reduced by 15 percent *absent any actions* to address climate change (See Figure 5, top left panel for a close up view). In this way, PVs are different than a technology like CO_2 capture and storage which will only be implemented in the presence of a carbon price. Second, the development of complementary technologies is critical for PVs prospects. 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 percent 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 4.8-5.7 cents/kWh, depending on the type of reactor. Only when PVs

[2] See page 22 of the DOE report on basic research needs for solar energy utilization [22]

reach this level or below do substantial benefits accrue. This is evidenced by the dramatic shift in the abatement cost function between 5 cents/kWh and 3 cents/kWh with storage.

Figure 5 shows the results in three different ways to more clearly illustrate the impacts. The panel on the top left simply shows the MAC from 0%-50% abatement. The panel on the bottom left shows the absolute difference between the MACs with technical change and the baseline MAC. From this figure we see that technical change is having an impact, and that the absolute level of the impact is larger at higher abatement. The panel on the bottom right shows the percentage difference between the MACs with technical change and the baseline, that is, the absolute difference divided by the baseline marginal cost. 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. This assumption would lead to a straight line in the bottom right panel.

Finally, Figure 6 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 solar alone, without storage, have the greatest impact for low and moderate levels of abatement.

4.3 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 advance 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 storage, since improvement in storage 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 Figure 5 we noted that the while the absolute difference between the baseline MAC and the

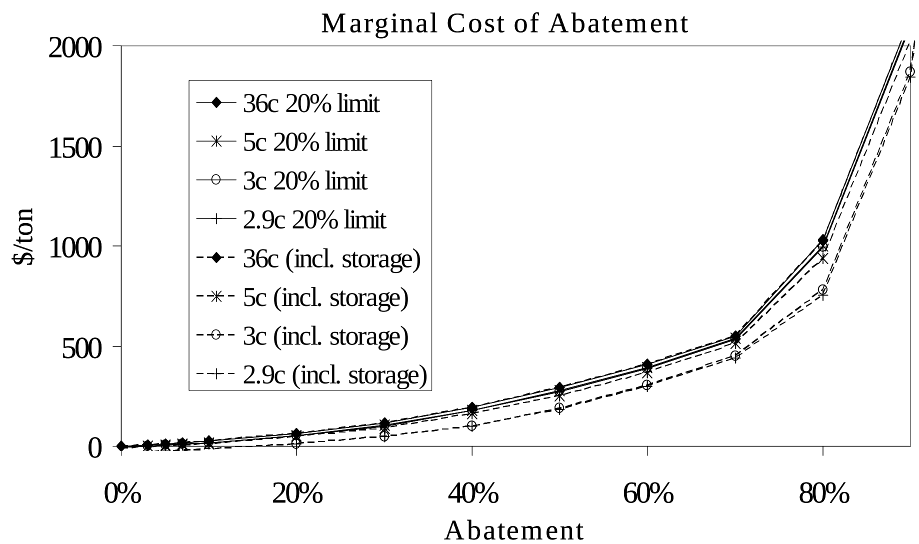

Figure 4: MAC curves for technical change with and without storage

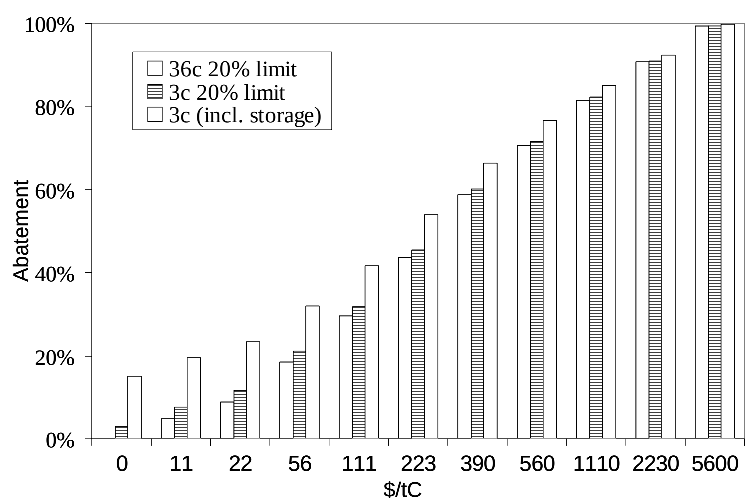

Figure 6: Impact on optimal abatement of technical change

MACs with technical change was increasing in abatement μ, the percentage difference was getting much smaller. In particular, we noted that the percentage difference in the top right panel of Figure 5 has an approximately logarithmic shape. Thus we hypothesize that we can estimate the empirical curves using the following equation:

