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Summary

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Decision Frameworks and the investment in R&D

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Abstract:

In this paper we provide an overview of decision frameworks aimed at crafting an energy technology Research & Development portfolio, based on the results of three large expert elicitation studies and a large scale energy-economic model. We introduce importance sampling as a technique for integrating elicitation data and large IAMs into decision making under uncertainty models. We show that it is important to include both parts of this equation – the prospects for technological advancement and the interactions of the technologies in and with the economy. We find that investment in energy technology R&D is important even in the absence of climate policy. We illustrate the value of considering dynamic two-stage sequential decision models under uncertainty for identifying alternatives with option value. Finally, we consider two frameworks that incorporate ambiguity aversion. We suggest that these results may be best used to guide future research aimed at improving the set of elicitation data.

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1. Introduction

The ultimate goal of collecting information on the impacts of R&D and of running simulations on Integrated Assessment Models (IAMs) is to inform decision making. In this paper we discuss how R&D data and IAM outputs can be used in different decision frameworks, and the impact that the different frameworks have on the ultimate results. We do this with an objective of providing insights into the optimal government funded energy technology R&D portfolio.

The Elicitation and Modeling Project (TEaM)[2] has provided a set of probability distributions over the outcomes of energy technology R&D investment, based on three sets of expert elicitations performed over 5 years by three different research teams [Anadon et al. [(2011), (2012), (2014)], Baker et al.[(2008), (2008), (2009), (2009), (2010), (2011)], Bosetti et al. [(2011), (2011), (2012)]]. The R&D outcomes are measured in terms of the future performance of energy technologies, including their costs and efficiencies. Though it is informative to consider the impact of R&D investments on these technological outcomes, it is also important to consider how specific technological outcomes are likely to impact economy-wide outcomes. The implications of R&D on the cost of a specific technology might be very large, but if there are less expensive alternatives to that technology, this impact might be smaller than one would expect prior to a general or partial equilibrium analysis. In order to evaluate the impact of technology improvements on societal outcomes, the TEaM project has used three IAMs – GCAM, Markal, and WITCH – to translate technological characteristics into metrics of interest, such as the cost to achieve a particular carbon emissions path, or the diffusion of different technologies into the economy. In this paper we focus on results from GCAM, but a similar analysis can be done using the results from the other IAMs.

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[2] http://www.feem.it/getpage.aspx?id=4278&sez=research&padre=18&sub=70&idsub=86&pj=ongoing

Baker et al. (2014) presented the results of the effort to collect, standardize, and aggregate the results from the expert elicitation surveys, highlighting the diversity of results that stem from differences across experts and studies. In the present paper we analyze the impact of this diversity, as well as the impact of the decision framework, on optimal decisions about R&D investment allocations.

While an understanding of the distribution of data about technology inputs is very important, it is not easy to anticipate *a priori* how data distributions translate into economic results and finally into optimal decisions. In some cases, a wide range of probability distributions may nevertheless lead to a single robust decision (Baker & Solak, 2011); while in other cases probability distributions that look very similar may lead to divergent decisions. It is important to note that the optimal decision under uncertainty is not necessarily some average of the optimal decisions under certainty, nor is it necessarily near the optimal decision under a central case ((Baker, 2009); (Dow & Werlang, 1992)). For example, Santen and Diaz Anadon (2014) show that the investment path in solar R&D is qualitatively different under uncertainty, with a high initial investment followed by a very low investment in the deterministic case, and a medium initial investment followed by high investments in the stochastic case.

Some past work has shown optimal technology R&D portfolios to be surprisingly robust to assumptions about climate damages, about the opportunity cost of R&D, and about the underlying policy environment (i.e. a Stern-type stringent policy vs a Nordhaus-type mild policy) (Baker & Solak, 2014). Other work has shown that the type of policy (e.g., whether CO_2 emissions are limited at all, through a cap and trade program, or through a clean energy standard for electricity) affects the optimal R&D investment portfolio (Anadon, et al., 2014).

Different questions require different decision support frameworks. In a world in which a stabilization

goal has been chosen through political negotiation, then clearly the best framework is one that takes this goal as given. However, in a world in which decisions about environmental goals are ongoing, and are likely to depend on the outcome of uncertainties, a framework that allows for flexible adjustment of the strategy once learning about technological outcomes and/or climate damages has taken place is more appropriate. Additionally, some people argue that in a world with multiple conflicting probability distributions, decision frameworks should account for ambiguity-aversion. In this paper we consider how the optimal R&D portfolio differs across elicitation teams, and when (1) the stabilization pathway is a second stage choice compared to when it is given; and (2) the impact on a one-stage model of using a simple ambiguity-averse framework.

We consider how to use both the set of expert elicitation data collected in the TEaM project and energy-economic models to best support decision making. A first, important question is what the purpose is of explicitly including uncertainty in energy-economic models, specifically into IAMs. One reason for explicitly including uncertainty into models is to avoid nasty surprises; in the jargon of economics, we are concerned about risk aversion. Decision makers may be willing to give up some value with certainty in order to reduce the chance of a very negative outcome. A second reason is that some alternatives may have what is called "option value": they may provide us with flexibility to react to uncertain outcomes in the future, thus increasing their overall value. These kinds of alternatives cannot be identified without explicitly considering uncertainty. A third reason is what Sam Savage has termed the "Flaw of Averages" (Savage, 2009), or what economists know as Jensen's Inequality: the expected value of a non-linear function is not generally equal to the function of the expected value. All three of these reasons have one thing in common – non-linearities. In a non-linear system it is crucial to explicitly include uncertainty, or else risk significantly mischaracterizing the situation. Energy technology R&D in the face of climate change is a highly non-linear problem. Finally, some of the literature has argued that

when the underlying probability distribution is deeply uncertain, ambiguity aversion should also be taken account of.

In the rest of this paper we discuss different frameworks for combining probabilistic data on energy technology R&D with IAMs in order to support decision making and present numerical results based on different elicitations and decision frameworks. In Section 2 we discuss a number of different frameworks and discuss the optimization models that we focus on. In section 3 we describe our detailed numerical example, comparing decision frameworks across different elicitation teams. Along with presenting assumptions, data, and solution methods, we discuss the methods for integrating the elicitation data into IAMs. In Section 4, we present the results of our numerical example; and provide a discussion and conclusions in Section 5.

Section 2: Frameworks for Uncertainty Analysis.

2.1. Decision frameworks

In this subsection we discuss a set of frameworks, including sensitivity analysis, Monte Carlo type analysis, single-stage decision making under uncertainty (DMUU), sequential DMUU, and full stochastic-dynamic programming. We conclude this subsection by discussing some frameworks to account for ambiguity aversion.

