# The value of better information on technology R&D programs in response to climate change

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**Abstract**

Expert elicitations are a promising method for determining how R&D investments are likely to have an impact on technological advance in climate change energy technologies. But, expert elicitations are time-consuming and resource intensive. Thus, we investigate the value of the information gained in expert elicitations. More specifically, given baseline elicitations from one study, we estimate the Expected Value of Better Information (EVBI) from revisiting and improving these assessments. We find that the EVBI is very large in comparison with the cost of performing expert elicitations. We also find EVBI is higher on technologies with larger budgets, and with net values that are not too high or too low.

*Keywords*: Value of Information; Technology R&D; Uncertainty; Environmental policy

# 1 Introduction

Technical change plays an important role in climate change and in optimal climate change policy. The results of numerous studies indicate that the costs of controlling climate change will be significantly lower if advanced technologies are available (See e.g.[19]). Thus, many governments are interested in supporting the development of these advanced technologies. This has given rise to significant interest in determining what portfolio of energy technology Research and Development (R&D) programs should be funded or otherwise supported by governments.

Allocating scarce dollars across an R&D portfolio is a hard problem, particularly in the face of climate change, because we face multiple uncertainties. First, the R&D process is itself inherently uncertain – we do not know which technologies will be successful and at what levels. Second, there is a great deal of uncertainty about the damages from climate change, and hence, the benefits from having a particular technology or portfolio of technologies. In order to analyze the optimal R&D portfolios we need to combine these two uncertain aspects together in an optimization framework.

R&D is not only uncertain, but it is also non-repeatable. Either we achieve a breakthrough in a particular technology, or we do not. Therefore, it is not possible to take a purely statistical or "frequentist" approach to estimating probabilities over successful portfolios. In particular, a statistical approach will never differentiate between particular technologies and particular programs. Thus, a common approach in R&D management is to perform *expert elicitations*: Decision Analytic techniques are used to obtain the necessarily subjective judgment of experts who are most familiar with the specific technologies [24][42][50].

Until recently there was a dearth of work collecting assessments on climate change energy technology. In the last few years, however, numerous studies (discussed below) have been started to perform just such assessments. Expert elicitations, however, can be quite resource intensive, especially if done with care. Thus, the question we address in this paper is, what is the value of the information gained in these elicitations? More specifically, given baseline elicitations from one study, what is the value of revisiting these assessments to get better information?[1]

The first challenge we face is in how to define the value of information in this case. Typically, people estimate the value of *perfect* information. However, that doesn't make sense in the context of R&D. In fact, R&D is itself a kind of search for information. Once we have perfect information, we are essentially done with the R&D program. Thus, we will consider the value of *better* information, rather than perfect information. Our concept of better information is based on the idea that there exists some ideal probability distribution, a distribution that would result if we could in fact perform experiments and use the frequentist interpretation of probability.

To calculate the Expected Value of Perfect Information (EVPI) in a simple case, one finds the optimal value of the decision problem assuming that each specific outcome is known before the key decision is made; and then applies the probability distribution over outcomes to those results. This gives the expected value of the decision problem *given* perfect information. In order to get the EVPI, the expected value of the decision problem without information is subtracted from this value. The expected value of the optimal responses with information always weakly dominates the optimization over uncertainty. The difference between these is the value of perfect information. Our process is analogous to this. But, rather than using specific outcomes, we will use specific probability distributions, namely the distributions produced by our individual experts. We assume that with better information we will learn the "true" probability distributions. We will find the optimal value of our decision problem assuming

[1]Note that we do not address the initial value of information gained from the original elicitations. This is for two reasons. First, since the elicitations have already been done, it would be an odd exersize, requiring us to pretend that we didn't know the outcome of the elicitations. Second, it is very hard to determine how one would go about deriving an *a priori* probability distribution without performing some form of elicitation.

that each specific distribution is known before the key decision is made; and then apply the probability distribution over experts to get the expected value of the decision problem given better information. We use this to calculate what we will call the Expected Value of Better Information (EVBI).

We find that gathering better information in this case has a very large value, ranging from \$100 million to over \$10 billion. The value is highest for technologies, such as nuclear, that require higher R&D budgets. Also, the value of information varies with the riskiness of climate damages (where we define increasing risk in the Rothschild-Stiglitz [47] sense of a mean preserving spread). Technologies that play a very big role when emissions are reduced to near zero, such as Carbon Capture and Storage, have a higher EVBI in high risk cases.

The rest of the paper is organized as follows. In the next section we provide some background, discussing the literature on the value of information and providing information on the climate change R&D portfolio problem. In Section 3 we discuss our approach to estimating the value of better information in some detail. In Section 4 we present our elicitation data, our mathematical portfolio model, and discuss our solution method. In Section 5 we present the results, and conclude in Section 6.

# 2 Background

## 2.1 Expert Elicitations and Value of information

The most common calculation related to information in both operations research and economics is for the EVPI. See [1][34][53] for examples related to environmental policy and climate change. The EVPI gives an upper bound to the value of information, but it is often not seen as realistic to consider perfect information. Thus, other concepts have arisen. Nordhaus and Popp [41] investigate the value of *early* information – the value of moving the revelation of perfect information to an earlier time period. They also investigate what is sometimes called *partial perfect information* – the value of perfect information on one particular random variable, while other variables remain uncertain. This is relevant to our study, since we will consider the EVBI on each technology separately. Finally, there is a well developed literature on the Expected Value of Imperfect Information (EVII; see e.g. [48] [12]). This is the value of getting a signal about the random variable of interest (rather than learning the value of the variable) before the key decision is made. Linville [36] uses Monte Carlo and reweighting to estimate the EVII over climate sensitivity and three other variables related to climate change decision making. Baker [2] analyzes the related idea of the *marginal* value of information, and applies this to climate change.

Most of these studies are agnostic about where the information, perfect or not, is going to come from. Here, we are interested in information that is derived from expert elicitation, and specifically in the value of improving such information. Expert elicitations have been used for many years to support decision making under uncertainty, in particular when a frequentist approach is not viable. Generally, analysts aim to get multiple expert views and combine them, then use the combined probabilities in the analysis (See e.g. [52]). There are a number of ways to combine probabilities, including a range of mathematical approaches (such as averaging the log-odds) and behavioral approaches (such as consensus as a result of a meeting) [25]. Our analysis is based on the elicitations described in [5][6][7]. In each of these elicitations, there were 3-4 experts. In the portfolio analyses based on these [11][43][49], the experts' probabilities were averaged, to get a single probability to be used as input to the model.

Before we go on, we will address the argument that it is better to avoid combining expert views, if possible [35]. The alternative to combining expert opinions is to use each individual expert's opinions as model inputs, and report the range of results from the model. This provides two particular difficulties for our project. First, while it might be possible in theory to run every combination of expert's results, it is largely impractical in reality. The elicitations cover three quite distinct technology categories, thus experts were only queried for one category. This means that if we have $n$ experts per category and $m$

categories, we would have a total of $n^m$ probability distributions over the set of technologies. In our case, this would be about 48. Moreover, some individuals did not answer every question even within the category. Thus, to be comprehensive we would need to have multiple probability distributions for these experts incorporating all the possible combination of the other expert's probabilities. When this is added to the computational complexity of the portfolio problems, it suggests that this direction is not practical. Second, such an output as would be obtained from this exercise may be quite overwhelming for any decision maker to interpret. Thus, combining expert opinions in some way is a useful exercise in order to obtain insights.

The question we are addressing in this paper is, what is the value of improving the results of the elicitation? We may be able to get more accurate probability distributions through a number of avenues. For example, Clemen and Winkler [23] consider the improvement in *assessments* (as opposed to *decisions*) from combining multiple experts and from combining multiple methods. They find that both lead to significant improvements, and that combining experts is more efficient than combining methods. Beyond adding experts or methods, elicitations can be improved by paying experts to provide paper-quality discussions of their subjective probabilities, using scoring rules, and other similar resource-intensive interventions. In this paper we don't address the question of how the combined results are improved, but estimate the value of improving them through some method or other.

