Climate Change Energy Technology R&D Portfolio

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1 Introduction

Addressing climate change in a cost effective way will require the development of better energy technologies. It is clear that the optimal Research & Development (R&D) policy will involve investing in a *portfolio* of technologies. It is not clear, however, what technologies the portfolio should contain. Answering this question involves a number of issues, and in particular requires explicitly incorporating uncertainty over multiple dimensions [9]. The process of R&D is inherently uncertain – we cannot predict whether any particular program will be successful, or the degree to which it will meet or exceed goals. In the case of climate change, we also have deep uncertainty on the benefits side – there is considerable uncertainty about the damages that will be caused by climate change, and hence, the benefits from reducing emissions. This feeds back, to create uncertainty about the value of having any particular technology available. In this paper we perform a portfolio analysis to get insights about the optimal R&D portfolio, and how it changes with increasing risk in climate damages. We will implement data collected from expert elicitations, on how government funding impacts the probability of success in three key climate change energy technologies – solar photovoltaics (PV), nuclear power, and carbon capture and storage (CCS).

The rest of the paper is organized as follows. In the next section, we start by discussing the relevance of the Marginal Abatement Cost Curve (MAC). We then go on to summarize our prior work in which we combined expert elicitations with economic analysis to derive random marginal abatement cost curves. In Subsection 2.3 we show some expected MACs that result from investing in different R&D programs. In Section 3 we present a climate change R&D portfolio model, and in Subsection 3.1 we discuss the Stochastic Programming formulation of this model. In Section **??** we present our preliminary results, and we conclude briefly in Section **??**.

2 Uncertain Marginal Abatement Cost Curves

In this section we discuss how we combined expert elicitations with a technologically-detailed Integrated Assessment Model to derive uncertain Marginal Abatement Cost Curves (MACs). We begin by providing our motivation for focussing on MACs.

The uncertainties in both climate damages and in technical change are dynamic, in that we expect to learn more about each as time goes on. The value of a particular R&D program for a particular technology depends not only on whether the technology development is successful, but may depend on the severity of climate change damages in the future. Some technologies, such as improvements in fossil fuel efficiencies, may have the largest impact if climate change turns out to be mild and only small reductions in emissions are called-for. At very high abatement levels society will tend to substitute away from fossil fuel, and thus improvements in those technologies will have less impact. Other technologies, such as electric vehicles, may have the most impact if climate change turns out to be very severe, calling for an almost total reduction in greenhouse gas emissions. Electric vehicles may not be adopted at low abatement levels, but may prove to be a widespread alternative at very high abatement levels.

We have shown in past work [6] that it is particularly important to understand how new technologies will impact the Marginal Abatement Cost Curve (MAC). This is the curve that reflects the cost of reducing emissions by an additional ton. Figure 1 illustrates how the impact of technical change on optimal abatement varies by technology and by the severity of marginal damages. The solid upward sloping line represents the original MAC. The two dashed lines represent different types of technical change. The horizontal lines represent two levels of marginal damages. On the horizontal axis we show the optimal level of abatement in each case, where μ_{ij} represents optimal abatement given damages $i = H, L$ and MAC curve $j = 0, 1, 2$. Note that the technical change embodied by MAC_1 has no effect when marginal damages are low, but a significant effect when damages are high; the impacts of MAC_2 on optimal abatement are nearly the reverse. By paying attention to the impact of technology all along the curve (rather than just a point estimate), we gain information about how optimal behavior will change with changes in marginal damages. In this paper, we combine probability distributions over MACs with uncertain marginal damages to analyze climate technology policy.

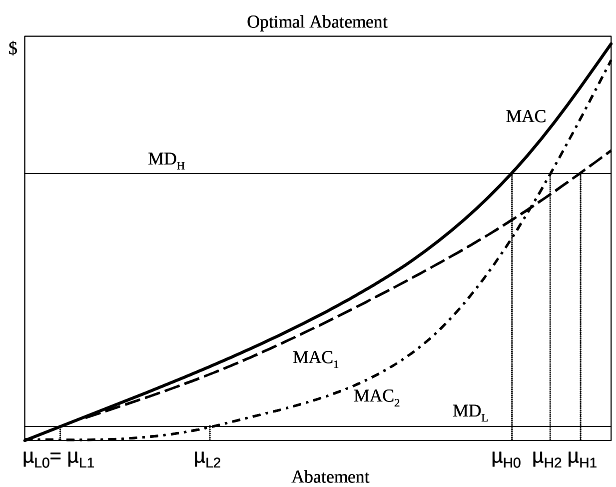

Figure 1: Stylized representations of technical change impact on the MAC; and resulting optimal abatement levels.

2.1 Deriving Probability Distributions over MACs

We will address this dynamic decision problem by incorporating the uncertain returns to R&D in a stochastic program. In order to do this, we must first answer two questions: (1) How will different technologies impact the MAC; and (2) What is the probability distribution over different outcomes of technical change? In this section we discuss our prior work, which provides some initial answers to these questions.

2.1.1 Elicitation Data

In [4], [3], and [5] we have performed expert elicitations on CCS, nuclear, and solar PV technologies. (Also see [8] for batteries for vehicles). The products of the elicitations included explicit definitions of endpoints for each technology, and probabilities of achieving those endpoints for given funding trajectories. In Tables 1 - 4 we report the relevant results. The first column identifies the technology category and the second column lists the sub-categories we considered for each technology. The third column gives the Net Present Value (NPV) of the funding trajectory considered. The funding trajectories themselves varied by yearly amount and by the number of years. We have used a discount rate of 5% to calculate the NPVs. We considered multiple funding trajectories for some technologies. The fourth column reports the average probability of success elicited from the experts. In some cases, we had defined two different levels of success. In these cases, the probability on the top is the probability for high success, on the bottom for lower success. For example, Organic solar cells have two levels of success for each funding trajectory; Inorganic solar cells have only one level of success. The fifth column represents the impact on the MAC and will be discussed in Section 2.1.2 below.