Sensitivity Analysis: When there is uncertainty over the values of inputs, the first level of analysis is sensitivity analysis. This is the most common approach taken by Integrated Assessment modelers. Sensitivity analysis can reveal which parameters are most important to carefully characterize, and can

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sometimes provide an estimate for how outputs of interest change with the uncertain input parameters. An example of sensitivity analysis is provided in this issue, in (Bosetti, et al., 2014). In this paper they consider how a range of technological parameters impact emissions paths and costs of stabilization. They find that the results vary somewhat by model, but that changes in the cost of nuclear seem to be important in a wide range of cases.

The benefits of sensitivity analysis are that it is relatively easy to undertake this analysis, and it nicely provides comparative statics, that is it shows how one output changes when an input changes. This allows modelers to get an idea of which parameters are most important to model carefully; and it can give some policy insights into how outputs change with inputs. The limitation of sensitivity analysis is that it will often not address the impact of non-linearities if they are present, as indicated above. That is because, as expressed in Jensen's inequality, the best alternative under uncertainty may not be equal to some kind of average of the best alternatives under certainty. Moreover, sensitivity analysis is generally done in the absence of probabilities, thus the analyst is unable to determine whether "interesting" effects have much, or even any, likelihood of arising.

Monte Carlo-type Analysis: When a probability distribution over one or various uncertain inputs is available, a Monte Carlo-type analysis can be performed. In this type of analysis, the analyst is able to estimate the distribution of the outputs by using draws from the distribution of the inputs. (We call it "Monte Carlo-type" analysis to include more sophisticated sampling techniques such as Latin Hyper Cube). In the case of TEaM, we can use Monte Carlo to estimate the probability distribution over outcomes of interest, given a particular R&D portfolio. This approach is numerically tractable when only a few uncertain inputs are used, although it gets computationally intensive with a growing number of uncertain inputs if one wants to ensure that the variance of outputs truly reflects that of inputs. Monte

Carlo-type analysis can provide a layer of insights above sensitivity analysis. It is particularly useful for descriptive models, in which we are most interested in gaining an understanding of the state of world. It is slightly less useful for decision models, in which we are most interested in understanding near term optimal decisions. In fact, the key limitation to Monte Carlo is that, generally, each run of the model is run under the assumption of the certainty of the sampled input values. It is possible, but not often done, to restrict early decisions in a model to be identical across all samples. However, this early scenario tends to be arbitrary, rather than any response to the actual uncertainty. Monte Carlo cannot tell us what the impact of uncertainty on the optimal decisions is, just what range of uncertainty over the outcomes is.

Single Stage Decision under Uncertainty: Like Monte Carlo, this framework explicitly incorporates uncertainty. Unlike Monte Carlo, this method includes an optimization component that allows the analyst to determine the impact that uncertainty has on near term optimal decisions, therefore accounting for the effects of non-linearity. However, this framework does not include learning or recourse, therefore will miss alternatives with "option value". It can provide insights into non-linear problems and problems with risk aversion.

Two-stage Decision under Uncertainty: One step up from the previous is to add a second stage, in which a second set of decisions may be made after some or all the uncertainty is resolved. Adding this second stage has proved to be very powerful, allowing for a number of insights not otherwise available. The most prominent example of this was the work on investment under uncertainty, and the idea of "real options" (Dixit & Pindyck, 1994). That book, and many others since then, showed that the optimal near term action is not only significantly quantitatively different, but often qualitatively different as well. Some near term alternatives have "option value," that is, they allow for more flexibility in the future to

change course once the uncertain outcomes have been revealed.

Multi-Stage Decision Making under uncertainty: In the real world, of course, information is revealed over time, and many decision points exist. In order to reflect this, some models use a framework of multi-stage sequential DMUU. This framework can be implemented using sophisticated techniques such as stochastic programming or dynamic programming, with approximate dynamic programming (ADP) gaining popularity recently. For example, Santen & Anadon (2014) applied ADP techniques to solve R&D and power capacity expansion decisions in a realistic electricity systems model. Regardless of the solution technique, it is very computationally intensive. Therefore, most models implement considerable simplifications in order to implement this framework. Whether the addition of extra stages beyond 2 or 3 adds considerable insight is an open question [(Baker E. , 2006), (Webster, Santen, & Parpas, 2012)].

Frameworks to Account for Ambiguity Aversion: There is an increasing literature that suggests that policy makers should take ambiguity aversion into account when choosing climate change policies [(Lemoine & Traeger, 2012), (Kunreuther, Heal, Allen, Edenhofer, Field, & Yohe, 2013), (Gilboa, Postlewaite, & Schmeidler, 2009), (Heal & Millner, 2014)]. The idea is as follows: there is deep uncertainty around climate change (and climate change technologies) in the sense that scientists do not agree on a single prior probability distribution. It has been shown that behaviorally many people are in fact ambiguity-averse (See Ellsberg (1961) for classic case); that is they will choose an alternative with lower expected value if that alternative is presented as having "certain" probabilities rather than "ambiguous" probabilities, or as having an aggregated probability distribution rather than a compound probability distribution. While the Savage (Savage L. J., 1951) Subjective Expected Utility (SEU) framework, based on a set of very reasonable axioms, does not allow for ambiguity aversion, there exist

alternate sets of axioms that do allow for ambiguity-aversion in decision making. There is not, however, widespread agreement on which framework to use in order to account for ambiguity aversion. In this paper we apply two simple frameworks found in the literature. The first is MiniMax Expected Utility (Gilboa & Schmeidler, 1989). This framework allows for using existing probabilities (as opposed to some frameworks which ignore all probabilities in favor of using very worst-case scenarios). This framework finds the expected utility for all possible priors, and then chooses the alternative that gives the highest expected utility under the worst case prior. This approach reflects an extreme ambiguity aversion since it does not rank or weight the possible priors. It has been shown that a more moderate framework such as "smooth ambiguity" often will give the MiniMax solution as ambiguity aversion moves to its maximum (Millner, Dietz, & Heal, 2010). The second approach we consider is a MiniMax Regret Expected Utility framework. It is similar to a traditional MiniMax Regret framework, but uses the priors to calculate expected utilities. This framework minimizes the regret of the expected utility for all possible priors, under the worst case prior.