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

where $MC\left(\mu\right)$ is the baseline marginal abatement curve, assuming 36 cents/kWh; and $M\tilde{C}\left(\mu,\alpha\right)$ is the marginal cost after technical change parameterized by α. This equation implies that for low abatement levels, the technology is having 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 for comparison. We present the results in Table 2. The R^2 values range from 1 to .999971. 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 Figure 7 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 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 2 that the efficiency multiplier and alpha are not perfectly correlated. In particular, the first improvement, from 26 cents/kWh to 10 cents/kWh, results in a very large impact on the MAC, increasing alpha 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 MAC.

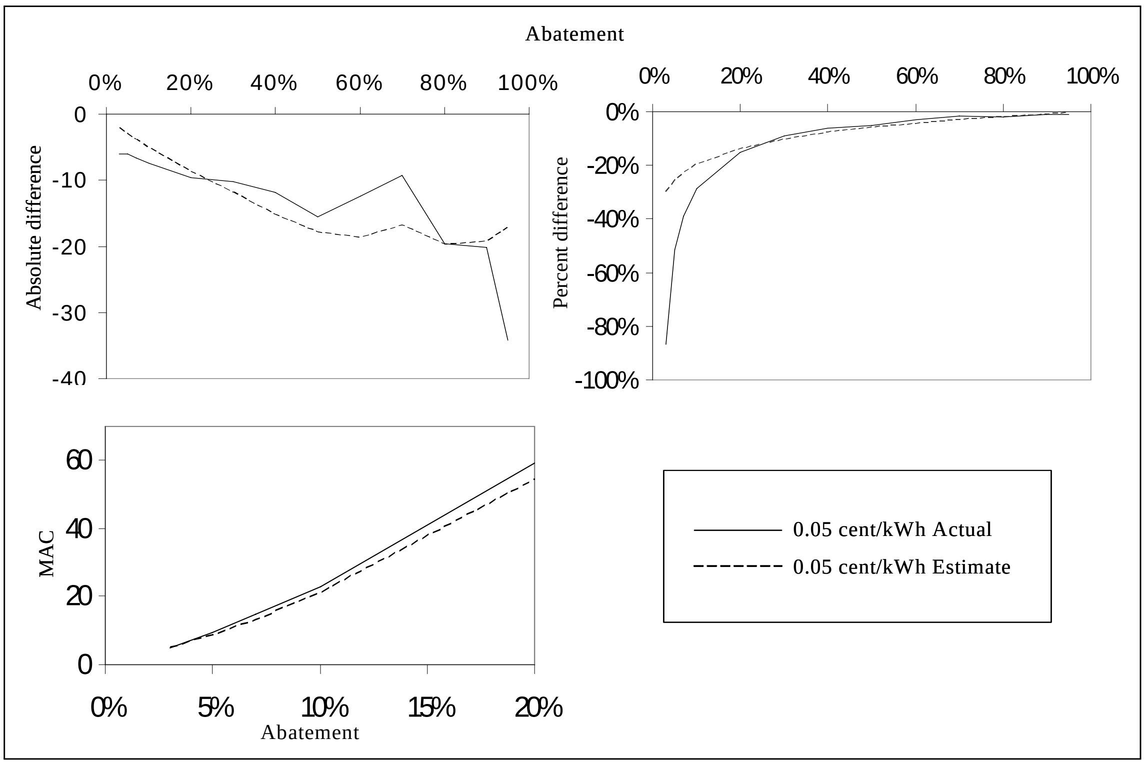

Figure 7: Absolute and percent difference curve estimation at 0.05 cent/kWh

In this section, we have estimated the impact on the MAC of successful technologies. In the next section we estimate probabilities of achieving such success, and in section 6 the impact and probability estimates are combined in order to analyze the net potential impact of R&D funding.