### 2.2 Climate Change portfolio R&D

There is a large body of work on endogenous technical advance in the context of climate change. This literature covers technical change that is in some way induced by policy, generally by the indirect effect on market actors, but also as a control variable. For surveys of the literature, see [20][21][22][29][32][37][51]. While the papers covered in these surveys are largely deterministic, they indicate that technology development and deployment are an important part of climate change policy evaluation. Technical change can come through two channels— investment in R&D and learning by doing. We focus on R&D in this paper; but expert elicitations on the potential for improvements in technology has some relevance to learning by doing.

There is some recent literature investigating the optimal investment in energy technology R&D in the face of uncertainty (see [10] for an overview). Some papers consider uncertainty in the climate damages [3][8][9][28], while some consider uncertainty in technical change [15][16][17][30], and one paper considers both [4]. However, all of these studies consider investment in one technology at a time, rather than a portfolio of technologies. While the conclusions of these papers vary, it appears that optimal investment in R&D is often much higher when uncertainty is explicitly included.

A small number of papers have studied the impact of uncertainty on a *portfolio* of energy technologies. [31] and [33] consider the question of how diversified the near term technology portfolio should be when the rate of technological learning is uncertain. However, they consider technical change through the avenue of learning by doing, rather than through R&D. Two studies [13][14] consider the question of the optimal R&D portfolio when there is uncertainty in both technical change and climate damages, with a focus primarily on the drivers of diversification in the portfolio. They show that it is not enough to just consider the potential value of new technologies, but that the uncertain relationship between program funding and effectiveness is just as important.

More generally, a number of researchers have investigated the question of how the presence of uncertainty and learning impacts near term optimal climate policy (see [3] and [10] for reviews). The answer to this question seems to be "it depends": optimal near term decision variables, such as R&D investment, may increase or decrease with increases in risk or increases in learning. Thus, it underlines the importance of characterizing the uncertainty explicitly and implementing this into policy models.

In the last few years multiple projects have been begun to collect probabilistic data on R&D through

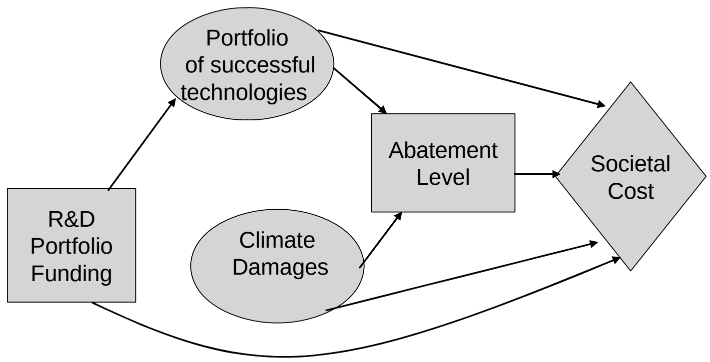


Figure 1: Influence Diagram Representing R&D Portfolio Problem

the use of expert elicitations. These include the project we will discuss below, as well as the ICARUS project out of FEEM[2], the Energy, Research, Development, Demonstration, & Deployment project out of Harvard[3], an NAS study [38], a project in the EERE section of DOE, and multiple studies from Carnegie Mellon Climate Decision Making Center[4] (see e.g. [46]).

### 2.2.1 Conceptual Model of Climate Change R&D

Figure 1 is an Influence Diagram illustrating the decision problem we are working with.[5] Square nodes represent decisions. The key decision we focus on, labeled "R&D Portfolio Funding" is *which* set of programs to fund. The oval nodes represent uncertainties. We are uncertain about which technologies will be successful in the future. The arrow into the "Portfolio of successful technologies" node means that the probability distribution over successful programs depends on R&D funding. Climate Damages are also uncertain. We model a second stage decision, choosing an abatement level, where abatement is defined as a reduction in emissions below a Business as Usual (BAU) level. The arrows going into this node indicate that the abatement level is chosen with knowledge of the portfolio of successful technologies available and the climate damages. The overall objective is to minimize the cost of abatement, the cost of damages, and the cost of R&D. Each funded portfolio results in a probability distribution over successful portfolios, and each successful portfolio is associated with a particular abatement decision. Note, we are not modeling the impacts of learning by doing in this model – technical change results from focused investment in R&D.

In this paper we will explore the value of gather better information – spending more resources on expert elicitation – to the R&D portfolio optimization problem in a framework based on Baker and Solak [11].

## 3 Method: Value of better information

In this section we discuss what we mean by the value of *better* information, and how we go about calculating it. The most common calculation of this type is the Expected Value of Perfect Information (EVPI). The EVPI is calculated through a process of "flipping" a decision tree. The first step is to

[2]http://www.icarus-project.org/
[3]http://belfercenter.ksg.harvard.edu/project/10/energy_technology_innovation_policy.html?page_id=213
[4]http://cdmc.epp.cmu.edu/
[5]Influence Diagrams, commonly used in Decision Analysis, are Bayesian Networks with decision nodes.

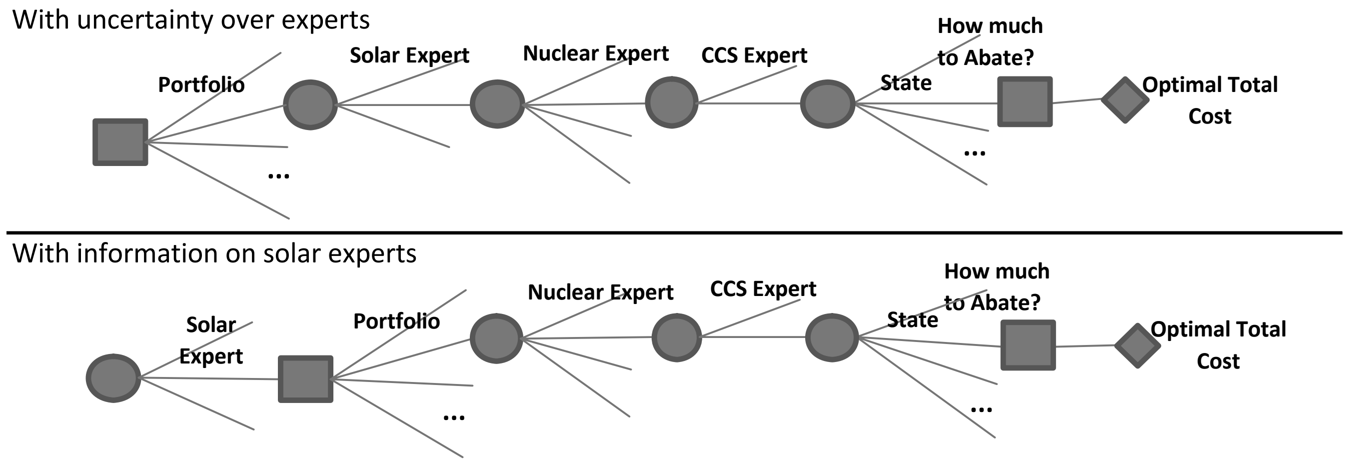


Figure 2: Decision trees for the two problems used to find the EVBI. The top tree assumes that the funding decision is made before any uncertainty is resolved. The second tree assumes that the uncertainty over solar experts is resolved before the funding decision is made.

calculate the optimal choice and its associated value under each realization of the random variable of interest. Next, the probability distribution over the random variable is applied to these values to get an expected value *given* perfect information. Finally, the value of the original problem is subtracted from this value to get the EVPI. This provides the maximum amount that a decision maker should be willing to pay for perfect information prior to making a decision. In this paper we will provide an estimate for the value of improving our information before making a decision. In particular, we focus on the value of spending more resources in order to get better expert elicitations.