In **Errore. L'origine riferimento non è stata trovata.** we present influence diagrams for the one-stage and two-stage decision frameworks that we consider in this paper.
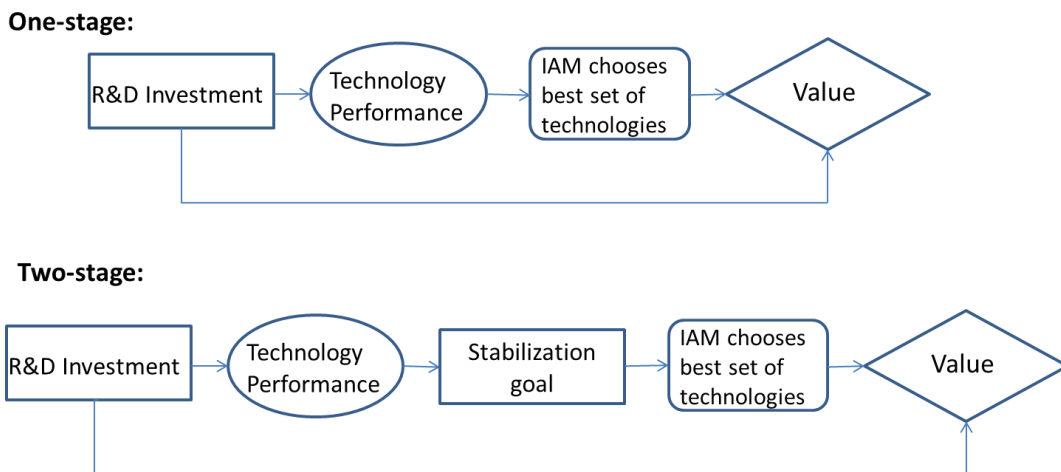
Figure 1: Influence Diagrams representing the two decision frameworks. Square nodes represent decisions; oval nodes represent uncertainties; rounded squares represent functions; diamond nodes represent values.

The top Influence diagram is a one-stage problem. The key decision (represented by a square node) is how much to invest in which technologies. The key uncertainty (represented by an oval node) is the performance of the technologies starting in 2030. The arrow going into the oval indicates that the probability distribution over technology performance is conditional on the R&D investment decision. We model the next step as a function: each IAM, when given a set of technology performance parameters and a Representative Concentration Pathway (RCP)[3] , minimizes the cost of the RCP by choosing deployment investments in different energy technologies. The overall objective (represented by the diamond value node) is to minimize the cost of abatement plus the climate damages plus the cost of R&D investment. Climate damages have some relevance in this framework even though damages are primarily related to the RCP; different technological outcomes can lead to slightly different emissions paths under the RCPs and therefore to different damages. In the unconstrained cases, technology is the only thing that drives any differences in the damages.

The lower Influence diagram represents a two-stage problem of sequential DMUU. In this problem the RCP – either 2.6 W/m^2, 4.5 W/m^2, or unconstrained – is chosen after the decision maker learns about the technology performance parameters. Climate damages play a more important role in this model, as information about the level of climate damages is in many cases the primary reason for choosing one RCP over another one. Everything else in this problem is the same as the one stage problem.

The decision maker is a social planner, considering both the cost of the public R&D and the global costs and benefits of stabilization pathways.

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[3] We consider two RCPs, 2.6 and 4.5 W/m^2, roughly equivalent to a 450ppm and 550ppm stabilization goal in the GCAM model. See Van Vuuren et al. [(2011) , (2013)] for more details on RCPs.

2.2. Optimization models

To implement these frameworks we use a multi-model framework consisting of an IAM and simple optimization models. The IAM provides the estimated abatement costs and temperatures from climate change; and the optimization models determine the optimal R&D portfolio. In this section we describe the specific optimization models that we use to examine the importance of the different decision frameworks.

2.2.1 One-stage

For this framework, we take the RCP as given. The objective is to minimize the expected total abatement cost to achieve the given RCP plus climate damages plus the R&D cost.

$$\min_{I} \left\{ E_I \left[TAC_s + D_s \right] + \kappa F_I \right\} \tag{1}$$

Where TAC_s is the total abatement cost (the Net Present Value over the entire time horizon) to achieve the given RCP s, where $s \in \{2.6, \ 4.5, \ unconstr\}$. The TAC_s is a random variable whose outcome depends on the technological outcomes. The probability distribution over the technological outcomes depends on the portfolio, $I = \left[I_1, ..., I_5 \right]$ where I_j is the level of investment in technology j. F_I is the R&D funding amount for portfolio I:

$$F_I = \sum_{j=1}^{5} I_j \tag{2}$$

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The opportunity cost of R&D funding is represented by a multiplier, κ. We include D_s, the estimated damages given RCP s, to be consistent with the second framework. They play some role, but a small one, since damages are dominated by the RCP, s. We will refer to this as a traditional SEU framework, in contrast to the MiniMax and MiniMax Regret frameworks below which account for ambiguity aversion.[4]

2.2.1.1 One-stage MiniMax Models

The MiniMax EU model is presented here:

$$\min_{I}\left\{\max_{\tau}\left[E_{I(\tau)}\left[TAC_s + D_s\right] + \kappa F_I\right]\right\} \tag{3}$$

Where τ represents the elicitation team, $\tau \in \{\text{FEEM, Harvard, UMass}\}$; the τ in parentheses means that the expectation is being taken using the probability distribution from team τ. In this model, for each portfolio I we find the team that produces the highest expected cost; we then choose the portfolio that minimizes this cost.

The MiniMax Regret EU model is as follows:

$$\min_{I}\left\{\max_{\tau}\left\langle\left[E_{I(\tau)}\left[TAC_s + D_s\right] + \kappa F_I\right] - \min_{I_\tau}\left[E_{I_\tau(\tau)}\left[TAC_s + D_s\right] + \kappa F_{I_\tau}\right]\right\rangle\right\} \tag{4}$$

Where I_τ represents a portfolio for team τ. The second "min" expression finds the optimal portfolio for a given team τ. The expression inside the triangle brackets gives the regret, the difference in cost

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[4] We are minimizing costs rather than maximizing utility. We are not accounting for risk aversion.

between the portfolio under consideration and the optimal portfolio. We maximize this value across the teams to find the team distribution that gives us the most regret. Finally, we choose the portfolio that minimizes this regret.

2.2.2 Two-stage

In this framework, the RCP is a decision rather than an assumption. The objective is to minimize the expected total abatement cost plus climate damage cost plus R&D cost. This framework is solved only under traditional SEU.

$$\min_I \left\{ E_I \left[\min_s TAC_s + D_s \right] + \kappa F_I \right\} \tag{5}$$

All variables are as defined in the section above. Note that the difference between this framework and the one-stage is that the RCP, s, is being chosen, and it is being chosen after we learn about the outcome of technological change. Thus, this is a two stage decision model, with sequential DMUU, albeit a very simple one.

2.3 Damages and Abatement Cost

The climate damage, represented by D_S, is calculated as follows:

$$D_S = \sum_t \delta^t \pi T_{t,S}^2 G_t \tag{6}$$

Where $T_{t,s}$, is the global mean temperature at time t, under RCP s; δ is the discount factor; π is a multiplier that converts the square of temperature to a fraction of GDP lost (based on the formulation in DICE (Nordhaus 2008); and G_t is the GDP (in trillions of dollars) at time t. This results in damages in the unit of trillions of dollars. The damages will show some variation under different technology scenarios, since different scenarios lead to slightly different abatement choices through time. However, these differences are small under an RCP.