5 Expert Elicitations: Probabilities

This section describes the elicitation of probability assessments for the technologies in this study. We describe the process of structuring these assessments and conducting surveys to obtain judgments from multiple experts, the raw results of these surveys, and discuss how the multiple probabilities may be combined.

5.1 Process

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. The experts described the challenges to achieving the desired level for each of the endpoint dimensions, and discussed more specific challenges that research would have to overcome in order to achieve 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 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 having molecules be stable enough to ambient air and water, and of 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 semi-transparent conductor as well as the costs of other materials used, e.g., polythiephene. The influence diagram in Figure 8 was useful in clarifying the interactions between the challenges that needed to be considered. Considerations were similar, though details differed, for the other solar technologies.

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 \$15M/year, corresponding to about 10 full research groups, for 10 years. The high funding trajectory (with the more aggressive definition of success) of \$80M/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 \$10M/year for 10 years 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 50M/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 Figure 9 below is $p_1 \cdot p_2 \cdot p_3$.

5.2 Assessment Data

Tables 3 and 4 below summarize the set of assessments, giving each experts' probability of each hurdle being achieved for each technology.

In some cases, there was substantial agreement among the experts, for example that achieving efficiency of 15% with organic PVs will be easily obtained. 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

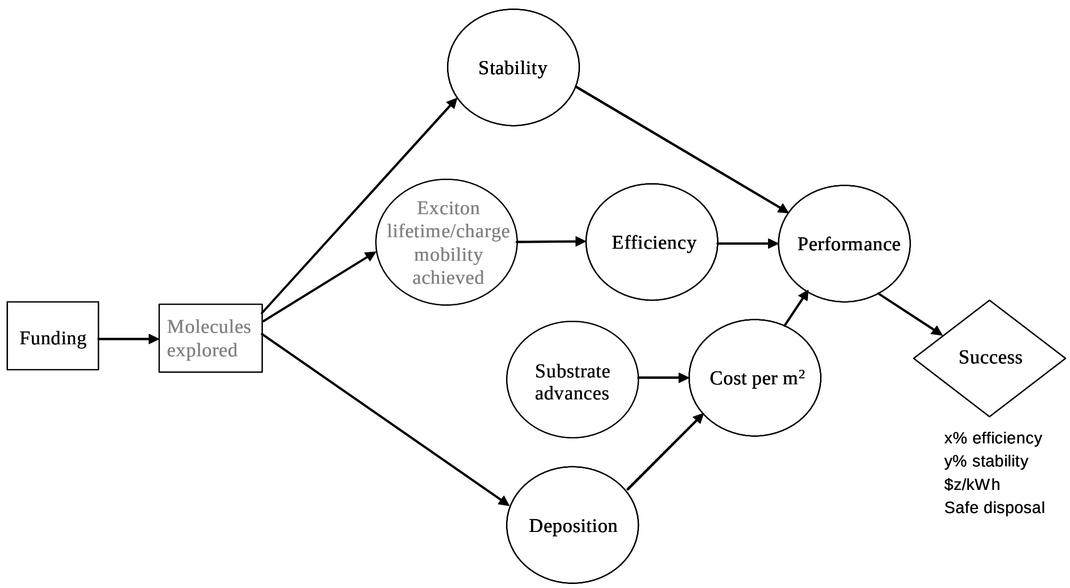

Figure 8: An Influence Diagram for Organic Solar Cells

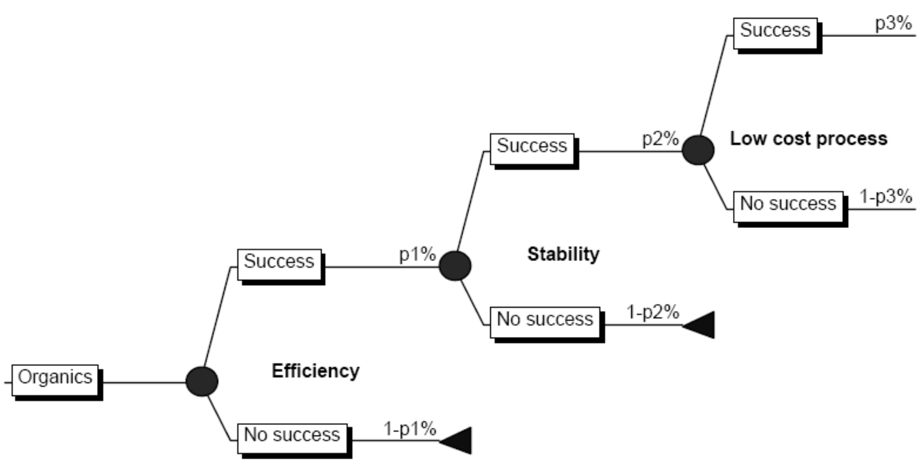

Figure 9: Overall probability estimation tree

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) 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 Figure 10, 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 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 3 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.

5.3 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. More sophisticated methods [11] 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 robust [30]; 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, Figure 11 shows each of the expert's judgments together with the average.

6 Data Analysis

In this section we combine the information on the impacts on the MAC from Section 4 with the probabilities provided by the experts in Section 5. We analyze and present the data in a number of ways. We use two different metrics to represent technical success: the efficiency multiplier, and α, the summary statistic that represents the impact of the technology on the MAC, both discussed in Section 4. We discuss how the data can be translated into information about the returns to R&D. In order to do this, we need to hypothesize funding orders – a rule 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 the metrics; on the probability of success; and on percentiles of the metrics.