Technology	Project	NPV of Funding (000,000)	Probabiltiy of success	Alpha
Solar	Organic	$116	0.0%	0.045
			13.0%	0.038
		$830	3.9%	0.045
			24.8%	0.038
	Inorganic	$39	26.7%	0.038
		$77	44.3%	
	3rd Generation	$386	2.0%	0.045

Table 1: Summary of Assessment Results for Solar.

2.1.2 Computational MACs using MiniCAM

We then determined how the technologies would impact the MAC, if they achieve the defined endpoints. Specifically, we derived MACs for the year 2050 under different assumptions about technological pathways. We considered only one technological success at a time. For example, in the solar scenarios we assumed that no CCS was available. The analysis was conducted using the MiniCAM integrated assessment model. MiniCAM is a global model that looks out to 2095

Technology	Project	NPV of Funding (000,000)	Probabiltiy of success	Alpha
CCS	Pre-Com	$39	2.7%	0.296
		$154	11.0%	
		$386	22.3%	
	Chem-Loop	$19	8.0%	0.358
		$38	29.5%	
		$56	42.0%	
	Post-Com	$52	59.0%	0.233
		$224	70.0%	
		$519	78.5%	

Table 2: Summary of Assessment Results for CCS.

in 15-year timesteps. It is a partial-equilibrium model, with 14 world regions that includes detailed models of land-use and the energy sector. See Brenkert et al. [10] and Edmonds et al. [13] for more discussion of the model. Assumptions for technologies other than the specific technologies we were considering were based on the version of MiniCAM used in the Climate Change Technology Program (CCTP) MiniCAM reference scenario [11]. See [4][3][5] for more detailed discussions of our methods and assumptions on related technologies.

Here we will briefly address some of the difficulties we faced in modeling each of the technologies. First, since solar is an intermittent resource – that is it cannot be turned off and on – it potentially poses problems for integration onto the electricity grid. The baseline assumption in MiniCAM is that when the penetration of solar into the electricity grid reaches 20%, every additional kW of solar installed requires the installation of a kW of gas-fired backup generation. We have labeled this scenario as "20% limit." We have also modeled the other extreme, simply assuming that there is no problem with grid integration. This would arise if, say, we had free electricity storage, thus we have labeled this scenario "free storage." These two scenarios give an envelope of the impact that solar might have, and illustrate the benefits to developing technologies to address grid integration problems.

We faced a range of difficulties in modeling nuclear power. Many of the advantages of new technologies, such as high-temperature reactors and Fast reactors, are not easily modeled or valued. These include a reduction in proliferation concerns, a reduction in radioactive waste, and a reduction in the complexity of the technology. Moreover, the nuclear science experts we worked with gave us relatively low costs for our technological endpoints, of $1500 or $1000/kW; nuclear economists have commented that these costs may be unrealistic. The baseline assumption in MiniCAM is that LWR will have a cost of $2100/KW in 2020. Our results focus mainly on improved LWR, and should be interpreted as reducing their cost by more than 50% below what otherwise would occur. We do not explicitly model limits to the penetration of nuclear due to political-economy reasons.

Finally, there is concern about the widespread implementation of CCS. The DOE Carbon Sequestration and Technology Roadmap [12] lists a number of challenges, including permanence; monitoring, mitigation and verification; permitting and liability; and public acceptance. Our

Technology	Project	NPV of Funding (000,000)	Probabiltiy of success	Alpha
Nuc	LWR	$173.18	21.25%	0.208
		$259.77	33.75%	
		$346.36	60.00%	
	HTR	$772.17	0.30%	0.221
			0.90%	0.096
		$1,544.35	17.00%	0.221
			9.20%	0.096
		$3,088.69	30.15%	0.221
			10.13%	0.096
	FR	$1,158.26	0.13%	0.224
			7.39%	0.103
		$4,633.04	0.50%	0.224
			32.00%	0.103
		$15,443.47	16.25%	0.224
			43.75%	0.103

Table 3: Summary of Assessment Results for Nuclear.

elicitations did not consider these issues explicitly. An NAS study [14], however, did considered public opposition based on the risk of sequestration; regulatory issues; and physical siting requirements. They report that the "average panel probability that the large-scale sequestration would be allowed is .66 without DOE's research support and increases to .77 with DOE's support." We use a baseline value of 70% as the likelihood that CCS will be allowed.

2.2 Parameterization of the MAC

We then parameterized the impact on the MAC to produce a probability distribution over MACs (in terms of our parameter α) for different levels of funding of different projects. We used the data generated by MiniCAM to estimate a smooth relationship between technical change and the impacts on the MAC. We observed that the effect on the MAC is a combination of a downward pivot and a downward shift. See Figure 2 for an example. We wanted to parameterize the shift by just one parameter, α. Thus, we let

$$\widetilde{MAC}\,(\mu;\alpha) = (1-\alpha)\left[MAC\,(\mu) - (A\alpha + B)\,MAC(0.5)\right] \tag{1}$$

where the tilda represents the MAC after technical change parameterized by α and $MAC\,(\cdot)$ is the original MAC, before technical change. The first term on the right hand side pivots the MAC down. The second term in the square brackets shifts the MAC downward by a fixed amount. The constants A and B are constant across each technology (i.e. for solar with no storage). In order to make the parameterization portable to multiple models, we anchored the shift to the marginal cost of 50% abatement. We estimated the values for α, A, and B using a least squares

Technology	Project	NPV of Funding (000,000)	Probabiltiy of success	Alpha
Battery	Phev LI-ion	$231.65	15.32%	0.1296
			12.43%	0.0981
		$540.52	32.00%	0.1296
			14.10%	0.0981
	Phev LI-metal	$77.22	3.15%	0.1804
			4.94%	0.1182
		$308.87	8.91%	0.1804
			9.94%	0.1182

Table 4: Summary of Assessment Results for Batteries.

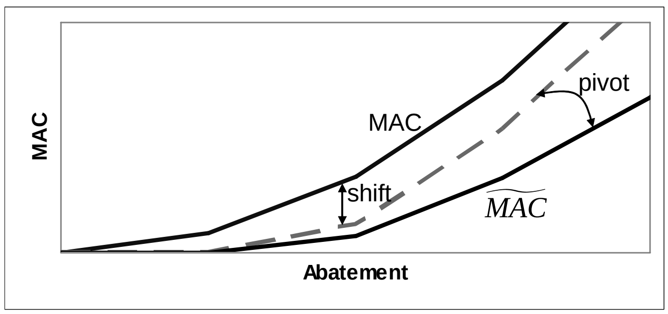

Figure 2: A stylized example of a shift and a pivot to the MAC.

method. The values for the α's are given in Tables 1 - 4; the values for the $A's$ and $B's$ for solar and nuclear are given in Table 5; The CCS technology did not have a significant shift.