Similarly, the TAC is defined as

$$TAC_s = \sum_t \delta^t AC_{s,t} \qquad (7)$$

Where $AC_{s,t}$ is the annual abatement cost (in trillions of dollars) at time t, under an RCP. Note that the IAMs only report values for every 5 years. We assume that the temperature and the AC are linear between the reported years.

Section 3 Numerical Example

In this section we describe the numerical example we use to illustrate the roles of the different decision frameworks.

3.1 Technologies

We consider 5 technology categories: Solar PV, Electricity from Biomass, Liquid Biofuels, Nuclear Fission, and Carbon Capture and Storage (CCS). We use data on 8 parameters: Levelized Cost of Electricity ($/kWh) for solar PV; non-energy cost for electricity from biomass ($/KWh) and for liquid biofuels ($/gallons of gasoline equivalent); conversion efficiency for electricity from biomass and for biofuels (both in %); overnight capital cost for nuclear ($/kW); additional capital cost for CCS ($/kW); and Energy Penalty for CCS (%).

3.2 Generation of Payoffs using Energy Economic Models

Frameworks for DMUU (as opposed to sensitivity analysis and Monte Carlo) can be quite computationally intensive, and therefore are sometimes quite difficult to use with technologically-detailed IAMs. There have been a number of implementations of 2-stage and multi-stage DMUU frameworks using versions of models in the DICE family, a relatively simple IAM (See for example (Webster, Santen, & Parpas, 2012), (Lemoine & Traeger, 2012), (Crost & Traeger, 2010), (Yongyang, Judd, & Lontzek, 2012), (Traeger, 2013)). Even using the simple DICE model, however, most of the multi-stage frameworks have made simplifications of the original model. Moreover, DICE has a simplified technological set up, so while it might be very useful in investigating problems that look into

climate system uncertainties, it provides fewer insights when studying problems concerned with technological change uncertainty and R&D decision making.

A couple of medium-sized IAMs have made some headway at incorporating stochastic programming, including WITCH ((Bosetti & Tavoni, 2009), (Johannes & Tavoni, 2013)), and MERGE (Durand-Lasserve, Pierru, & Smeers, 2010).

One approach that can be found in the literature is to take a multi-model approach. In this method, a technologically-detailed IAM is used to estimate the impact of technological change. Then, outputs of this model are used as input into a simpler decision framework that can explicitly incorporate sequential decision making. Examples of this approach can be found in Blanford (2009), combining MERGE with a simple decision model; Baker and Solak (2011) combining GCAM with a simple decision model; Baker and Solak (2014) combining GCAM with a stochastic programming version of DICE; and Anadon et al (2014), combining MARKAL with an analysis model to determine an optimal portfolio. In this paper we provide an example of this kind of analysis. We use modeling outputs from GCAM (Kim, Edmonds, Lurz, Smith, & Wise, 2006) to compute the payoffs that are used in simple one-stage and two-stage decision models. The GCAM model follows a protocol that encompasses one unconstrained baseline and two different RCPs, 2.6 and 4.5 W/m^2. A detailed description of the generation of the outputs we use here is in (Barron & McJeon, 2014); model characteristics and some basic results of a scenario-based model comparison are provided in (Bosetti, et al., 2014).

Importance Sampling: For this project we have piloted a new use for an old technique, importance sampling. Importance sampling has generally been used as a version of Monte Carlo -type analysis, when the area of interest in the input distribution has very low probability. That is, sometimes the

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function of concern is only non-zero over a portion of the distribution with very low probability. If one samples the distribution randomly, it is possible that there are no points in the sample from the area of interest. Importance sampling allows one to sample more frequently on the most valuable part of the distribution, and renormalize back to the actual distribution of interest, correcting for the use of an importance distribution (Owen & Zhou, 2000).

We use it here for a different reason. We wanted to be able to minimize the number of times we ran the large IAMs. As we have four alternative sets of distributions (one for each of the three elicitation teams plus the Combined distribution) and 3^5 possible portfolios (three levels of R&D for each of the five technologies), the number of runs for the IAMs would have been exceedingly high. Thus, we defined a single "importance sample" for each technology parameter that defined the IAM runs. Given this sampling of the technology performance space, alternative portfolios can be mimicked by simply correcting for the different R&D distributions. Chan and Anadon (2014) have also implemented the use of importance sampling for the Harvard elicitations in a one-stage decision framework for a portfolio of R&D investments in 6 technology areas and 25 specific technologies using MARKAL to translate technology into societal/economic outcomes.

We first sample from an importance distribution q_j for each technology j. We choose this distribution so that it covers the range of the elicited distributions of all teams. The elicited distributions are called the *nominal distributions, $p_{j\tau k}$*, where there is a nominal distribution for each funding level *k*, team *τ*, and technology *j*. We then reweight the sampling distribution using the likelihood ratio

$$\frac{p_{j\tau k}(x)}{q_j(x)} \tag{8}$$

Specifically, we generated a 1000-point sampling distribution for each technology parameter. We assume that all technology parameters are independent of each other. This produces an 8-dimensional 1000-point sampling distribution (to account for the 8 technology parameters). Then, for each funding level for each technology and each team, we reweight the sampling distribution using the elicited probability distributions $p_{j\tau k}$ described in ((Baker, Bosetti, Anadon, Henrion, & Reis, 2014)). Finally, we multiply the probabilities across the 8 parameters (and re-normalize) to get the probability of each 8-dimensional point. Thus, each IAM only had to run 1000 points, yet we can analyze a very large number of underlying probability distributions, for different teams and for different portfolios. These probability distributions are used to calculate the expected Total Abatement Cost (TAC) and the expected damages. Such a reweighted sample will have the same expected value as the nominal distribution.

Methods for choosing the importance sample. For the numerical example provided below we used importance samples that over-weighted the low cost regions of each technology. The idea is that the high-cost regions for most of the technologies will not be of much interest: when a particular technology has a high cost it will generally not be competitive and therefore, small differences in the actual cost will have very little effect on the economy. **Errore. L'origine riferimento non è stata trovata.** illustrates a nominal distribution for Solar LCOE along with the covering distribution. A disadvantage of this method in this case is that, because it samples heavily from the far left of the distributions, and because we are working with a large number of different underlying nominal distributions that have different supports (that is the low and high values differ considerably) many of the individual points in the importance sample have a probability of zero in many of the elicited distributions. This is compounded when we calculate the probability of the joint event – the eight individual cost and efficiency outcomes. In some