6.1 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. In reality, when solving a portfolio problem, there is no fixed "funding order." Rather, this is known as a *knapsack problem*, and the funding order may change depending on the total budget available (*the amount of space in the knapsack*). Any returns function has an implicit assumption underlying it about which projects are funded first, second, etc.

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.

The most natural funding order can be described as "bang for the buck." In order to determine this funding order, we simply calculate the expected impact (on either alpha or the efficiency multiplier) per dollar 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 focussing 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 [2]. 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 payoff 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 "bang for the buck" using both alpha and efficiency. We calculate the expected alpha (efficiency) per dollar as the probability of success *times* the alpha (efficiency) if successful *divided by* the present value of the funding investment. 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 alpha per dollar funding; expected efficiency multiplier per dollar funding; or alpha 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 1a,1b,2a,4,3,2b. There are two exceptions. The first is if we fund by efficiency multiplier per dollar funding. In this "high risk" case, 3rd generation moves up to be funded second. The order remains the same otherwise: Projects 1a,4,1b,2a,3,2b. The second exception is if we fund by probability of success per dollar funding. In this "low risk" case, CIGS and 3rd generation switch places compared to the baseline order: Projects 1a,1b,2a,3,4,2b. Below we present representations of the returns to R&D for each of these three orders.

6.2 Returns to R&D

6.2.1 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 Figure 12 we show the expected benefits in terms of alpha on the left and the efficiency multiplier on the right, for the main, high and low risk funding orders. First we note that there is no qualitative difference between the curves for alpha and for efficiency. Second, note that the main funding order shows the classic shape of a returns curve, increasing and concave. Using a "bang for the buck" order 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 $200M mark, where we are funding the slightly safer CIGS project before the 3rd generation project. Finally, we have not included Project 4, the high cost organics, since this project leads to a lower expected value of alpha and the efficiency multiplier. Thus, if decisions were being made based on expected values, project 4 would never be funded.

These functions could be approximated and used as deterministic returns-to-R&D functions. 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 alpha or efficiency multiplier, not the average.

In Figure 13 we again show the expected efficiency multiplier, but this time we have separated the various experts out. This is one way of assessing the variability in the estimates. We see that our experts seem to encompass an optimist, a pessimist, and a middle-ground. Nevertheless, despite their differences in magnitudes, the experts mostly agree on the order of investment. The only exception is expert 2 – this expert would skip both low cost inorganics and CIGS altogether.