2.3 Results: Expected MACs

In this section we compare the *Expected* MACs for investments in different technologies. We use the average of the probabilities provided by the experts, as reported in Tables 1 - 4. First, we assume that technologies will be funded in order of the expected α per funding dollar. For example, the expected α per funding dollar for a low investment in inorganic solar cells is $\frac{26.7\% * .0477}{38.61} = 0.0003$. This is the highest value for solar, so we assume that this project will be funded first. We then calculate the expected alpha for each possible funding level for that technology. For example, one potential solar portfolio includes a high investment in inorganics

	A	B
Solar	0.24	0.01
Nuclear	0.41	-.02

Table 5: Shift Constants

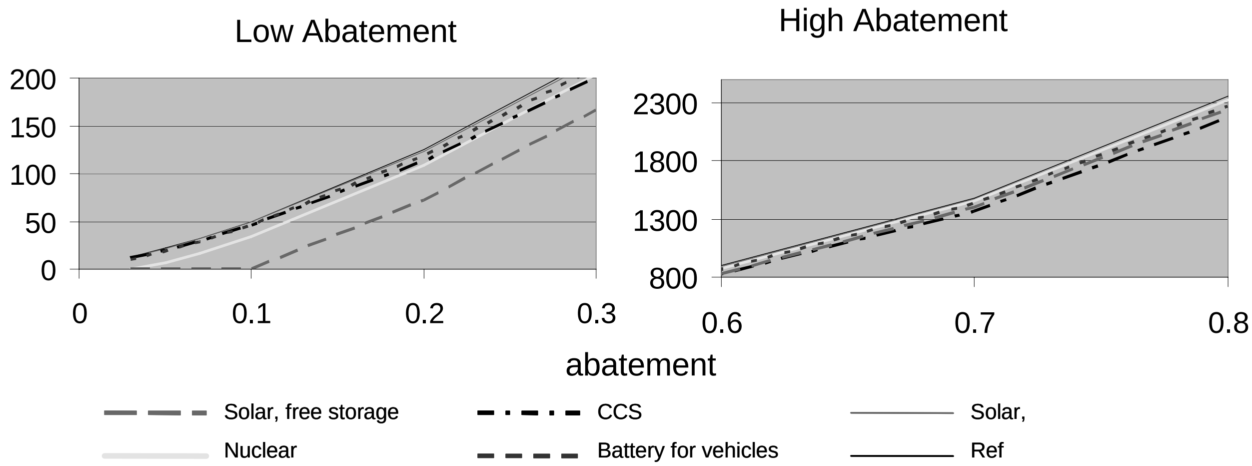

Figure 3: Marginal Abatement Cost Curves

plus a low investment in organics, for a total NPV of \$77.22 + \$115.83 = \$193.04. Finally, for all technologies except nuclear, we simply interpolate between funding levels to estimate the expected alpha for intermediate levels. For nuclear, we interpolate except for between \$0 and \$173. For this low amount we assume the relationship is quadratic, to account for the large returns to scales seen in the nuclear elicitations.

Figure 3 shows the expected MACs for a very low investment in each technology, with an NPV of \$38 Million. The left panel show the impacts on low abatement levels and the right panel for high abatement levels. We have included two different assumptions regarding solar.

The left panel in Figure 3 shows that, even at a very low investment level, solar has a large potential to reduce marginal costs, *if* the grid integration problem is solved. (Regular solar is indistinguishable from the reference MAC). After solar, the technology with the largest impact at low abatement levels is nuclear, even assuming very large returns to scale. Note, however, that CCS starts to have a large impact even at 30% abatement, and by 80% abatement, is more important even than solar with no grid integration problems.

Figure 4 shows the expected MACs for a much higher investment, with a NPV of \$2.2 billion. At this investment level, nuclear power has a very large impact on the MAC at low abatement, nearly as good as solar with no grid integration problems. Note that the high investment has changed the expected MAC for nuclear significantly, but made an almost imperceptible difference for solar. This is because in our elicitations, the solar projects had fairly low funding amounts, and one project in particular had a very high expected return. Thus, at \$38 million, almost all of the value in the solar portfolio has been achieved. On the other hand, Nuclear requires very large investments and has increasing returns to scale. In the right panel, we see that again, CCS has the greatest impact on the MAC. This implies that CCS provides a hedge against high climate damages and the need for high levels of abatement. Notice also, that batteries for vehicles have the same expected impact on the MAC as solar with no integration problems. Batteries also have some impact at lower emissions and so provide a stable alternative to solar and nuclear, which both have technological problems exogenous to our model.