In our previous work, in order to get a probability distribution over successful portfolios we averaged probabilities across the experts in the elicitations. This is a standard method and results in great computational savings. However, it is possible to use an alternative approach, to explicitly include the uncertainty over experts into our problem. The tree in the top panel of Figure 2 illustrates this alternate method. For any given funded portfolio, we first have an uncertainty over which solar expert, CCS expert, and nuclear expert is "correct". Then each individual expert's probabilities are used to derive a probability distribution over the successful portfolios, which we have labeled as the "state" in the figure. We have suppressed uncertainty over damages in this tree, and just show the abatement decision following the revelation of the state of the technology portfolio. This tree can be "rolled back" to get an optimal portfolio selection. We did not use this method in the previous papers because of the computational complexity and the fact that not every expert answered every question. In this paper we will use this alternate method.

For our value of information analysis, we assume that one of the experts is "correct", in the sense that if we spent an infinite amount of resources collecting expert judgements, the mean judgement would tend toward one of the expert's judgements. The lower tree in Figure 2 represents the ex-ante decision tree with better information. In this tree we know which expert is "correct" *before* we choose our portfolio. But, *a priori*, before we have actually spent the resources gathering better information, we do not know which expert is "correct", so we start the tree with uncertainty over the experts. We make the simple assumption that each expert is equally likely to be correct. This tree gives us the expected value of the decision if we had better information. Finally, to calculate the value of better information we take the difference between the two trees. In our case, both trees give us an expected cost, so we subtract the expected cost of the tree with better information from the expected cost of the tree with full uncertainty.

We want to point out that this is just an estimate of the value of better information. There is no single best way to calculate this value. One specific issue is that the "correct" probability distribution may in fact be closer to the average over the experts than any one expert; or it may be a combination of individual expert's probabilities (one expert may be "correct" about organic solar cells, while another expert may be correct about inorganics). We discuss how this would impact the EVBI in Section 5. We do believe that this will give us an estimate that is in the ballpark; and that the relative value of information between technologies and across damage risk scenarios should be robust.

# 4 Data, Model, and Solution Method

In this section we will summarize the data that was collected in the previous expert elicitations, describe the R&D portfolio model in more detail, and discuss our solution algorithm, which uses a simple greedy heuristic in order to solve this problem of very large magnitude.

## 4.1 Expert Elicitation

In previous work we have performed expert elicitations on solar photovoltaics, Carbon Capture and Storage (CCS), and nuclear fission technologies [6][7][5]. Please refer to these earlier papers for details on the elicitations. Here we briefly summarize the results. Table 1 lists the three key subtechnology categories that we assessed, along with the Net Present Value (NPV) of the US government funding trajectories that we considered. We discuss each technology here, and provide a summary of the results of the elicitations in Figures 3 - 4. In each case, the figure is showing the probability of achieving a pre-determined endpoint for the technology. In many cases, the experts were asked compound questions to arrive at the probability of the final endpoint.

| Technology | Project 1 | NPV of Funding ($M) | Project 2 | NPV of Funding ($M) | Project 3 | NPV of Funding ($M) |
|---|---|---|---|---|---|---|
| Solar | Organic PV | $116 | Inorganic PV | $39 | 3rd Generation PV | $386 |
| | | $830 | | $77 | | |
| CCS | Pre Combustion | $39 | Chemical Loop | $19 | Post Combustion | $52 |
| | | $154 | | $38 | | $224 |
| | | $386 | | $56 | | $519 |
| Nuclear | Light Water Reactor | $173 | High Temperature Reactor | $772 | Fast Reactor | $1,158 |
| | | $260 | | $1,544 | | $4,633 |
| | | $346 | | $3,089 | | $15,443 |

Table 1: Summary of Technologies.

We considered three categories of Solar Phototvoltaic (PV) technology: purely organic solar cells, inorganic cells made with new materials (i.e. not silicon or CIGS), and third generation solar cells, which included quantum dots and multi-junction cells. We considered two technology endpoints (labeled HO and LO for High and Low Outcomes, respectively) for organic cells and two different funding levels (high funding level HF and low funding level LF). For inorganic cells we had only one endpoint, but

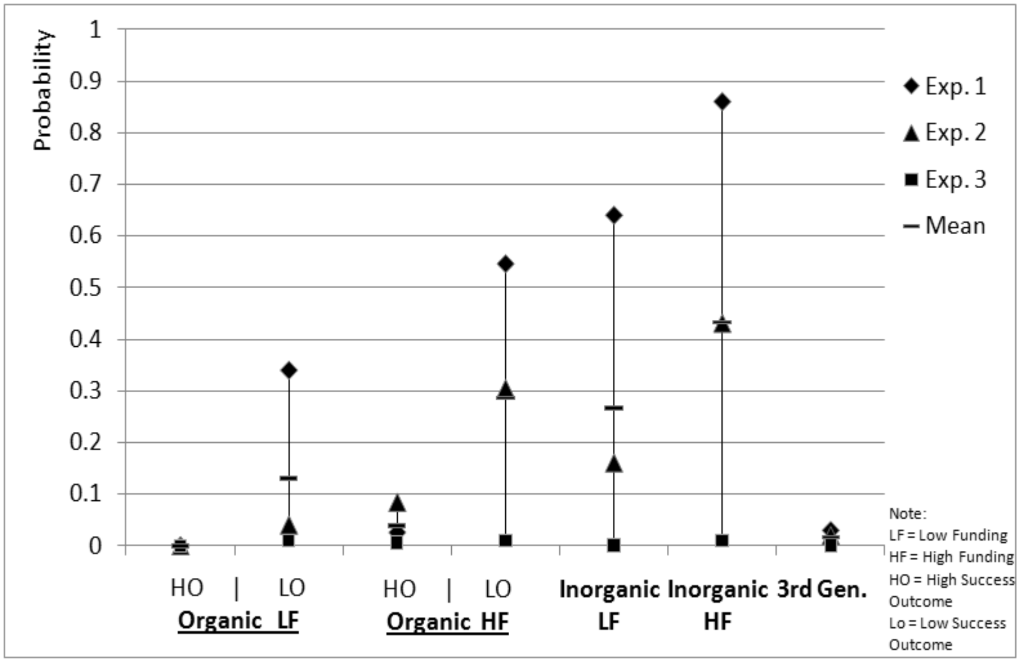


Figure 3: Experts' Assessments on Solar PV Technologies: Probability of achieving technical success endpoints

two different funding levels. For third generation cells we had one endpoint and one funding level. Figure 3 summarizes the results for individual experts. The probabilities shown for the low outcomes are cumulative, in that they include the probability of achieving the low outcome or better.

We also considered three technology categories of CCS: pre combustion, chemical looping and post combustion. Each CCS category has one technology endpoint and three funding levels (LF, MF, HF). We invited four experts to assess these technologies. Two of them were very optimistic about the success of CCS programs, while the other two were pessimistic. Additionally, one of the optimists and one of the pessimists did not answer all of the questions. Thus, in all of our calculations below, we combine the experts into one composite optimist and one composite pessimist. Figure **??** shows the probabilities of the composite experts, as well as the maximum and minimum success probability, for each CCS program.

We considered three categories of nuclear technology: light water reactor (LWR), high temperature reactor (HTR) and fast reactor (FR). We considered three funding levels for each technology; one technology endpoint for LWR, and two endpoints each for HTR and FR. We invited four experts to assess these programs. In Figure 4, we show the probability from each expert and the mean probability value for each program. Note that Expert 2 and Expert 3 did not provide probabilities on HTR programs. In our analysis below, we use the average probabilities for the HTR programs for these two experts.