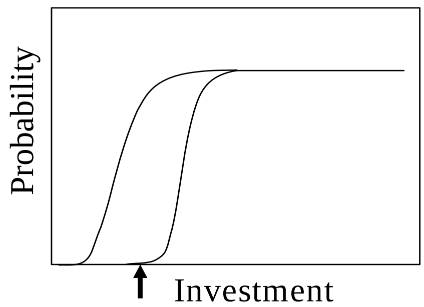

Figure 10: S-shape of R&D return curves

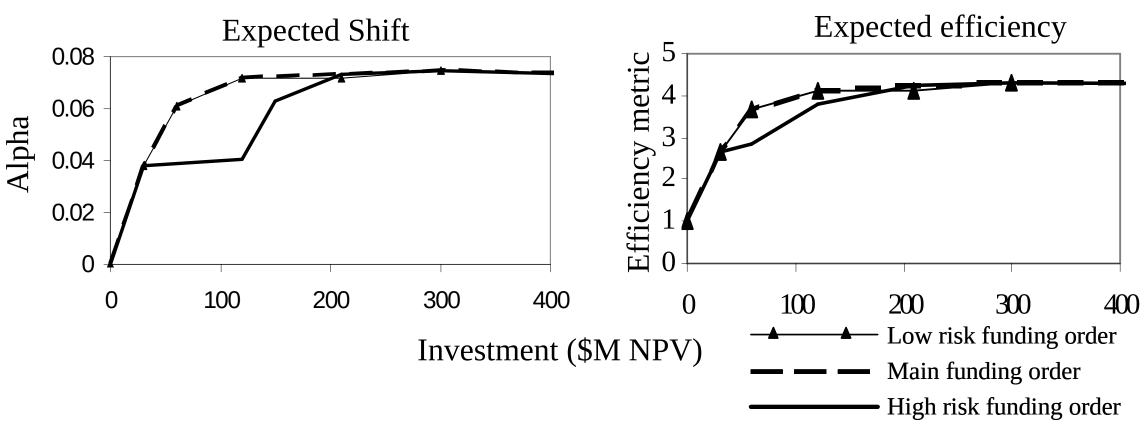

Figure 12: R&D returns in terms of expected shift

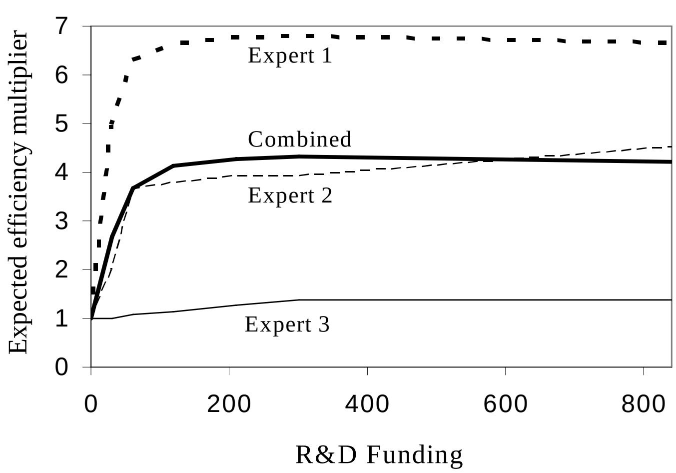

Figure 13: Returns to Solar R&D

6.2.2 By Probability

One way to present the results that includes variability is to show how the probability of success changes with investment. To simplify the figure, 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 efficiency multiplier 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. Figure 14 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.[3] 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 $200M 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 [4][5]). 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.

6.2.3 By Percentiles

In this section we represent the data in a way that is analogous to the method in Subsection 6.2.1, in that it uses the value of alpha or the efficiency multiplier, but includes variability. Here, instead of showing the expected return as a function of investment, we show the percentiles for the actual returns. Figure 15 shows the 10th, 50th, and 95th percentiles for the main and high-risk funding orders in terms of alpha. The 95th percentile line

[3] We did not explicitly elicit what the relation between the low-cost and high-cost organic programs are. 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 2b might fail in that goal, but still achieve the more conservative goals of Program 2a.

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 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.