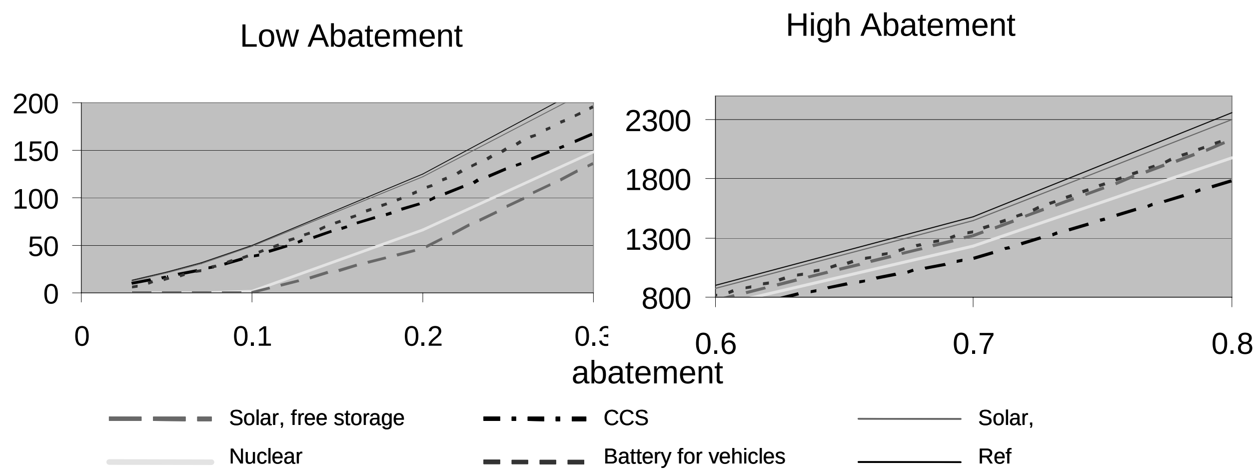

Figure 4: Marginal Abatement Cost Curves after a high investment in R&D

3 The Portfolio Model

The traditional Decision Analysis (DA) R&D model is represented as an influence diagram in the upper panel of Figure 5. In this model, a firm decides which portfolio of projects to invest in, which in turn impacts the eventual portfolio of technologies that are successful. The market value of each successful portfolio can be estimated, but is also uncertain. The profits are based on the market value of the successful portfolio. The objective is to choose the investment portfolio to maximize expected profits. Climate Change, however, is better represented as a dynamic decision problem, represented in the lower panel of Figure 5. In this model, the portfolio of successful technologies results in an abatement cost *curve;* similarly, damages are represented by a damage *curve* that depends on the stock of greenhouse gases in the atmosphere, which in turn depends on abatement. The future decision about how much to abate will be made based on knowledge about the set of technologies available and about climate damages.

The overall goal of the model is to minimize the sum of expected abatement costs and expected damages for a given R&D budget. The first stage decision is *which set of R&D projects to fund*. For this paper we will focus on three categories – PV, nuclear fusion, and CCS. Within each category we consider 3-4 projects based on specific sub-technologies (such as Purely Organic Solar Cells, Light Water Reactors, or Post-combustion separation), and 2-3 funding levels for each sub-technology. Each potential funded portfolio leads to a probability distribution over *successful* portfolios (based on our expert elicitations). Each successful portfolio will determine a Marginal Abatement Cost Curve, based on our parameterizations as described above. See Table 1 for details.

Climate change damages are also uncertain. We calibrate a baseline damage function, as a function of abatement, to the DICE-2007 model. We develop three-point probability distributions over the damages using estimates from Nordhaus [15]. Part of our analysis is to perform sensitivity analysis over these probability distributions to understand the role of increasing risk.

The second-stage decision is *how much to abate*, for a given damage and abatement cost curve. In the absence of a corner point, abatement will be chosen so that the marginal cost of

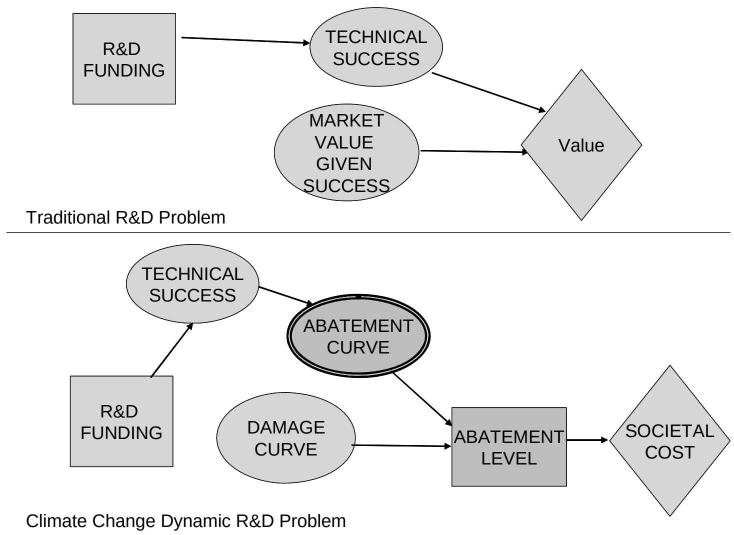

Figure 5: Influence Diagrams of R&D Decision Problems

abatement, after technical change, is equal to the marginal damages. We will consider corner points where the marginal cost of abatement is less than marginal damages and full abatement is optimal.

Specifically, we let the indices i and j represent the technology category (solar, CCS, nuclear) and the specific project within the category. The index $k = l, h$ represents the investment level. The key integer decision variables are X_{ijk} , which equal 0 if there is no investment in project ij at funding level k, and 1 otherwise. The second stage, continuous decision variable is abatement $\mu \in [0...1]$, the fraction of emissions reduced below a Business-as-Usual level. This variable is conditioned on the state of climate damages, represented by a random multiplier Z; and by the state of the technology, represented by a random vector $\mathbf{Y}$. The objective is to minimize the sum of abatement costs and damage costs, as follows:

$$\min_{X,\mu(\mathbf{Y},Z)} E\left[c\left(\mu; \overrightarrow{\alpha}\left(\mathbf{Y}\right)\right) + ZD\left(\mu\right)\right] \tag{2}$$

Note that the investment in technology is made without information on technical success or climate damages; abatement, however, is chosen conditional on technical success and damages – it is a second stage decision. We are constrained by the R&D budget B, and by the fact that we can only invest in a project at one level:

$$\sum_{i,j,k} F_{i,j,k} X_{i,j,k} \leq B \tag{3}$$

$$\sum_{k} X_{i,j,k} \leq 1 \ \forall i, j \tag{4}$$

The random matrix $\mathbf{Y}$ has entry $y_{ij} = 1$ if project ij is successful, and 0 otherwise. We assume that the probability of technical success in any technology is independent of other technologies (and of the damages of climate change). Thus, the probability of any given $\mathbf{Y}$ is simply the product of the probability of the individual parts of that scenario. According to our elicitation, the probabilities of success for individual projects depend on whether that project has been invested in or not, as seen in Table 1 above. In order to use stochastic programming, however, we will model this slightly differently. We will calculate the probability of each scenario exogenously, using the probability of success if funded. We then multiply each α_{ijk} by X_{ijk} to assure that the probabilities match up with the outcomes.