#### 4.1.1 Opportunity Costs

In our elicitations, the funding trajectory represented an amount of money assumed to be in the hands of the top researchers in the field. If the experts considered \$1M per year, they thought about how many principal investigators and graduate students this amount would fund. The question we ask in

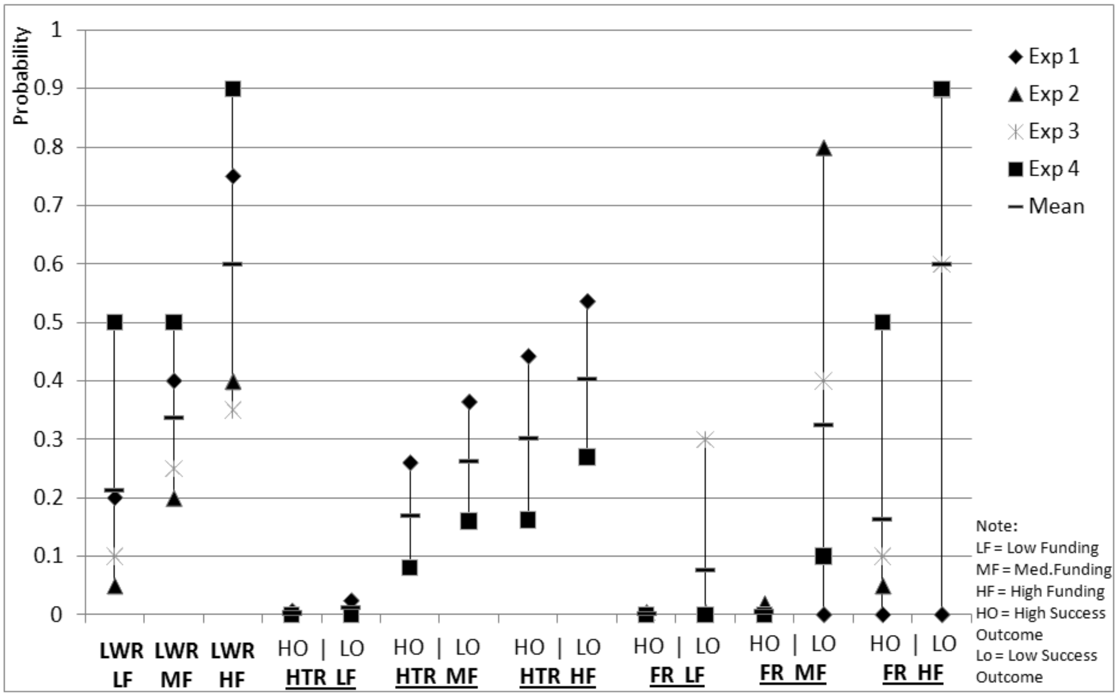


Figure 4: Experts' Assessments on Nuclear Technologies: Probability of achieving technical success endpoints

this section is, what is the cost to the economy of getting $1M into the hands of the most qualified researchers? Clearly, there is some administrative cost to do this. Next, there is the possibility that some money will be allocated for purely political reasons and may not go to the most appropriate researchers. Finally, there is the question of the "opportunity cost" of R&D. There are arguments that R&D funding may have a large opportunity cost. First, R&D investments generally have a very high return compared to other investments, often estimated to be about four times as high. Second, there are arguments that R&D funding into one particular area is likely to reduce R&D funding into other areas. One part of this argument says that the government will tend to have a fixed amount to allocate on R&D, so it is a zero sum game. Another part of this argument suggests that researchers themselves are in limited supply, therefore if more money goes to energy R&D, some top quality biological researchers will move from, say, medical research into energy research. See [44] for fuller discussion.

In order to address this, we will assume that the total cost of R&D investment is *four times* the amount in the elicitation. This is in line with other estimates in the literature [40][45].

## 4.2 Impact on Abatement Costs

In order to use the elicitation data in our model, we needed to estimate how the technologies would impact the cost of greenhouse gas abatement, assuming that they achieve the defined endpoints. To do this, we derived Marginal Abatement Cost curves (MACs) for the year 2050 under different assumptions about technological pathways. We considered each of the technologies on their own, as well as all combinations of technologies in order to model interactions. Our baseline MAC assumed no CCS, solar PV at 12 cents/kWh, and current nuclear technology at about 4.7 cents/kWh in 2050.

The analysis was conducted using the GCAM integrated assessment model, which integrates an

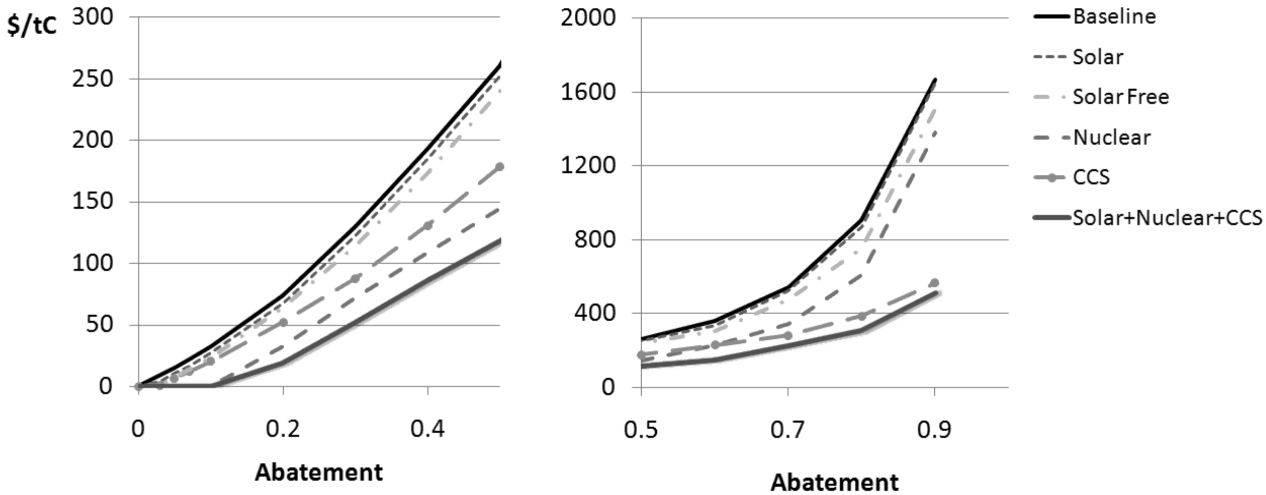


Figure 5: Representative MACs

economic model with a climate model. It looks out to 2095 in 15-year timesteps through a partial-equilibrium model with 14 world regions that includes detailed models of land-use and the energy sector [18] [27]. Assumptions for technologies other than the specific ones considered were based on the version of GCAM used in the Climate Change Technology Program (CCTP) MiniCAM reference scenario [19].[6]

Here we briefly address one particular complexity that we encountered in modeling solar PV. Since solar is an intermittent resource – it cannot be turned off and on – it potentially poses problems for integration onto the electricity grid. The baseline assumption in GCAM is that when the penetration of solar into the electricity grid reaches 20%, every additional kW of solar installed requires either the installation of a kW of gas-fired backup generation or storage. This reduces the impact that solar has on the costs of controlling climate change. Moreover, there is a great deal of uncertainty about the limits to integrating solar onto the grid. Thus, we ran our data in GCAM a second time with a less restrictive assumption. We assumed that the cost of storage was free. This is an extreme assumption, but it gives us an idea of the envelope over the impact that solar might have. Our results are presented under these two assumptions.

In Figure 5 we present five representative MACs plus the baseline. Besides the baseline, we show the MACs generated assuming (1) success in organic solar cells only under baseline assumptions, labeled Solar; (2) success in organic solar cells only assuming free storage, labeled Solar Free; (3) success in chemical looping CCS only, labeled CCS; (4) success in LWR only, labeled Nuclear; and (5) success in all three of these technologies simultaneously under baseline assumptions, labeled Solar+Nuclear+CCS. The left panel shows the impacts on low abatement levels and the right panel for high abatement levels.