7 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 this 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 storage have a larger impact that PVs with a cost of 2.9 cents/kWh but no 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, we see that these will tend to have the most significant impact (in terms of changing behavior as well as reducing costs) at moderate levels of abatement, up to about a 20% reduction below our baseline, equivalent to stabilizing at about 550 ppm. The reason these improvements

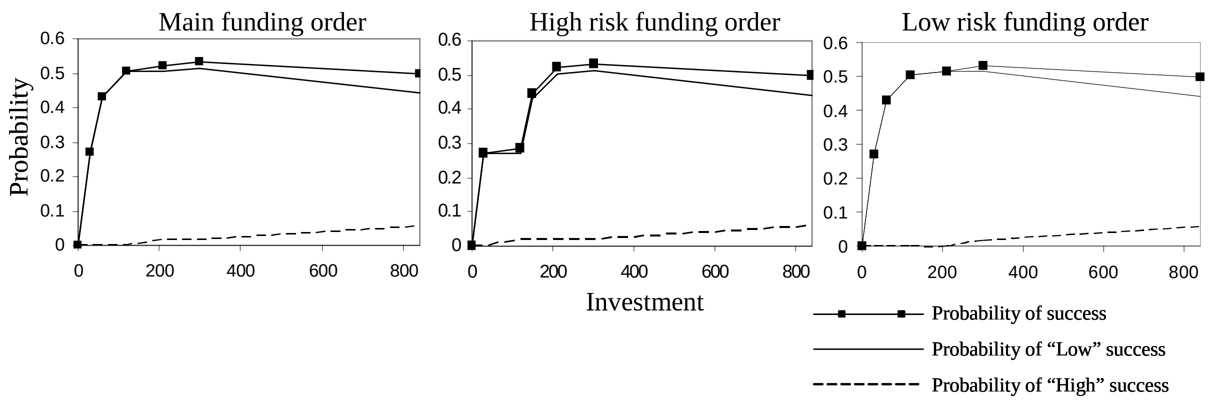

Figure 14: Probabilites of success as a function of investment

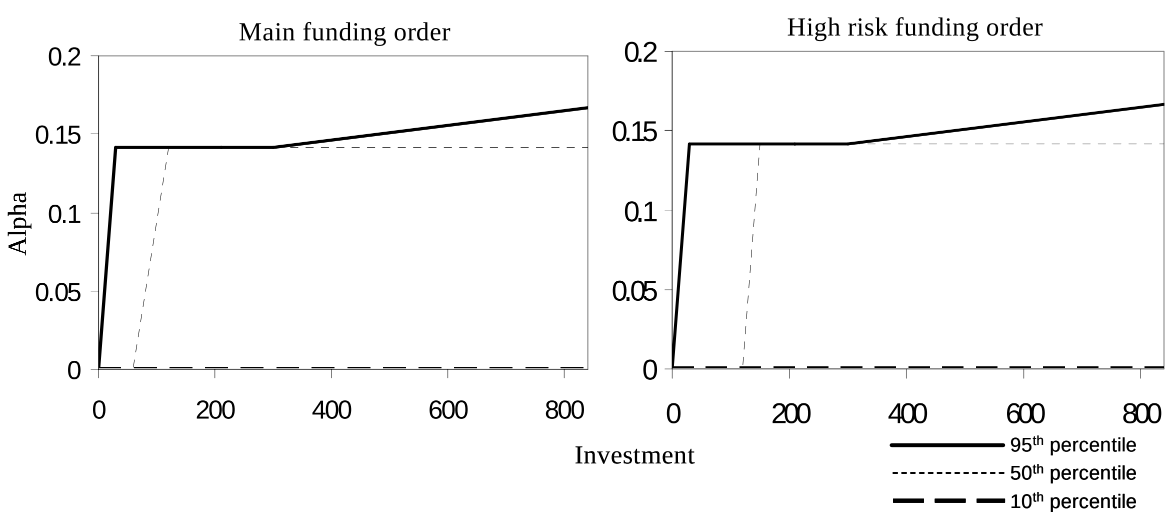

Figure 15: Actual returns percentiles

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.

Third, there is significant disagreement among experts about the efficacy of R&D expenditures, especially on reducing the costs of manufacturing. This has implications for future work: a) facilitated interaction between experts such as a workshop setting could aid experts in sharing information and coming closer to agreement about underlying assumptions; b) making explicit assumptions about industry activity and funding; c) using a longer and higher funding trajectory could make 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 could even incorporate judgments from scientists working on each component of the individual technologies.