cases well over half of the 1000 points in the importance sample have probability zero. Thus, in a situation like this, it may be better to choose an importance sample that more closely mimics the underlying distributions at hand.
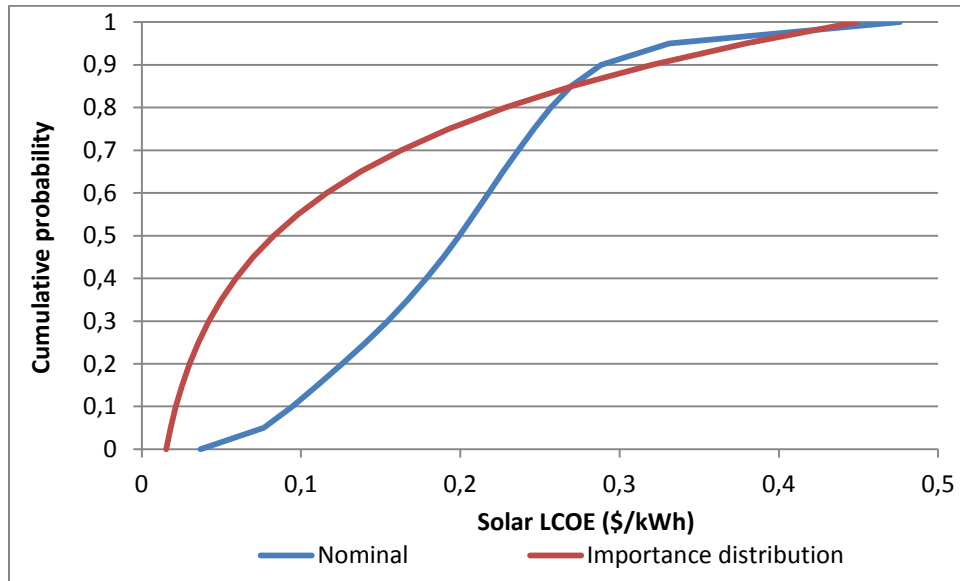
Figure 2: An illustration of how the importance distribution oversamples low costs. The Nominal distribution shown is for Harvard Low Funding Solar LCOE.

3.2   Solution Methodology and Model Calibration

3.2.1 Solution Method for One-Stage and Two-Stage decisions

All frameworks are solved using a simple dynamic program, implemented in Excel and Matlab. For framework two, the two-stage decision, the RCP is chosen in Excel, based on the minimum of the sum of damages and abatement cost, and then this is used in the Matlab model. The MiniMax and MiniMax Regret frameworks are solved in Matlab by cycling over each of the teams' probability distributions for each technology.

3.2.2   Calibration

Here we describe some key assumptions and calibration parameters that determine model outputs.

Discount rate: We take δ=5% for our central discount rate when calculating the TAC and Damages, the discount rate used in GCAM.

Model Outputs: The IAM produces a number of outputs for each of the 1000 points in the importance sample, including annual abatement $AC_{s,t}$ costs and temperature $T_{t,s}$. GDP is exogenous for GCAM. The damages, D_s, and total abatement cost TAC_s are calculated from the outputs as discussed above. The GCAM model timespan runs until the year 2095.

R&D Funding Amounts: The funding amounts vary considerably by team. One key difference between the teams is whether the amount includes development, demonstration, and deployment. The Harvard values include these expenditures; the UMass values do not. FEEM values are based on EU investments; they include research, development, and dissemination. A second difference is that the UMass team developed funding amounts in a bottom up way, discussing the number of labs needed to give a breakthrough a reasonable change; the other teams developed them in a top down way, by looking at current total government spending.

In this paper we use the same R&D funding amounts for each team: the simple average of the funding amounts across the three teams (Baker, Bosetti, Anadon, Henrion, & Reis, 2014). One exception to this is the bioenergy technologies – biofuels and bio-electricity. As Harvard elicited Bio-Fuels and Bio-Electricity together, we combine both technologies into one category called Bio-Combined in the Harvard case. For the MiniMax and MiniMax Regret frameworks, we constrain the Bio-Fuels and Bio-

Electricity funding levels (that is, Low, Mid, or High) to always be the same, so that we can compare all three teams across the same portfolios.

The team funding amounts were presented as annual amounts in (Baker, Bosetti, Anadon, Henrion, & Reis, 2014). Here we convert them to Net Present Values using a discount rate of 3% and a time span of 20 years. Each technology has only three alternative funding amounts, a Low, Mid, and High funding amount.

The technology funding amounts represent actual dollars spent. Theory suggests that the cost to the economy may be considerably greater, particularly if the funding is being diverted from other R&D projects. Thus, we consider an opportunity cost multiplier: a value $\kappa \geq 1$ is multiplied by the funding amounts. Our central assumption for the opportunity cost is κ=4 ((Nordhaus, 2002), (Popp, 2006). We also ran experiments using $\kappa = 2$ and $\kappa = 8$.

Probabilities: Each elicitation team derived probability distributions over each of the 8 technology parameters, based on the elicitation data. In order to get the Combined probability distributions, each of the 8 parameters the probability distributions of the three teams were aggregated using a simple linear average (Baker, Bosetti, Anadon, Henrion, & Reis, 2014) The four nominal distributions used in the importance sampling include the Combined probability distributions and each of the three teams' distributions.

Damage parameter π: This parameter converts the square of the temperature into a fraction of GDP lost. The baseline value in DICE99 (Nordhaus W. D., 2008) is .0035[5]; we use this for our Low Damage value. A value of 0.017 is chosen for the High Damage value because it leads to a case where the optimal

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[5] The form of the damage function is slightly different in DICE99, but the baseline damages are very similar.

RCP varies between 2.6 W/m² and 4.5 W/m². We use this value to compare the one-stage and two-stage frameworks.

3.3 Experimental Design

For this example, our experimental design combines sensitivity analysis over some aspects (the elicitation teams, the climate damages, and the framework) with one-stage and two-stage DMUU.
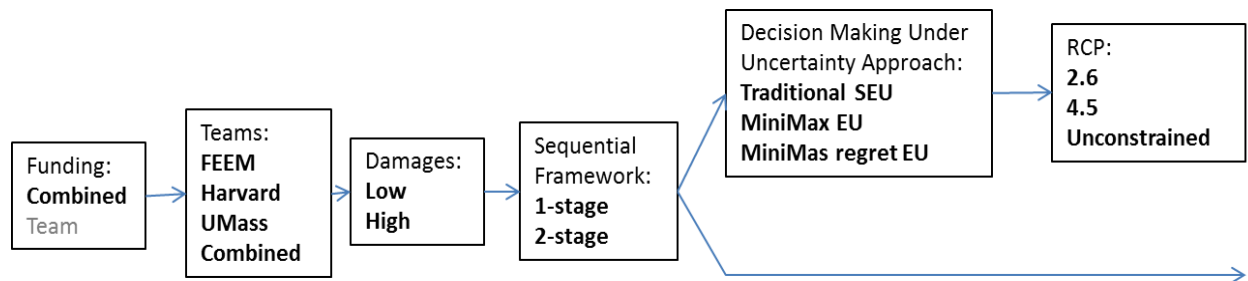
Figure 3: Framework Description

Errore. L'origine riferimento non è stata trovata. provides a chart illustrating the many choices that can be made in running these models. In this paper we will focus on results using only the "Combined" funding amounts (discussed in Section 3.2.2), rather than the individual funding amounts for each team. For the one-stage Framework we consider three possible approaches to DMUU and three RCPs. For the two-stage framework the RCP is a decision that is made after the outcome of technological change is known and we only use a traditional SEU framework.