Nuclear and CCS have different types of impacts on the MAC. At low abatement levels, nuclear has the greatest impact. In particular, success in the nuclear LWR implies that carbon emissions would drop by about 10% even in the absence of a carbon policy. At high abatement levels, however, CCS begins to dominate, significantly reducing the MAC at abatement levels above 70%. Nuclear (and solar) tend to shift the MAC curve downward; CCS tends to pivot the curve around zero. Finally, the combined MAC shows that the technologies are substitutes to a large degree.

In order to reduce the computational complexity we estimated pivot and shift parameters to describe

[6]More detailed discussions of our methods and assumptions on related technologies are included in [6][7][5].

how the MACs deviate from the baseline. See [11] for details.

### 4.3 The R&D Portfolio Model

In this section, we discuss how we implement the stochastic R&D portfolio model described in Section 2.2.1 above. Let $i$ represent the technology category (solar, CCS, nuclear) and $j$ the specific program within the category. The index $k$ represents the investment level (high, medium, low). The key integer decision variable is $X_{ijk} \in \{0,1\}$. $X_{ijk}$ equals 1 if there is an investment in program $ij$ at funding level $k$, and 0 otherwise. The abatement level $\mu \in [0,1]$ is a continuous decision variable in the second stage of our model. It represents the fraction of emissions reduced below a BAU level. This variable is chosen once the state of the technology, represented by the technological advance variable $\alpha$ and the state of climate damages, represented by a random multiplier $Z$ have been realized. The objective is to minimize the sum of R&D cost, abatement cost $c$ and damage cost $D$. In the first stage the decision is which programs to invest in, represented by $X$; in the second stage the decision is how much to abate, represented by $\mu$.

$$\min_X \left\{ \beta \sum_{i,j,k} F_{ijk} X_{ijk} + E_{\alpha,Z} \left( \min_\mu \left[ c\left(\mu;\alpha\right) + ZD\left(\mu\right) \right] \right) \right\} \tag{1}$$

where $F_{ijk}$ is the amount of funding required for program $ijk$ and $\beta$ is the opportunity cost multiplier. We can only invest in a program at one funding level:

$$\sum_k X_{ijk} \leq 1 \ \forall i,j \tag{2}$$

The technological advance parameter $\alpha \in [0,1]$ directly measures the pivot in the cost curve, and is multiplicative among different technology categories. We assume that only the best technology within a category competes in the economy:

$$\alpha_i = \max_j \left[\alpha_{ij}\right] \tag{3}$$

The *probability* of any particular $\alpha = (\alpha_s, \alpha_c, \alpha_n)$ depends on the investment portfolio $X$ and can be derived by combining the probabilities of the individual programs. The expected value in (1) is calculated using these probabilities.

The abatement cost, given $\mu$ and $\alpha$, is given by

$$c\left(\mu,\alpha\right) = \prod_i \left(1-\alpha_i\right)\left(c\left(\mu\right) - hc\left(0.5\right)\mu\right) \tag{4}$$

where $c\left(\mu\right)$ is the cost before technological advance; and $h$ represents a downward shift of the baseline abatement cost curve and can be determined by the values of the $\alpha_i$. We have anchored the shift to the cost of abatement when $\mu = 0.5$ in order to make the parameterization portable. We have based our baseline abatement cost on DICE 2007 [39]:

$$c\left(\mu\right) = b_0 \mu^{b_1} \tag{5}$$

and the damage function is assumed to be quadratic as follows:

$$D(\mu) = M_0(S - M_1\mu)^2 \tag{6}$$

We calibrated $b_0, b_1, M_0, M_1$ and $S$ to DICE 2007. The stock of emissions in the atmosphere $S$ is set equal to stock of emissions in 2185 under the BAU scenario in DICE, equal to 2.5 trillion metric tons of carbon. The damage constants $M_0, M_1$ are set so that our damages equal the Net Present Value of damages between 2005 and 2185 in DICE under the BAU and "optimal" scenarios. We used the BAU scenario to calculate that $M_0 = 2.74$. We take the optimal level of abatement (with no technical change) to be the average of the optimal abatement in DICE 2007 over the period 2005 to 2185, or 0.46. Given this, $M_1 = 0.597$. We use the value of $b_1 = 2.8$ from DICE, and set $b_0 = 10.4$ so that the optimal abatement is 0.46. The opportunity cost multiplier, $\beta$, is set to 4, as discussed in Section 4.1.1 above.

We consider three cases for uncertainty over climate damages $Z$, represented in columns 2, 3 and 4 of Table 2. In each case, the climate damage multiplier $Z$ can take on two values, $Z_h$ or $Z_l$, where $Z_l = 0$ in each case. The top row of the table shows the value of $Z_h$. The next two rows show the probabilities of $Z_l$ and $Z_h$. The fourth row shows the optimal level of abatement when $Z = Z_h$ and there is no technical change. Specifically, this value is $\mu^*(Z_h)$ where

$$\mu^*(Z_h) \equiv \arg\min_{\mu \leq 1} \left[c(\mu) + Z_h D(\mu)\right] \tag{7}$$

and $\mu^*$ is represented as a percentage.

| Risk Level | No Risk | Medium Risk | High Risk |
|---|---|---|---|
| $Z_h$ | 1 | 3 | 14.6 |
| $P[Z = 0]$ | 0 | 0.667 | 0.931 |
| $P[Z = Z_h]$ | 1 | 0.333 | 0.069 |
| Optimal Abatement if $Z = Z_h$ | 46% | 80% | 100% |

Table 2: Three Uncertainty Cases.

High damages, where $Z = 14.6$, are equivalent to a 20% loss in GDP given a 2.5°C increase in mean temperature. Each risk scenario has a mean of 1. As we move from left to right, climate damages get riskier, in the sense of a Mean-Preserving Spread.

### 4.4 Model Solution Algorithm

The curse of dimensionality causes this model to be very difficult to solve using traditional stochastic programming techniques, even with simulation. For example, a fully funded portfolio has nearly $14,000$ endpoints, and there are over $260,000$ possible portfolios. Thus, we discuss how we solve the model using a simple greedy heuristic implemented in *Matlab*.

We start the search process using a fully funded portfolio – that is, a portfolio in which each program is funded at its highest funding level. We found that starting with this portfolio (rather than say, a no-funding portfolio) reduced the convergence time. At each iteration of the algorithm, we loop over all nine technologies. For each technology, we evaluate the objective function at each funding level for that technology. In order to evaluate the objective, we find the optimal value of $\mu$ for each combination of $Z$ and $\alpha$ using a simple Matlab solver, *fminbnd*. We update our portfolio with the funding level that achieves the lowest total cost. We repeat this process for all technologies. At the end of each iteration, if the total cost of the portfolio did not change, the search stops. We use this locally optimal portfolio to approximate the global optimum. The algorithm converges within 2 or 3 iterations.

In order to test the reliability of this algorithm, we selected 20 cases to test. We compared the results using a genetic programming approach from [43], with results from this simple greedy algorithm, and found that the results matched in each case. The greedy algorithm, however, significantly reduces the computing time by more than 90%. This is important, since each EVBI calculation requires 3 - 5 runs to calculate.