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.

Importantly, 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.

There are limitations to our study. 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 [31]. 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 a preliminary.

We have generated MACs using MiniCAM, a particular integrated assessment model, with its own unique set of assumptions and foibles.[4] Ideally, the data we have collected will be used with other IAMs, to better confirm the qualitative and quantitative impact that advances in solar are likely to have on the MAC.

Finally, 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.

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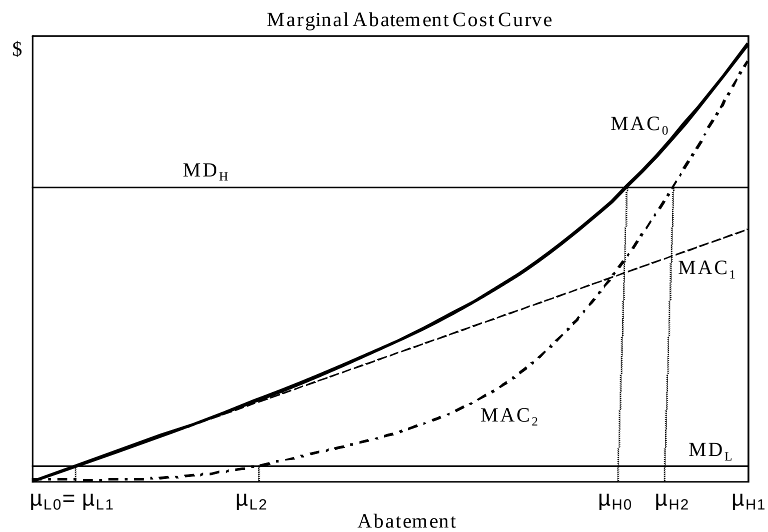