Specifically, the vector $\overrightarrow{\alpha}$ has entries α_i $i = S, C, N$. Within a technology category we assume that only the best technology project will diffuse in the economy, so

$$\alpha_i (X, Y) = \max_{j,k} [X_{ijk} \alpha_{ijk} y_{ijk}] \tag{5}$$

where α_{ijk} is a parameter taken from Table 1 above. Between the technology categories, we assume that the pivots are multiplicative, but that the shifts are substitutes. Thus, the shift in the MAC, h is defined:

$$h (\overrightarrow{\alpha} (\mathbf{Y})) = \begin{Bmatrix} 0 & \text{if } \alpha_i = 0 \\ \max_i [A_i \alpha_i (\mathbf{Y}) + B_i] & \text{otherwise} \end{Bmatrix} \tag{6}$$

and the cost is:

$$c (\mu; \overrightarrow{\alpha} (\mathbf{Y})) = \prod_i (1 - \alpha_i) [c (\mu) - h (\overrightarrow{\alpha} (\mathbf{Y})) c (0.5) \mu] \tag{7}$$

where $c (\mu)$ is the cost before technical change. Notice that the shift is multiplied by μ; this is because the parameterization above was done on the MAC and now we are working with the cost. We have based our baseline cost on the DICE 2007 model:

$$c (\mu) = b_0 \mu^{b_1} \tag{8}$$

The damage function is assumed to be quadratic:

$$M_0 (S - M_1 \mu)^2 \tag{9}$$

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 Business As Usual (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 $M_1 = 0.597$. The value of $b_1 = 2.8$, the value in DICE. We set b_0 so that the optimal abatement is 0.46. This leads to a value of $b_0 = 10.4$.

We consider three cases for uncertainty over climate damages, represented in table 6. High damages, where $Z = 14.6$, are equivalent to a 20% loss in GDP given a 2.5C increase in mean temperature. Each risk scenario has a mean of 1. The High Risk case has the highest possible probability for the high damages without allowing negative damages (i.e. benefits). The medium risk case is a Mean-Preserving Spreads (MPS) of the no risk case (See Rothschilds and Stiglitz for a definition and discussion of MPS [16]). The High risk case is an MPS of both the no-risk and medium risk case.

Zh :	1(no risk)	3(medium risk)	14.6(high risk)
$P[Z=0]$	0	2/3	.931
$P[Z=Zh]$	1	1/3	.068
Optimal abatement if $Z=Zh$	46%	80%	100%

Table 6: Damage Uncertainty

3.1 Stochastic Programming Formulation

The model described above is a stochastic optimization problem with two decision stages. In the first stage, the portfolio selection decisions are made based on the distribution of damage uncertainty, i.e. Z and the distributions of project performances, which are defined in terms of the random vector α. The second stage decisions involve the abatement level μ, which is assumed to be determined after the observation of technical success levels and climate damages. Hence, it is possible to consider the problem as a two-stages stochastic programming model. More specifically, the problem can be expressed as follows:

$$\mathbf{SP}: \text{Minimize } \mathbf{E}_\omega\{Q(\mathbf{x},\omega)\} \tag{10a}$$
$$\text{subject to } \sum_i\sum_j\sum_k f_{ijk}x_{ijk} \leq B \tag{10b}$$
$$\sum_k x_{ijk} \leq 1, \quad \forall i,j \tag{10c}$$
$$\mathbf{x} \in \{0,1\}. \tag{10d}$$

where

$$Q(\mathbf{x},\omega) \equiv \text{Minimize } \prod_i (1-\alpha_i)(b_0\mu^{b_1} - c_{0.5}h\mu) + Z^\omega M_0(S-M_1\mu)^2 \tag{11a}$$
$$\text{subject to } \alpha_i = \max_{j,k}\{\alpha^\omega_{ijk}x_{ijk}\} \quad \forall i \tag{11b}$$
$$h = \{0, \text{if } \alpha_i = 0 \quad \forall i; \quad \max_i\{A_i\alpha_i + B_i\}, \text{ otherwise}\} \tag{11c}$$
$$0 \leq \mu, \alpha, h \leq 1. \tag{11d}$$

Although the second stage problem $Q(\mathbf{x},\omega)$ has few variables, the dimension of the random vector ω results in a large set of possible scenarios and thus, a relatively large scale problem. While such problems can typically be handled through decomposition based methods, the highly non-convex structure of the second stage cost function in SP is a complicating factor. Hence, classical approaches are not applicable, and a convex approximation or reformulation approach is necessary. To this end, we reformulate the problem by defining some new variables and revising the definition of some parameters as follows.

Let ϕ_i be a nonnegative variable such that it is equal to the value of $-\ln(1-\max_{j,k}\{\alpha_{ijk}\})x_{ijk}$. Further, we define a new nonnegative variable $w = h+\mu$, and binary indicator variables δ_{ijk},

β_i, ψ_i, γ to represent the modified problem structure, where β_i corresponds to the case with no investment in technology i, and γ indicates whether $\alpha_i = 0$ for all i. In addition, we let the random parameter $\bar{\alpha}^{\omega}_{ijk}$ represent $\ln(1 - \alpha^{\omega}_{ijk})$. In the Appendix, we present the deterministic reformulation RSP that is equivalent to SP.

RSP is an integer linear program with a nonlinear objective function and linear constraints, and it can be solved using any nonlinear integer programming solver or through a branch and bound implementation, provided that the number of considered scenarios is not large. For large number of scenarios, which is the case for the climate change energy technology portfolio model, sampling based procedures based on solving randomly sampled small scale instances can be used to determine good or near-optimal solutions. This is especially suitable for RSP, as it is relatively easy to evaluate the second stage objective function for given values of the $\mathbf{x}$ vector, which we obtain by solving smaller sample problems. Information from the sample problem solutions are then used to infer about the optimal solution for a given problem configuration. A similar sampling based procedure is also implemented on a more generalized multiple stage R&D portfolio optimization model in [17].

4 Results

We studied several configurations of the problem parameters, and reached some conclusions about the composition and behavior of the optimal portfolio with respect to these parameters. More specifically, we considered different R&D budget levels and observed the impact of damage uncertainty on the solutions over varying budget levels. These conclusions are summarized below.