4 Results

4.1 Framework I: One stage decision making under uncertainty

Errore. L'origine riferimento non è stata trovata. summarizes the results of the one stage problem, under the assumption of an opportunity cost multiplier equal to 4 (the results were nearly identical for

opportunity cost multipliers of 2 and 8). The figure shows the optimal portfolio that is obtained using the probabilities from each team, from the Combined probabilities, and from the MiniMax and MiniMax Regret implementations, for each RCP assumption and damage level. We show 2.6 W/m^2 only once since the optimal portfolio is always the same between the high and low damages. Note that FEEM did not elicit CCS; the results shown use the combined CCS probabilities in conjunction with the FEEM data, thus we have shaded these results differently.

We find that, given our data, the most common level of funding in the optimal portfolios is "Low". To emphasize this, we have striped any funding level that is different from the "Low" funding level. At this time we do not have a zero funding level, so we cannot confirm whether the preponderance of "Low" funding levels is because (1) the investments do not provide a good return on investment and the optimal would be something closer to zero; or (2) the Low investments are highly productive and so the marginal returns from higher investments are not warranted.
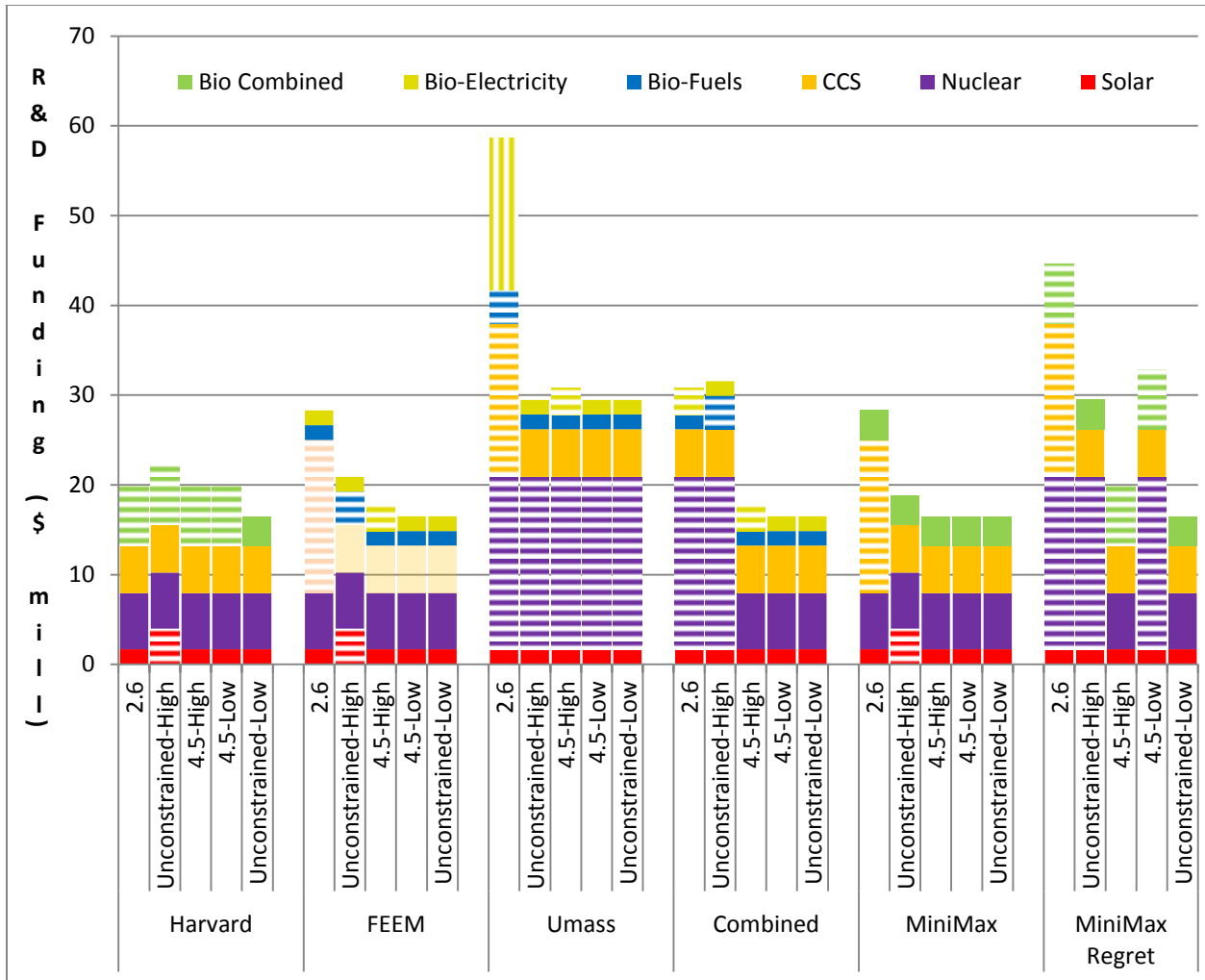
Figure 4: One Stage Decision Framework Results. The Figure compares the results of each of the teams' distributions with the Combined, the MiniMax, and the MiniMax regret strategies. Horizontal and vertical stripes indicate Medium and High investment respectively. The CCS blocks are pale for FEEM since they did not elicit CCS values; these results are based on Combined values.

First we focus on the traditional SEU results and consider how they compare across elicitation teams and the Combined elicitation results. First, as one would expect, the more stringent 2.6 W/m^2 stabilization generally has (weakly) more investment in each technology than the 4.5 W/m^2 RCP. The one exception, and therefore the most interesting, is that when using the FEEM elicitation data we find that a Mid-level investment in bio-electricity is optimal under 4.5 W/m^2 when damages are high; but only a Low investment is in the 2.6 W/m^2 portfolio, which features CCS instead. Note that FEEM did not elicit CCS, this result is based on the probabilities in the "Combined" distribution.