Figure 2: Representations of technical change impact on the MAC

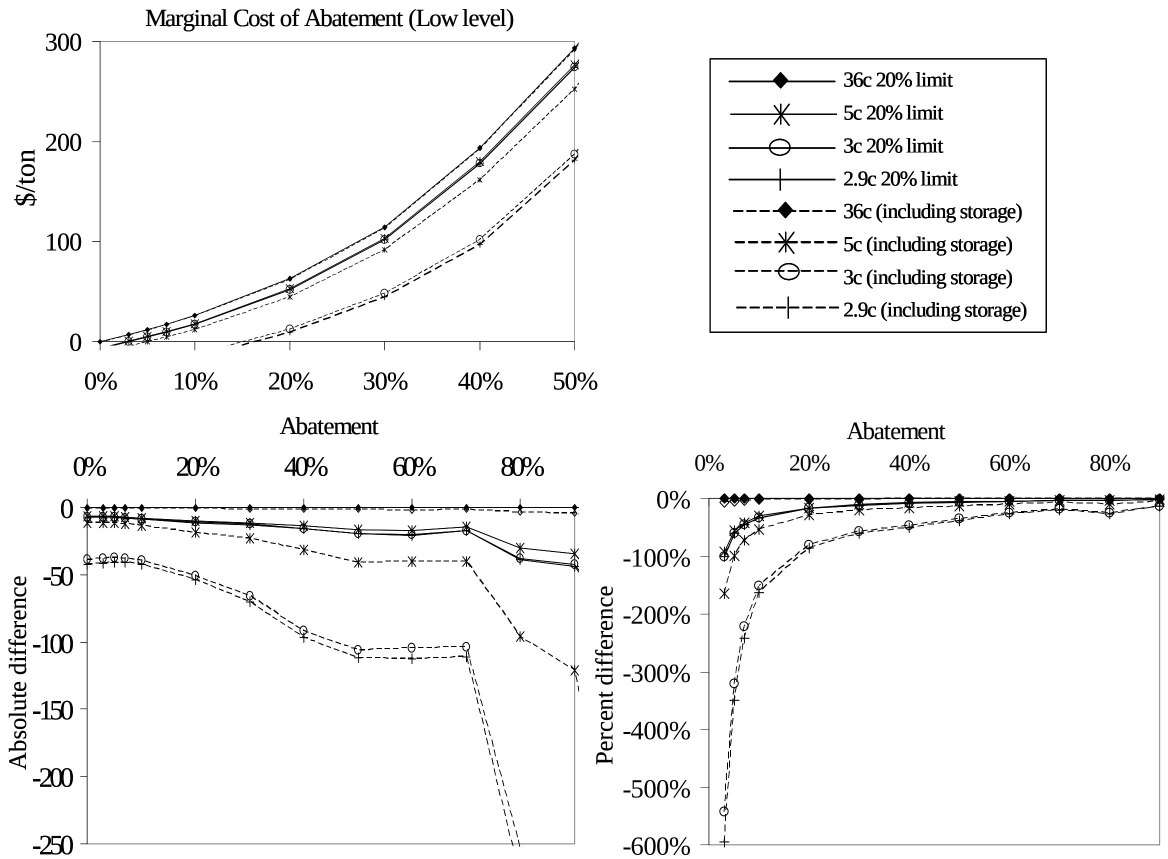

Figure 5: The top left panel shows the MAC for abatement between 0% and 50% for emphasis. The bottom left panel represents the absolute difference between the MACs with technical change and the baseline MAC. The bottom right panel shows the percentage impact on the MAC.

Scenario (cents/kWh)	0.26	0.10	0.05	0.03	0.029
Efficiency Multiplier	1.4	3.6	7.2	12	12.4
Alpha	0.0061	0.0493	0.1418	0.1666	0.1690

Table 2: Statistics for selected success levels

Technology	1a. Purely Organic			1b. Purely Organic			2a. New Inorganic			2b. New Inorganic		
	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	0.013

Table 3: Summary Assessment Results

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	0.025
Probability of indium shortage	0.95	1.00	0.30	N/A	N/A	0.3
Total probability	0.04	0.00	0.02	0.03	0.02	0.013

Table 4: Summary of Assessment Results (continued)

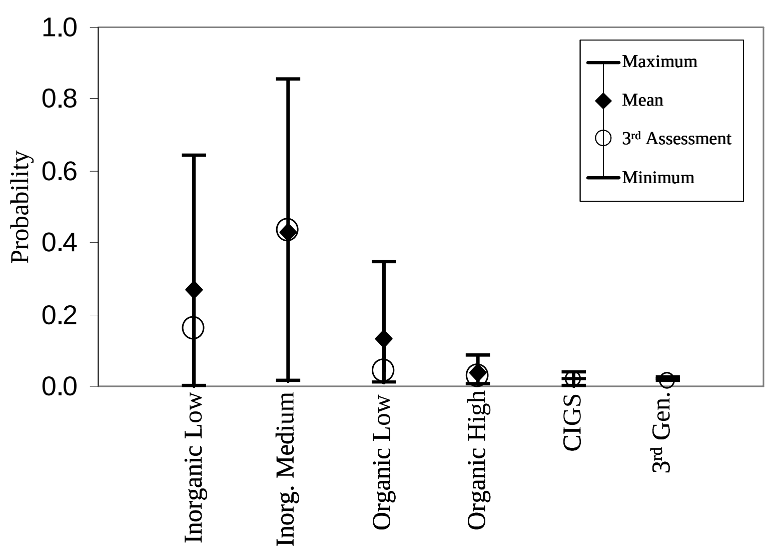

Figure 11: Experts' Assessments

Project	1a. Inorganic low	1b. Inorganic medium	2a. Organic low	2b. Organic high	3. CIGS	4. 3rd Gen
Expected Alpha/Dollar	0.0013	0.0010	0.0003	0.00001	0.00003	0.00003
Expected Efficiency/Dollar	0.0648	0.0516	0.0156	0.0008	0.0016	0.0024
Alpha/Dollar	0.0047	0.0024	0.0024	0.0003	0.0016	0.0019
Efficiency metric/Dollar	0.2400	0.1200	0.1200	0.0200	0.0800	0.1400
Probability of success/Dollar	0.0090	0.0072	0.0022	0.0001	0.0002	0.0002

Table 5: Technology metrics