The first result is that the optimal portfolio did not change under different levels of damage risk. Figure 6 shows the composition of the optimal portfolio. We know from previous research that damage risk can impact the optimal investment in technology [2][7]. In this case, the data has lead to projects that are fairly differentiated – some projects (such as chemical looping and LWR) have high probabilities and high payoffs, and therefore get funded regardless of risk. Additionally, the problem is somewhat sparse, and so there are not a large number of possible portfolios at different budget levels. In future work we will perform extensive sensitivity analysis to see if this results holds under different parameters. If it does hold, it is good news that the optimal R&D investment is robust to uncertainty in climate damages.

Second, we see the effects of this being a "knapsack" problem. We see that solar, in particular, goes in and out of the portfolio at different budget levels. The solar projects are less efficient than some of the other projects, but also less costly. Thus, for example, we see a significant investment in solar at the $200 million budget level; but this investment is reduced in favor of nuclear when the budget increases. We do see strong diversification – all three technology categories come in to the optimal portfolio even at a fairly low budget. At higher budget levels, not shown here, nuclear dominates the portfolio.

Figure 7 shows how the expected total social cost (damages plus abatement) is impacted by R&D investment, in the no-risk and high-risk cases. We have normalized the high-risk case to be on the same scale as the no-risk case.[1] Notice that R&D is very efficient. The lowest budget we considered, has an NPV of $200 million and reduces the total social cost by about $500 billion

[1]Total Expected Cost is lower under risk, since abatement is increased when damages are high. See [1] for a discussion of this.

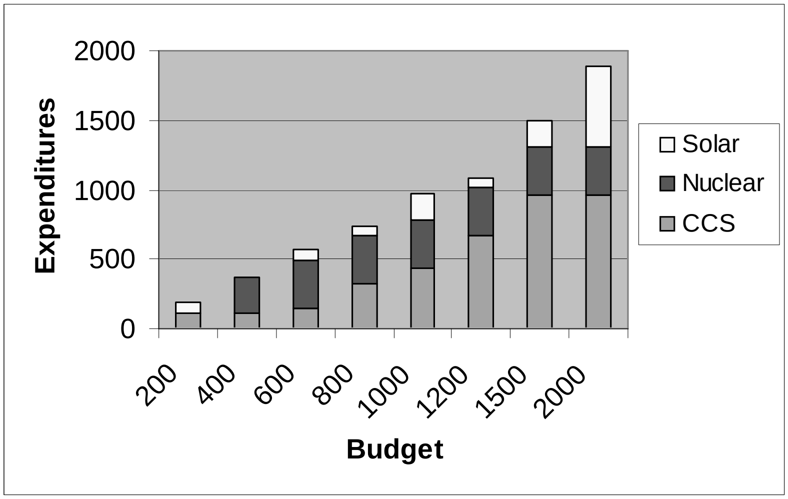

Figure 6: Optimal Portfolios

in the no-risk case. An additional \$400 million investment leads to an additional \$300 billion reduction in costs. Even in the high risk case, the additional \$400 million reduces costs by \$58 billion, a benefit-to-cost ratio of 145 to 1.

Figure 7 shows that R&D has less value in the high risk case. This is because in that scenario we either have no damages and no abatement, or we have very high damages that lead to full abatement regardless of the technology. Thus, the technology reduces the cost of abatement, but has no environmental-side effect. In the no risk case, the presence of technology not only lowers the costs of abatement for a given level of abatement, but also leads to optimally lower abatement. That is, the technology has an environmental-side benefit as well as a cost-side benefit. Thus, it has overall more value. Note that this phenomenon will occur if we have a fixed target for abatement (or equivalently a fixed concentration target). In these cases, technology will lower the costs of hitting the fixed target, but will not have an impact on the target. Thus, the focus on a concentration target, rather than an optimal level of abatement, reduces the value of R&D to society.

We have highlighted a couple of points in Figure 7 that show that the value of particular portfolios vary with the damage risk level. The first portfolio we have highlighted has a budget of \$800 million and consists of high investments in chemical looping, inorganic solar, and nuclear, plus a medium investment in post-combustion and a low investment in pre-combustion. This point is a kind of "elbow" point in the high risk case, after which investments show a lower return. The second point we have highlighted is the "elbow" point in the no-risk case. It has a budget of \$1.2 billion and includes the same projects, but with a high investment in pre-combustion. What is interesting is that this particular portfolio has almost no marginal value in the high risk case – the total cost for this portfolio is almost exactly the same as for the \$800 million portfolio. Yet, there is a large difference between the two portfolios in the no risk case. The reason for this again comes back to the optimal level of abatement. CCS technologies, because they pivot the MAC, have a large effect on the optimal level of abatement, but a smaller effect on total cost. Thus, in the no-risk case, the additional funding in pre-combustion leads to a benefit through

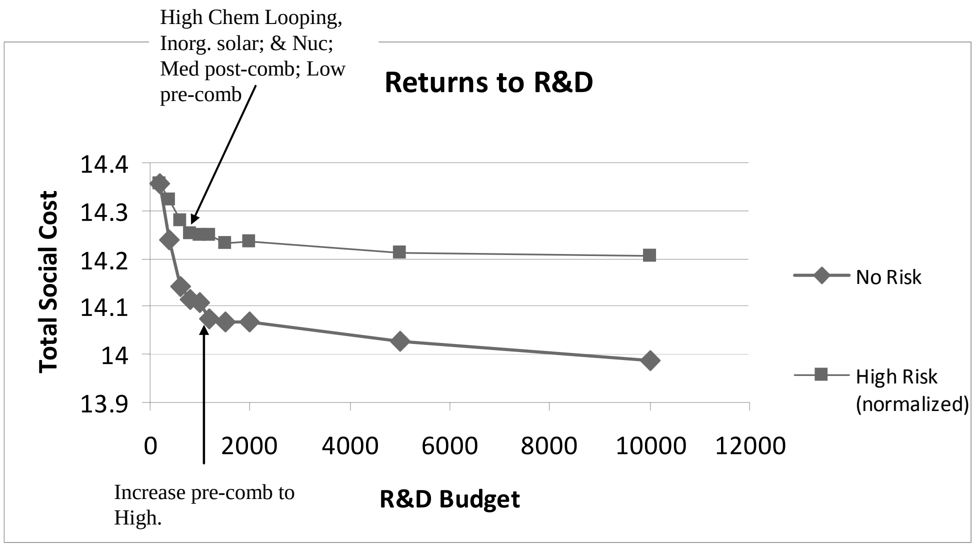

Figure 7: Expected Total Social Cost

increased abatement. In the high-risk case it has little effect because it does not reduce the cost of abatement significantly.