The second interesting result is that the Unconstrained stabilization scenario with high damages actually has some of the highest technology investment. This is because the R&D model is trying to minimize the cost of abatement plus cost of damages plus R&D investment. The cost of the R&D investment is made up for by the reduction in damages in the high damage case. Note that the reduction in damages is due entirely to the improvement in technology: there is no abatement in GCAM in the unconstrained case. This implies that, in the absence of clear climate policies, investing in technology is still worthwhile and has some benefits. We have seen in many studies that technology is not enough – climate change will not be solved by technological breakthroughs alone. But this result says that even if we don't see any significant climate policy on the horizon, it still makes sense to forge ahead with investment in energy technology R&D

Third, if we compare the optimal portfolios to the elicitation results, we see that the optimal portfolio doesn't entirely follow the elicitation results. That is, just because a technology has a higher expectation of technological improvement, it may not justify a higher investment. Based on the elicitations for each study, in the FEEM elicitation bio-electricity has the lowest improvement. Yet, in the 4.5 W/m^2-high scenario, bio-electricity is the only technology that is invested in at a Mid (rather than Low) level under the FEEM distributions. In the Harvard study, CCS has the highest return, but is invested in at a Low level in all portfolios.   Finally, we see, given this data, a great deal of disagreement when using the technology inputs from the different teams performing the expert elicitations. Given this disagreement, one possible direction is to look at other optimization approaches such as the MiniMax models, which we turn to now.

We see that, given the set-up of this model, using the MiniMax EU framework tends to lead to smaller

investments, taking a more pessimistic view of the R&D returns. This may be because the uncertainty in this case is only about technology, not about climate damages. In this framework, the RCP and the level of damages are taken as given; therefore in an extreme ambiguity-averse framework, these factors receive less negative weight.

The MiniMax Regret, on the other hand, tends to be more optimistic, with larger overall investments than the MiniMax, the Combined case, and most of the individual teams. This is because in this framework the objective is to minimize the regret of not being in the best state, so it tends to be the most optimistic prior that chooses the portfolio.

The question is what to do with this information, especially when frameworks designed to take ambiguity aversion into account give such differing results? Given near term uncertainty over the prospects for advancement in climate technologies, how should a decision maker interpret these results? Since there is no single framework or set of axioms that leads to one ambiguity-aversion framework, it is difficult to recommend that policy-makers choose one or the other. One potential way to use these results is to focus on the cases where there is the most difference between the solutions of the different DMUU approaches, and investigate these particular cases. For example, the key difference between the optimal portfolios among the three aggregated approaches (Combined, and the two MiniMax) in the 2.6 W/m^2 case is the investments in nuclear and CCS, and to some degree the investments into the bioenergy technologies. This indicates that we may want to look very closely at these elicitation data sets. When going back to the original elicitations, we see that there is the most disagreement among the teams in the Nuclear technology; and that the CCS technology results rely strongly on the elicitation of one team. The bioenergy technologies required significant assumptions for two of the teams in order to differentiate between efficiency and non-energy costs. This suggests that

an analyst supporting a decision maker should (1) go back and consider weighting the current set of elicitations based on a judgment of quality; and/or (2) put resources toward additional, careful elicitations in these topics.

For the first approach, the analyst can first perform a sensitivity analysis to determine how skewed the weights need to be from equal in order to change the optimal portfolio. They could then look back at the studies and judge them for quality. For example, the nuclear elicitation that is most different from the others also has a very small number of experts. It would be reasonable to consider weighting the elicitations based on the number of experts in each study. For the second approach, a first step would be to review the full set of elicitations and other data that is available. For CCS, for example, there have been a number of studies that could be added into this aggregation [(Rao, Rubin, Keith, & Granger, 2006), (National Research Council, 2007), (Chung, Patiño-Echeverri, & Johnson, 2011), (Jenni, Baker, & Nemet, 2013)]. If additional studies don't exist, then a full-scale elicitation may well be justified. Previous work indicates that the value of better information in the form of careful, well-funded elicitations is far above the cost of such elicitations (Baker & Peng, 2012).

4.2   Framework II: Two-stage decision making under uncertainty

In the two-stage framework, there is an "option" – to choose an RCP based on the outcome of technical change. When damages are low, then it is optimal to choose 4.5 W/m^2 about 80-100% of the time (depending on the R&D portfolio), and unconstrained the rest of the time. In this case of low damages, the two-stage results are not very interesting: in three out of four cases we find that the optimal portfolio is the same for the 2-stage problem, the unconstrained-low 1-stage, and 4.5 W/m^2-low 1-stages; for Harvard, the 2-stage portfolio matches their 4.5 -low. The high damage case is more interesting and the results are shown in **Errore. L'origine riferimento non è stata trovata.**, where we

compare the results for the 1-stage problem under 2.6 and 4.5-high alongside the 2-stage results. When damages are high the investment in technology has a large impact on how often the 2.6 W/m^2 RCP is chosen over the 4.5 W/m^2. In the Combined case, when investment is low in all technologies, 2.6 W/m^2 is optimal only 5% of the time. But, when investment is high in all technologies, 2.6 W/m^2 is optimal 43% of the time. Thus, in this case, technology not only reduces the cost of a given RCP, it also causes the optimal RCP to become more stringent, thus reducing damages.