## 5 Results and Discussion

We start this section by discussing the detailed results of the optimal portfolios. In Tables 3 – 5 we show the optimal portfolios that result from using the individual expert's probabilities as well as the optimal portfolio that results from using all experts, labeled *combined*. We show the level of investment in each particular technology, plus the total investment in the portfolio, and the total social cost (equal to the cost of abatement plus the cost of damages plus the cost of R&D). Finally, we show the EVBI, which is simply the difference between the total social cost of the combined portfolio and the average of the individual portfolios. In each case we have highlighted when the individual portfolio differs from the combined portfolio. It is these differences which drive the EVBI. If each individual portfolio were the same as the combined portfolio the EVBI would be zero. Before explicitly discussing the EVBI, we will mention a few interesting features of these results.

First, as we showed in [11], increasing risk in climate damages has a non-monotonic impact on the optimal R&D investment, with investments being (weakly) highest in our medium risk case, and lowest in the high risk case. Please see [11] for a discussion of why this occurs.

Second, compare the total investments in the individual portfolios with the combined portfolios. In 24 out of the 27 cases the optimal investment is weakly lower for the individual portfolios than for the combined, and in 16 out of 27 it is strictly lower. The combined portfolio tends to be higher than any individual portfolio. To understand this, consider that the investment level is driven by two forces. One is the *overall value* of the technology – if the probability of success is too low there is not enough value to justify investment. The other is the *marginal value* of an increase in investment. If there is only a small increase in probabilities as investment increases, then investment will generally be optimized at a low level. What we see when we combine experts is that high probabilities tend to swamp low probabilities, and large marginal increases tend to swamp flat marginals. Consider the CCS results. In this case we see that the optimists have low investments because the marginal improvements are small; the pessimists have low investments because the probabilities are so low. When we combine the two the average probabilities are fairly high and the average marginals are fairly high, leading to a higher investment.

This is an intriguing result, because in many elicitation exercises, and in technology policy in general, often experts are asked for an estimate of how much R&D investment is necessary. If we assume that their answers would be consistent with a portfolio analysis, our results indicate that we may be systematically underestimating the best level of R&D funding.

Third, we see no clear pattern regarding optimists versus pessimists. In CCS, where we most clearly have an optimist and a pessimist, the pessimist's portfolios have higher investment. This is because the optimists are so optimistic that only a low investment is necessary to get to a very high probability. The pessimists, while having lower overall probabilities, have much higher marginals. On the other hand, in solar, expert 3 is clearly a pessimist, with very low probabilities across the board. The optimal portfolio resulting from these probabilities is lower than the other experts.

**EVBI Results.** Figure 6 shows the results for EVBI graphically. The panel on the left shows the raw EVBI for each technology and each damage risk level in billions of dollars. The panel on the right highlights how the EVBI changes with risk. It shows the EVBI as a ratio of the no-risk EVBI. Here we discuss three key points of interest.

First, note that the overall EVBI is very high compared to the cost of performing elicitations. The cost of performing an expert elicitation has been estimated to be between $\$100,000 - \$300,000$ [26]. Our *lowest* value of better information is 1000 times higher than this value. Thus, it implies that moving forward with fully-funded expert elicitations on the prospects for advancement in climate change energy technology is justified.

Second, the EVBI on nuclear is much higher than for the other two technologies. This appears to

## Baseline Scenario --- CCS

| No Risk | | | | Investments ($ million) | | | | | | Tot. Inv. | Tot. Cost |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CCS | Pre C | Chem L | Post C | LWR | HTR | FR | Org. | Inorg. | 3rd Gen | ($ bil) | ($ tri) |
| Optimist | 386 | 56 | 224 | 346 | 3089 | 4633 | 830 | 77 | 0 | 9.64 | 13.8277 |
| Pessimist | 386 | 0 | 519 | 346 | 3089 | 4633 | 830 | 77 | 0 | 9.88 | 14.0875 |
| *Combined* | *386* | *56* | *519* | *346* | *3089* | *4633* | *830* | *77* | *0* | *9.94* | *13.9582* |
| | | | | | | | | | | VOI | **0.0006** |

| Med Risk | | | | Investments ($ million) | | | | | | Tot. Inv. | Tot. Cost |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CCS | Pre C | Chem L | Post C | LWR | HTR | FR | Org. | Inorg. | 3rd Gen | ($ bil) | ($ tri) |
| Optimist | 386 | 56 | 224 | 346 | 3089 | 4633 | 830 | 77 | 0 | 9.64 | 11.8082 |
| Pessimist | 386 | 0 | 519 | 346 | 3089 | 4633 | 830 | 77 | 0 | 9.88 | 12.1159 |
| *Combined* | *386* | *56* | *519* | *346* | *3089* | *4633* | *830* | *77* | *0* | *9.94* | *11.9626* |
| | | | | | | | | | | VOI | **0.00055** |

| High Risk | | | | Investments ($ million) | | | | | | Tot. Inv. | Tot. Cost |
|---|---|---|---|---|---|---|---|---|---|---|---|
| CCS | Pre C | Chem L | Post C | LWR | HTR | FR | Org. | Inorg. | 3rd Gen | ($ bil) | ($ tri) |
| Optimist | 0 | 56 | 224 | 346 | 3089 | 0 | 0 | 77 | 0 | 3.79 | 10.3305 |
| Pessimist | 386 | 0 | 519 | 346 | 3089 | 0 | 0 | 77 | 0 | 4.42 | 10.4006 |
| *Combined* | *0* | *56* | *519* | *346* | *3089* | *0* | *0* | *77* | *0* | *4.09* | *10.3667* |
| | | | | | | | | | | VOI | **0.00115** |

Table 3: Optimal Portfolios CCS.

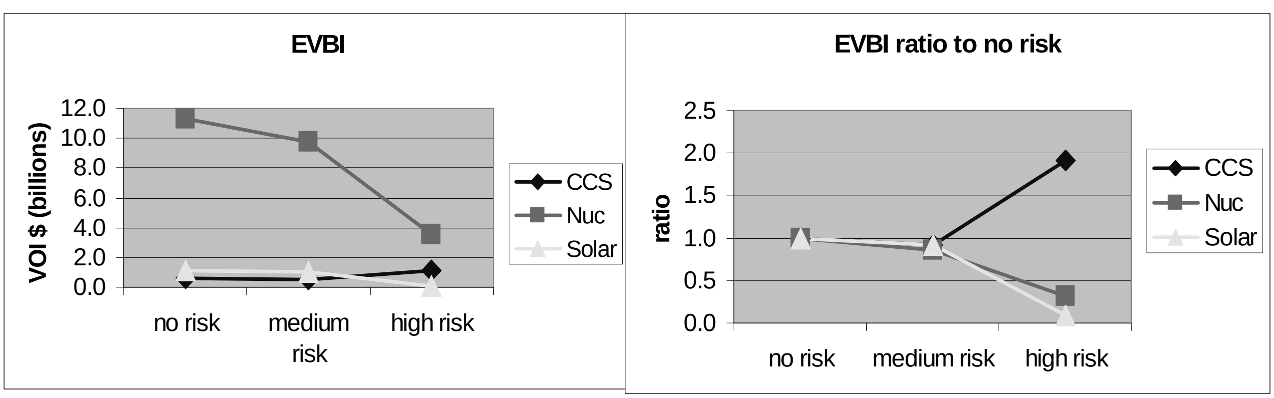


Figure 6: EVBI. The left panel shows the raw EVBI in $billions. The right panel shows the ratio of the EVBI at each risk level to the no risk level.