Figure 8 shows the marginal value of each portfolio – the reduction in social cost we get if we move from one budget level to the next. We have circled two cases in which the marginal value of the portfolio is quite different in the no-risk and high-risk case. In the first case, at a budget level of $400 million, the marginal project is a moderate investment in nuclear LWR. This apparently has a very high marginal value in the no-risk case, but much less so in the high risk case. In fact, this portfolio is not efficient in the high-risk case – we would prefer to invest $600 million to get a higher marginal value. In the next case, the marginal project is increasing investment in pre-combustion from moderate to high. This has a reasonable marginal value in the no-risk case, but essentially no value in the high risk case. These results are driven by two factors. First, as we have been emphasizing, some of these projects will have a large impact on the optimal level of abatement in the no-risk case; but may have a small effect on the total cost of abatement. This is particularly true of CCS. Second, at high risk it becomes more important to have some positive α level than the highest one, as it is likely that in most cases the α level will be insignificant due to the Z parameter being zero. Both the moderately funded LWR and the pre-combustion projects have low probabilities of success. Thus, in this very high-risk case, low risk projects have more value.

Figure 9 again shows the expected total social cost, but we have included the medium risk case here. We see that the value of R&D is non-monotonic in risk, increasing significantly in the medium risk case. This is because, when Z=3, we get both cost-side and environmental-side benefits. Our data shows that the expected damages decrease and the cost of abatement decreases. Figure 10 illustrates this point. The left-hand chart shows the impact of technical change when Z=1. Optimal abatement increases from 46% to about 65%, thus there is environmental-side benefit. The total cost of abatement is the area under the curve. It can be seen that the total abatement cost in this case is slightly higher after technical change. The right-hand panel shows