For the Harvard data, the optimal portfolio is the same for these three cases. For the FEEM data, the 2-stage optimal portfolio is the same as the 4.5 W/m^2-high; for UMass data is it the same as 2.6 W/m^2. But, the interesting result is for the Combined case. We see that the results of the two-stage framework is different from both 2.6 W/m^2 and 4.5 W/m^2-high, and not an average or combination of the two. Biofuels is not optimal at the Mid level in either the 2.6 W/m^2 or the 4.5 W/m^2-high; yet it is optimal in the 2-stage. This is an illustration of the kind of results that can only be seen if we explicitly consider a 2-stage problem. The investment in Biofuels, at least when using the combined data, has an option-value not seen in the 1-stage problems, allowing for lower damages by switching to 2.6 W/m^2 more often.
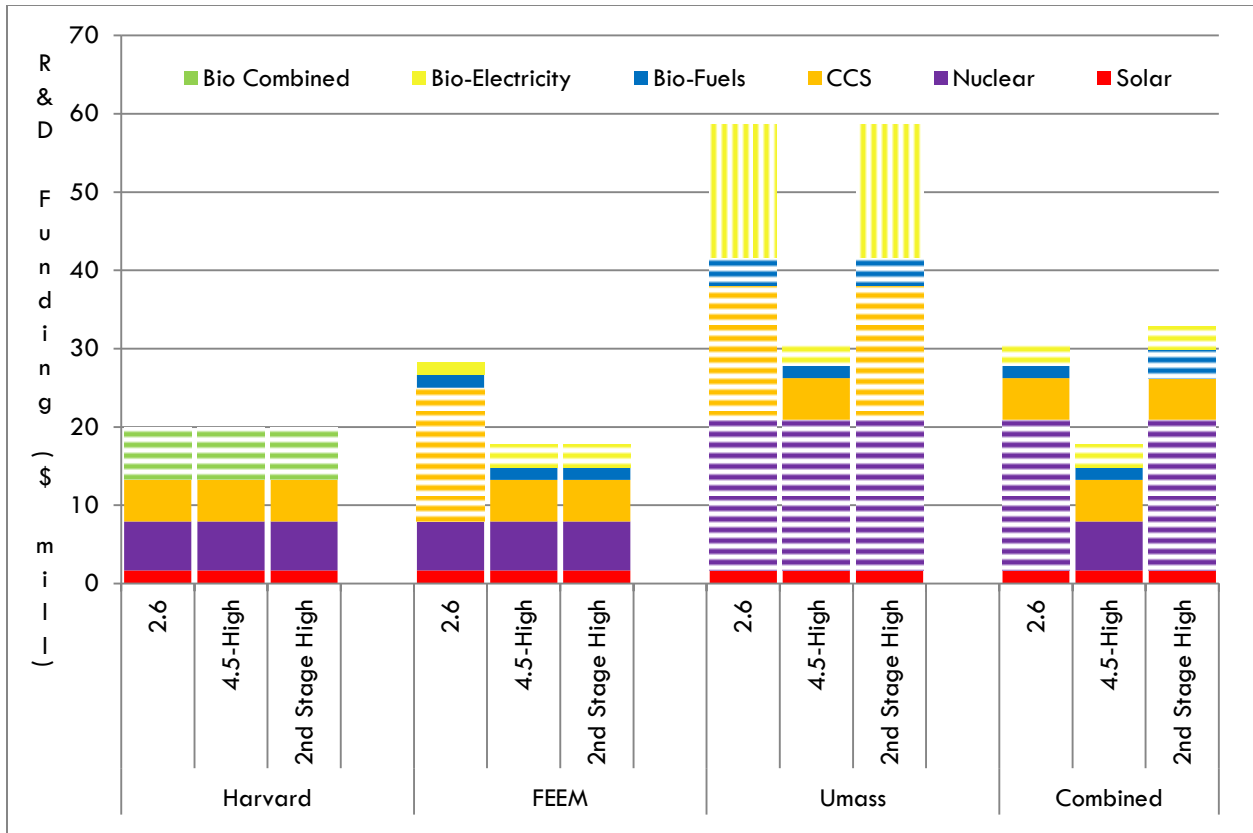
Figure 5: Comparison of One Stage - High and Two Stage - High Decision Framework Results

5   Conclusions

In this paper we provide a brief overview of decision frameworks that can be used to consider the optimal climate-energy technology R&D investment under uncertainty about the prospects for technological change. We then explore the implications of different decision frameworks, especially when there are multiple potential probability distributions for each technology.

Methodologically, we investigate this problem using importance sampling, a technique with great promise for combining large IAMs with expert elicitations. This is a different application of importance sampling, which has typically been used to estimate statistics in cases where the region of interest is of low probability. We use it, instead, to enable a numerically efficient way to use large IAMs for

uncertainty analysis. We choose one sampling distribution for each technology, and use that to generate

an importance sample. This sample is then run through IAMs to produce outputs of interest such as total

abatement cost. The method of importance sampling is then used to reweight the outputs using the

nominal distributions resulting from a set of expert elicitations. This allows us to consider the results of

multiple elicitation teams as well as multiple funding levels while keeping the number of runs of the

large scale models to a reasonable number.

In future work we suggest that the sampling distribution be chosen carefully to avoid a large number of

points with zero or near-zero probability. This is particularly important in a case like this where we have

probability distributions over 8 parameters that need to be combined through multiplication. Rather

than over-sampling at the low end of the distribution a better strategy may be to use a combination of

the low and high Combined distribution as the sampling distribution.

From the numerical example using elicitation results from three large scale multi-technology studies, we

note a set of findings. First, the results of the portfolio optimization do not directly follow the results of

the underlying elicitation data: the optimal investment depends on more than the just the technological

outcome. That is, one technology may have the most promising future in terms of the overall

improvement that can be achieved with R&D investment, but it may not turn out to be the best

investment. The overall benefit of an R&D program depends on how that technology competes with the

other technologies available in the economy and how it interacts with climate policy. On the other hand,

we see that the optimal portfolio does depend heavily on the underlying probability elicitations (by

looking at the differences between elicitation teams). Thus, the conclusion is that both parts of this

equation are crucial for crafting R&D policy – understanding the prospects for technological

advancement and understanding the complex interactions between technologies in the economy.

An interesting result that we have not seen explicitly in the literature is that energy technology R&D is valuable even in the absence of climate policy. We saw that the optimal portfolio was particularly high in the unconstrained scenario with high climate damages. While technology alone is not the solution to climate change, it is apparently better than nothing. This suggests that policy makers should move ahead with investment in energy technology R&D even if they are uncertain about the future climate policy environment. A similar result was found in Baker & Solak (2014), where the optimal portfolio was quite robust in the face of very different policy environments, from one based on Nordhaus' model (Nordhaus W. D., 1993) to one based on the recommendations of Al Gore[(2006)]. That paper, however, did not consider a "do nothing" policy.

By comparing a one-stage model, which takes the RCP as given regardless of the outcomes of technical change, and comparing it to a simple two-stage model, in which the RCP is chosen knowing which technologies have been successful, we illustrated that some technologies may have an "option value" that cannot be easily identified in one-stage frameworks. Specifically, in our example, we found that when the RCP was fixed at 2.6 W/m^2 or 4.5 W/m^2 the optimal investment in biofuels was Low; but when the stabilization was chosen after the realization of technical change, the optimal investment in biofuels was Mid. This implies that some care should be taken to identify technologies (and other near-term alternatives) that have option value, in allowing for more flexibility in the future to respond as more is learned.

There is a movement in part of the literature to take ambiguity aversion into account when making optimal policy [(Gilboa, Postlewaite, & Schmeidler, 2009), (Millner, Dietz, & Heal, 2010), (Lemoine & Traeger, 2012) (Kunreuther, Heal, Allen, Edenhofer, Field, & Yohe, 2013), (Heal & Millner, 2014)]. This suggestion is quite controversial and contentious [e.g. (Sims, 2001)]. We have presented results on the optimal portfolio using a traditional SEU framework with the results of two very simple MiniMax

frameworks. We find that different MiniMax frameworks can produce very different results – some with more and some with less investment than traditional SEU. We suggest that while these results may not give a clear guidance to policy makers, they may instead be more useful to guide future careful study and analysis of how to use available elicitations.

This analysis illustrates that optimization models are not the end of the analysis, providing a clear single best strategy. Rather, they are an important part of the analysis to inform decisions, and can provide insights that are not otherwise easy to see (such as which technologies have option value) or on the other hand provide evidence for existing intuitions that are otherwise difficult to support (such as the value of energy technology R&D even in the absence of climate policy). While there will always be aspects of policy decision making that cannot be captured by models or data, this analysis indicates the importance of using models and data to inform decisions.

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