| Baseline Scenario --- Nuclear | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| No Risk | Investments ($ million) | | | | | | | | | Tot. Inv. | Tot. Cost |
| | Pre C | Chem L | Post C | LWR | HTR | FR | Org. | Inorg. | 3rd Gen | ($ bil) | ($ tri) |
| Exp. 1 | 386 | 56 | 519 | 346 | 3089 | 0 | 830 | 77 | 0 | 5.30 | 13.8799 |
| Exp.2 | 386 | 56 | 519 | 346 | 3089 | 4633 | 830 | 77 | 0 | 9.94 | 14.0098 |
| Exp.3 | 386 | 56 | 519 | 346 | 3089 | 1158 | 830 | 77 | 0 | 6.46 | 14.0505 |
| Exp.4 | 386 | 56 | 519 | 346 | 1544 | 0 | 830 | 77 | 0 | 3.76 | 13.8472 |
| *Combined* | *386* | *56* | *519* | *346* | *3089* | *4633* | *830* | *77* | *0* | *9.94* | *13.9582* |
| | | | | | | | | | | VOI | **0.01135** |
| Med. Risk | Investments ($ million) | | | | | | | | | Tot. Inv. | Tot. Cost |
| | Pre C | Chem L | Post C | LWR | HTR | FR | Org. | Inorg. | 3rd Gen | ($ bil) | ($ tri) |
| Exp. 1 | 386 | 56 | 519 | 346 | 3089 | 0 | 830 | 77 | 0 | 5.30 | 11.8724 |
| Exp.2 | 386 | 56 | 519 | 346 | 3089 | 4633 | 830 | 77 | 0 | 9.94 | 12.0225 |
| Exp.3 | 386 | 56 | 519 | 346 | 3089 | 1158 | 830 | 77 | 0 | 6.46 | 12.0837 |
| Exp.4 | 386 | 56 | 519 | 346 | 3089 | 0 | 830 | 77 | 0 | 5.30 | 11.8329 |
| *Combined* | *386* | *56* | *519* | *346* | *3089* | *4633* | *830* | *77* | *0* | *9.94* | *11.9626* |
| | | | | | | | | | | VOI | **0.009725** |
| High Risk | Investments ($ million) | | | | | | | | | Tot. Inv. | Tot. Cost |
| | Pre C | Chem L | Post C | LWR | HTR | FR | Org. | Inorg. | 3rd Gen | ($ bil) | ($ tri) |
| Exp. 1 | 0 | 56 | 519 | 346 | 3089 | 0 | 0 | 77 | 0 | 4.09 | 10.3420 |
| Exp.2 | 0 | 56 | 519 | 346 | 3089 | 4633 | 0 | 77 | 0 | 8.72 | 10.3908 |
| Exp.3 | 386 | 56 | 519 | 346 | 3089 | 1158 | 0 | 77 | 0 | 5.63 | 10.3959 |
| Exp.4 | 0 | 56 | 519 | 346 | 0 | 0 | 0 | 77 | 0 | 1.00 | 10.3240 |
| *Combined* | *0* | *56* | *519* | *346* | *3089* | *0* | *0* | *77* | *0* | *4.09* | *10.3667* |
| | | | | | | | | | | VOI | **0.003525** |

Table 4: Optimal Portfolios Nuclear.

be directly related to the higher R&D cost of nuclear technologies. The full opportunity cost of the highest funded portfolio is about \$32 billion for nuclear, and only about \$4 billion for CCS and solar. If we look at the highest EVBI for each technology we see that in each case the EVBI is about $30-35\%$ of the highest funded portfolio. So, the magnitude of the EVBI appears to be higher for nuclear because the programs are much more costly.

In fact, the EVBI is bounded by the R&D investment amounts. It would never make sense to spend more than the investment itself on information that tells one whether to make the investment. Consider, for example, the CCS no risk case. From the table we see that the two alternate portfolios involve spending \$56 Million less on Chemical looping or $\$519 - \$224 = \$295$ Million less on post-combustion. This means that the maximum EVBI would be $0.5\,(56 + 295) * 4 = \$702$ Million[7]. We see that the actual EVBI is \$600 Million.

Third, consider how the EVBI changes under damage risks. The EVBI decreases slightly under medium risk, but this seems to be explained by the lower expected costs under medium risk. If we consider EVBI as a percentage of total social cost, it is just about the same under no- and medium risk. Under high risk, however, the EVBI changes significantly, and changes in different directions for the two different types of technologies. As we discuss above CCS primarily pivots the MAC down, whereas solar and nuclear primarily shift the MAC down with a small pivot effect. We can see from Figure 5 that CCS has a significant impact on the cost of abatement when abatement is very high. Thus, getting the information "right" in this case has higher value. On the other hand, since the chance of damages is low in the high risk case, nuclear and solar have less value, and therefore there is less EVBI.

**Free Storage.** We also did the analysis under the assumption that solar was combined with free storage. That is, we relaxed the concern about grid integration. This had very small effects on the EVBI for CCS and Nuclear. It had a larger effect on the EVBI for solar (see Figure 7). In general, when grid integration problems are not present, solar is more valuable and we invest in more solar. For example, under the no-damage-risk scenario the optimal investment increases from \$0.9 to \$1.3 billion. The overall expected cost decreases by \$17 billion, indicating that this is the approximate value of having a solution to grid integration. The value of better information on solar, however, decreases in the no risk and medium risk cases. This is because the higher value of solar pushes investment in solar up for all experts as well as the combined portfolio, leading to less difference between the individual portfolios and the combined portfolio, thus there is less value to information. On the other hand, when damages are high the combined investment in solar is low. But, with free storage, some of the experts' portfolios include higher investments. Thus, there is more difference between the individual portfolios and the combined, and a higher EVBI.

**Opportunity Cost.** All of the above results are based on the assumption that the true cost of R&D funding is four times the stated cost. Here we consider how assumptions about the opportunity cost (OC) impact the EVBI. The OC will effect EVBI in two ways. First, it will have a direct effect, since the EVBI is highly related to the R&D budget. Thus if the OC multiplier were half as much, we would expect EVBI to decrease by half through this direct effect. But the OC will have an indirect effect as well, affecting the overall net value of a portfolio. If the OC multiplier were 1, for example, then it is very likely that a wide variety of probability distributions would result in a fully funded portfolio in the no-risk and medium-risk cases. This is because the cost of R&D would be very small compared to the benefits from R&D. If the optimal portfolio is the same under a wide variety of probability distributions, then the EVBI will be zero, or near zero. On the other hand, if the OC multiplier were very high, then it is likely that a wide variety of probability distributions would result in little or no R&D. Thus, the EVBI would again be low. In Figure 8 we show the results of an experiment of this sort using Nuclear and deterministic damages. We do find that more decisions vary from the combined portfolio when the

[7]The 4 is for the opportunity cost.

## Baseline Scenario --- Solar

| No Risk | Investments ($ million) | | | | | | | | | Tot. Inv. | Tot. Cost |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pre C | Chem L | Post C | LWR | HTR | FR | Org. | Inorg. | 3rd Gen | ($ bil) | ($ tri) |
| Exp.1 | 386 | 56 | 519 | 346 | 3089 | 4633 | 116 | 77 | 0 | 9.22 | 13.9433 |
| Exp.2 | 386 | 56 | 519 | 346 | 3089 | 4633 | 830 | 77 | 0 | 9.94 | 13.9531 |
| Exp.3 | 386 | 56 | 519 | 346 | 3089 | 4633 | 0 | 77 | 0 | 9.11 | 13.9748 |
| *Combined* | *386* | *56* | *519* | *346* | *3089* | *4633* | *830* | *77* | *0* | *9.94* | *13.9582* |
| | | | | | | | | | | VOI | **0.001133** |

| Med. Risk | Investments ($ million) | | | | | | | | | Tot. Inv. | Tot. Cost |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pre C | Chem L | Post C | LWR | HTR | FR | Org. | Inorg. | 3rd Gen | ($ bil) | ($ tri) |
| Exp.1 | 386 | 56 | 519 | 346 | 3089 | 4633 | 116 | 77 | 386 | 9.61 | 11.9453 |
| Exp.2 | 386 | 56 | 519 | 346 | 3089 | 4633 | 830 | 77 | 0 | 9.94 | 11.9566 |
| Exp.3 | 386 | 56 | 519 | 346 | 3089 | 4633 | 0 | 77 | 0 | 9.11 | 11.9828 |
| *Combined* | *386* | *56* | *519* | *346* | *3089* | *4633* | *830* | *77* | *0* | *9.94* | *11.9626* |
| | | | | | | | | | | VOI | **0.001033** |

| High Risk | Investments ($ million) | | | | | | | | | Tot. Inv. | Tot. Cost |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pre C | Chem L | Post C | LWR | HTR | FR | Org. | Inorg. | 3rd Gen | ($ bil) | ($ tri) |
| Exp.1 | 0 | 56 | 519 | 346 | 3089 | 0 | 0 | 77 | 0 | 4.09 | 10.3625 |
| Exp.2 | 0 | 56 | 519 | 346 | 3089 | 0 | 0 | 77 | 0 | 4.09 | 10.3667 |
| Exp.3 | 0 | 56 | 519 | 346 | 3089 | 0 | 0 | 0 | 0 | 4.01 | 10.3706 |
| *Combined* | *0* | *56* | *519* | *346* | *3089* | *0* | *0* | *77* | *0* | *4.09* | *10.3667* |
| | | | | | | | | | | VOI | **0.00010** |