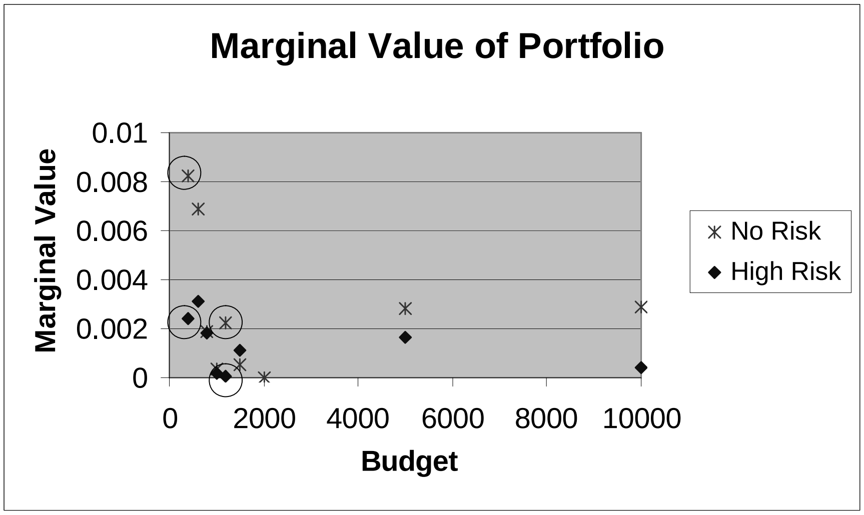

Figure 8: Marginal Value of Portfolios

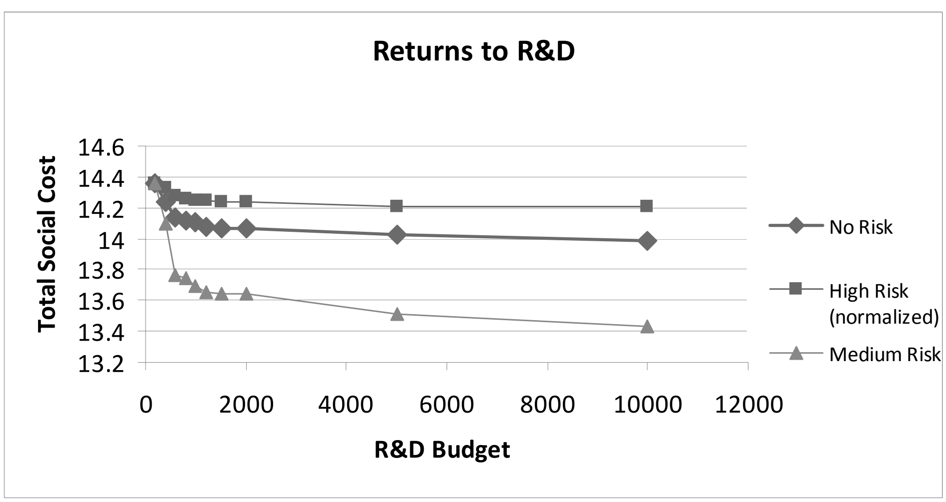

Figure 9: Expected Total Social Cost at three risk levels

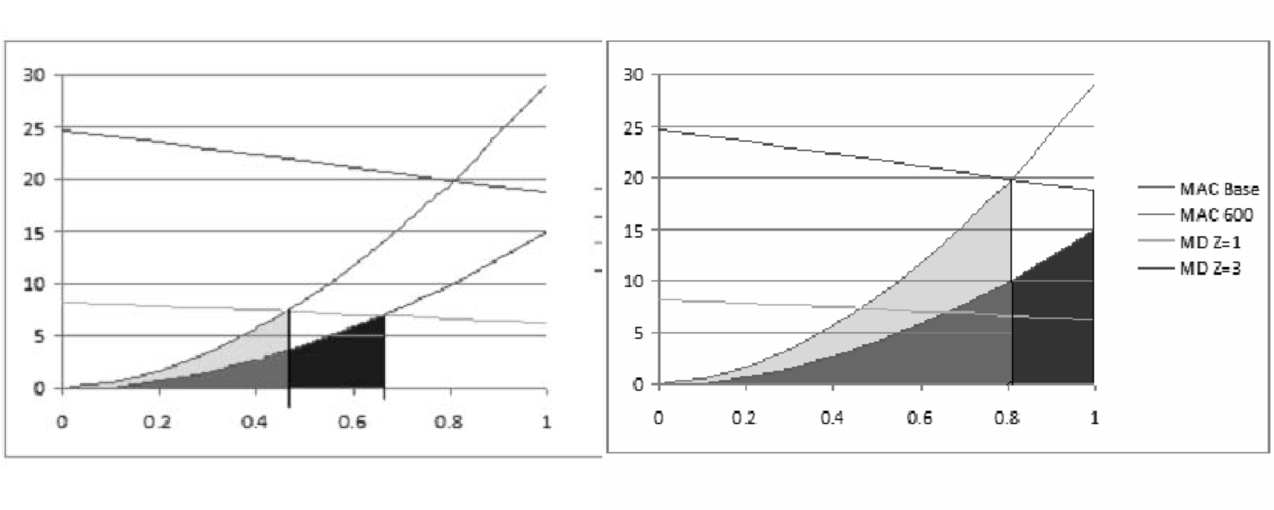

Figure 10: Optimal Abatement and Total Cost of Abatement

the impact of technical change when Z=3. Optimal abatement increases from 80% to 100%, thus again there is environmental side benefit. Overall abatement cost also decreases in this case, as can be seen by comparing the lightest wedge (cost saved after technical change) with the darkest trapezoid (costs added after technical change because of higher abatement). Thus, overall, technical change has more value in the second case than the first.

5 Conclusions

In this paper we have presented results on the expected Marginal Abatement Cost Curves given investments in different technologies; and presented preliminary results from a portfolio model. Examining the expected MACs provide some insights as to what the optimal portfolio will contain. Nuclear and Solar (with no grid integration problems) appear most promising for low abatement levels, levels consistent with a concentration target of about 600ppm. CCS is the most promising technology at high abatement levels, consistent with concentration targets of 450ppm or less. Batteries for vehicles provide a steady benefit at all levels, and have fewer concerns than the other three technologies.

Our R&D portfolio model has provided a number of insights. Given our data, the optimal portfolio is robust to climate damage risk. While this is a promising results, we feel it is to early to conclude that this will hold. We will do future work to study if this result holds for a wide variety of parameters. Second, we do see a high level of diversification, with even less promising technologies included in the portfolio, although this is partly a result of it being a knapsack problem. Third, we see that R&D and technical change has less value when emissions levels are fixed, such as is the case for very high risk, or for fixed emissions targets. CCS in particular seems to have the most value when emissions are flexible. Fourth, very high risk – when there is a chance of truly catastrophic damages that will induce full abatement – appears to favor technologies that reduce total cost (versus technologies that reduce the MAC) and low risk technologies that have a higher probability of success. Finally, the value of technology is non-monotonic in risk, with the maximum value being in cases where technology leads to higher abatement and significant reductions in abatement costs.

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6 Appendix

The following formulation is the deterministic equivalent of SP:

$$\textbf{RSP}\text{:Minimize} \quad \sum_{\omega} p^{\omega}(e^{-\sum_i \phi_{i\omega}+\ln(b_0\mu_{\omega}^{b_1}-\frac{1}{2}c(0.5)(w_{\omega}^2-h_{\omega}^2-\mu_{\omega}^2))}) + Z^{\omega}M_0(S-M_1\mu_{\omega})^2 \tag{12a}$$

$$\text{subject to} \quad \sum_i \sum_j \sum_k f_{ijk}x_{ijk} \leq B \tag{12b}$$

$$\sum_k x_{ijk} \leq 1, \quad \forall i,j \tag{12c}$$

$$\phi_{i\omega} + \bar{\alpha}_{ijk}^{\omega}x_{ijk} + M\delta_{ijk\omega} \leq M \quad \forall i,j,k,\omega \tag{12d}$$

$$\phi_{i\omega} + \bar{\alpha}_{ijk}^{\omega}x_{ijk} + m\delta_{ijk\omega} \geq m \quad \forall i,j,k,\omega \tag{12e}$$

$$\sum_j \sum_k \delta_{ijk\omega} + \beta_i = 1 \quad \forall i,\omega \tag{12f}$$

$$\phi_{i\omega} + \beta_i \leq 1 \quad \forall i,\omega \tag{12g}$$

$$h_{\omega} - A_i(\sum_j \sum_k \delta_{ijk\omega}\alpha_{ijk}^{\omega}) - B_i + M\psi_{i\omega} \leq M \quad \forall i,\omega \tag{12h}$$

$$h_{\omega} - A_i(\sum_j \sum_k \delta_{ijk\omega}\alpha_{ijk}^{\omega}) - B_i + m\psi_{i\omega} \geq m \quad \forall i,\omega \tag{12i}$$

$$\gamma_{\omega} + \sum_i \psi_{i\omega} = 1 \quad \forall \omega \tag{12j}$$

$$h_{\omega} + M\gamma_{\omega} \leq M \quad \forall \omega \tag{12k}$$

$$\gamma_{\omega} + (\sum_i \sum_j \sum_k \delta_{ijk\omega}\alpha_{ijk}^{\omega}) \geq \min_{ijk|\alpha_{ijk}^{\omega}\neq 0}\{\alpha_{ijk}^{\omega}\} \quad \forall \omega \tag{12l}$$

$$w_{\omega} = h_{\omega} + \mu_{\omega} \quad \forall \omega \tag{12m}$$

$$\delta_{ijk\omega} - x_{ijk} \leq 0 \quad \forall i,j,k,\omega \tag{12n}$$

$$\mathbf{x},\delta,\phi,\gamma,\beta \in \{0,1\} \tag{12o}$$

$$0 \leq \mu, h \leq 1; w \geq 0. \tag{12p}$$

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