Table 5: Optimal Portfolios Solar.

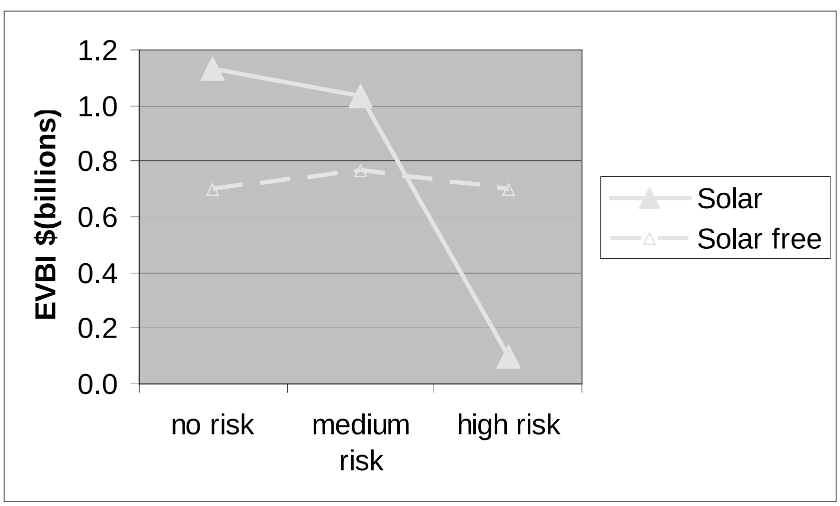


Figure 7: EVBI for solar with and without free storage.

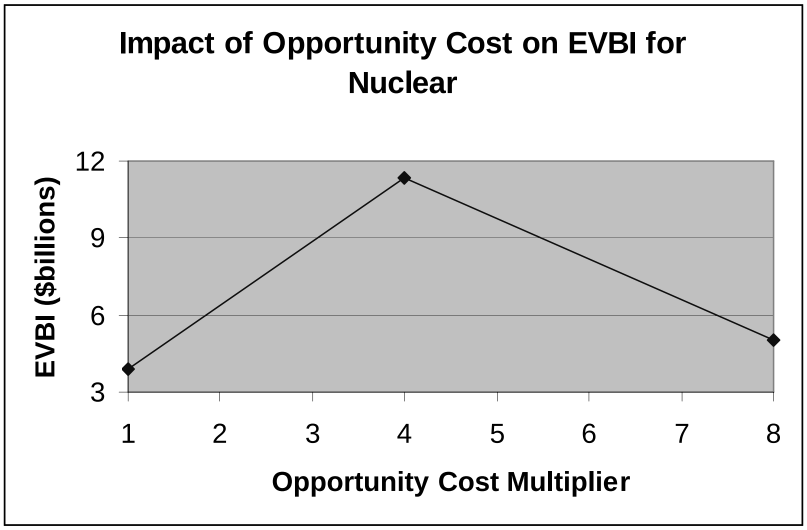


Figure 8: EVBI for nuclear, assuming deterministic damages, under different assumptions about opportunity cost.

OC multiplier is 4, and that the EVBI is higher for this value than for 1 or 8.

**Number of Experts.** The studies that we used to estimate the EVBI had a small number of experts, between three and four. In general, the point of calculating a value such as the EVBI is determine whether it makes sense to go back and collect more information, in this case whether to get more, higher quality elicitations. Therefore, it does not make sense to collect too much information before calculating the EVBI. We can discuss what is likely to happen to the EVBI estimates if there were more experts in our base study. In general, the EVBI will decrease in the number of experts. If, for example, we assume that the mean probability distribution is held constant, then an increase in experts will decrease the variance around the probability distribution, leading to a lower EVBI. This is logical, since if we had a very large number of experts, adding more would be unlikely to change the optimal choice. In reality, it is possible that adding another expert to a small number of experts would increase the variance of the probabilities and thus increase the EVBI. But, as our elicitations reveal a great deal of variance across the experts, this seems unlikely in this case. What our estimated EVBIs show is that it is valuable to gather additional information beyond the small sample that was initially collected.

**Is One Expert "Correct"?** What will happen to the EVBI if we relax the assumption that one of the experts is "correct"? In general the EVBI will decrease for the same reason it decreases with more experts. The easiest case to think about is when there is a positive probability that the combination of experts is "correct". In this case we can calculate the EVBI directly from the above tables. If, for example, we treat the combined expert as one of the individual experts and assign it an equal weight, then the EVBI for solar under high risk would be reduced from \$100M to \$75M. So our EVBI is an upper bound. Nevertheless, we would need a very large probability on the combined expert in order to bring the EVBI down to the same order of magnitude as the cost of a high quality elicitation. For solar under high risk (our lowest EVBI), if the probability that the combined expert is correct is 897/900 and each other expert is weighted 1/900, then the EVBI equals $\$333,333$, about the high end of the estimate of the cost of an elicitation. Thus, unless we feel extremely confident in our current elicitations, the value of collecting more information is high.

## 6 Conclusion

It is important to explicitly include uncertainty in the analysis of climate change policy, and especially when evaluating R&D policy. While there has been much work done on evaluating the benefits of technical change, and theoretical work evaluating technology policies, it is only recently that work has accelerated on determining how R&D investments are likely to effect technological potentials in climate change energy technology. We have used the results of one of these studies to estimate the value of collecting better information – spending resources to do more thorough expert elicitations.

We did not calculate the Expected Value of Perfect Information, because we argue that it is irrelevant in the case of R&D: it is only through investing in R&D that we will ever have perfect information about technological outcomes. Rather, our goal was to estimate the value of improving expert elicitations. There is, however, no widely accepted method for estimating this value. We have assumed that with better information the probability distribution over technological outcomes will converge to one of our current experts'. Using this assumption we estimated the EVBI.

Our raw estimates of the value of better information – ranging from \$100 million to \$11 billion for individual technology categories – indicate that it is many orders of magnitude larger than the cost of accruing such information. This indicates that it may be worthwhile to move forward with large scale, carefully managed elicitations on climate change energy technology.

We found that the EVBI is higher for the technologies that require larger R&D investments, thus the largest programs should be highest priority for performing detailed elicitations. We also found that the EVBI depends non-monotonically on the costs of R&D investments and the value of technical change. We can summarize these results by thinking about the net value of R&D – the value minus the costs. We find that if the net value of R&D is very high or very low, there is less disagreement about the optimal portfolio and thus lower EVBI. Thus, detailed elicitations should focus on technologies that do not appear to be clear winners or clear losers on the surface. Within our categories it suggests that Nuclear Feeder Reactors and Purely Organic Solar Cells will bear the most fruit in deeper work.

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