Climate Change and Optimal Energy Technology R&D Policy

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Public policy response to global climate change presents a classic problem of decision making under uncertainty. Theoretical work has shown that explicitly accounting for uncertainty and learning in climate change can have a large impact on optimal policy, especially technology policy. However, theory also shows that the specific impacts of uncertainty are ambiguous. In this paper, we provide a framework that combines economics and decision analysis to implement probabilistic data on energy technology research and development (R&D) policy in response to global climate change. We find that, given a budget constraint, the composition of the optimal R&D portfolio is highly diversified and robust to risk in climate damages. The overall optimal investment into technical change, however, does depend (in a non-monotonic way) on the risk in climate damages. Finally, we show that in order to properly value R&D, abatement must be included as a recourse decision.

Key words: R&D portfolio, energy technology, climate change, stochastic programming, public policy

1. Introduction

Emissions of greenhouse gases have risen more than 30% over the past two decades, and a further 36% increase is estimated between 2006 and 2030 (DOE 2006). While scientists largely agree these emissions are changing the climate, there is a great deal of uncertainty about the degree to which global warming will cause economic, social, and environmental damages in the future. Public policy responses to climate change are being developed under this uncertainty.

Possible near term policy responses to global climate change include both restrictions on emissions (through emissions limits or taxes) and investment in environmentally friendly technologies. Overall, addressing climate change in a cost effective way will almost certainly require the development of better energy technologies (Hoffert et al. 1998). As an example of recent policy actions aimed in this direction, the U.S. Government has allocated \$16.8 billion to U.S. Department of Energy (DOE) as part of the 2009 American Recovery and Reinvestment Act to support research and development (R&D) in energy technologies.

It is clear that the optimal energy technology 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 (Baker and Shittu 2008). The process of R&D is inherently uncertain – no one can 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, there is also deep uncertainty on the benefits side due to the 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

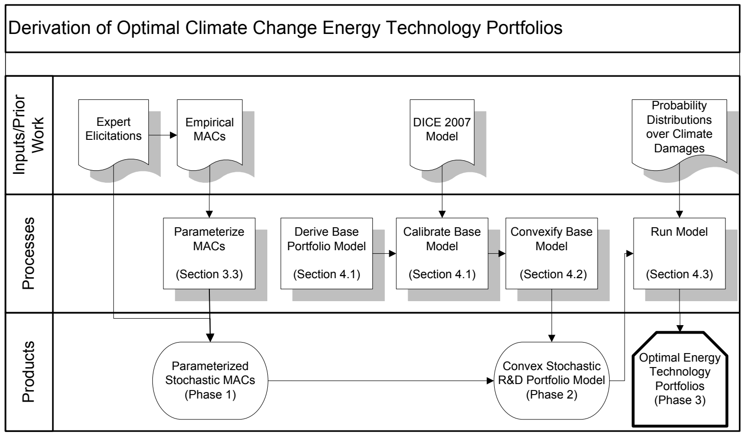

Figure 1 Components of the energy technology R&D portfolio analysis and their relationships.

having any particular technology available.

A number of researchers have investigated the question of how the presence of uncertainty and learning impacts near term optimal climate policy (see Baker and Shittu (2008) and Baker (2009) for reviews). The answer to this question seems to be "it depends": optimal near term decision variables, such as R&D investment, may increase or decrease with increases in risk or increases in learning. Thus, the next step is to try to characterize the uncertainty that we are facing and implement this into policy models.

In this paper we combine economics and decision analysis to get insights about the optimal energy technology R&D portfolio under uncertainty, and how it changes with increasing risk in climate damages. More specifically, we try to answer the following policy question based on actual empirical data gathered through expert elicitations: How should government funding in climate change energy technology R&D be allocated to different technologies and projects? In order to do this, we develop a modeling framework that is tailored to this particular problem and the data available. Thus, the model and application are integrated.

Using data collected from expert elicitations on how government funding impacts the probability of success in key climate change energy technologies, our approach to answering the above research question involves three phases. In the first phase, we combine the data with an economic model to derive stochastic marginal abatement cost curves that describe the cost of reducing emissions by one additional ton. In the second phase, we develop a stochastic programming based energy technology R&D portfolio model that uses this probabilistic information. In the third phase of the research, we analyze the structure of the optimal climate change energy technology R&D portfolio, and identify the resulting policy implications. The components of our analysis and their relationships are displayed in Figure 1. In this figure, the acronym MAC corresponds to the marginal abatement cost curves, which we discuss further in Section 3.1, and DICE 2007 is an economic model used to calibrate our model.

In addition to the derivation of a convex energy technology R&D portfolio model and its policy implications, our approach also presents a framework for turning empirical data into a working stochastic model. This is significant because most studies, as we note in the literature review below, either use purely theoretical probability distributions that are conveniently analyzed through a developed model, or they use simplified approaches to go with elicitations of specific variables.

These procedures, however, typically result in some loss of accuracy and validity in the analysis.

Our analysis has important policy implications. We show that, given our data, the composition of the optimal portfolio is robust to climate damage uncertainty. The value of technical change, however, does depend explicitly on uncertainty. We also show that the overall optimal investment in R&D changes in the riskiness of climate damages; but it changes in a non-monotonic way. Thus, there is real value in characterizing the uncertainty over climate damages. In addition, we investigate policies that fix abatement regardless of technological outcomes and draw conclusions about their efficiency.

The remainder of this paper is structured as follows. We continue in Section 2 with a review of the literature on climate change energy technology R&D policy and expert elicitations. In Section 3 we describe some theoretical background for the problem. In Section 4 we combine expert elicitations with economic analysis and derive stochastic marginal abatement cost curves. Based on this information, we then develop a climate change energy technology R&D portfolio model in Section 5, and describe a stochastic programming formulation and solution procedure. In Section 6, we present our analysis and policy implications based on the results from the model. Finally, in Section 7 we summarize our conclusions.

2. Relevant Literature

2.1. Climate Change and Energy Technology R&D

While there exists some significant research in technology portfolio management, a direct application of the proposed methods to the climate change R&D problem is not possible. This is due to the major differences that exist between the cost/return functions of traditional R&D investments and the energy technology investments under climate change uncertainty. More specifically, returns from climate change energy technology R&D are not calculated directly, but rather through the impact of successful technologies on an emission abatement function, which is further complicated by the uncertainty in damages due to climate change and interactions between different technologies.

In terms of energy technology R&D, there is a growing body of literature on endogenous technical advance in the context of climate change. This literature covers technical change that is in some way induced by policy, generally by the indirect effect on market actors, but also as a control variable. For surveys of the literature, the reader can refer to Clarke and Weyant (2002), Grubb et al. (2002), Loschel (2004), Sue-Wing (2006), Clarke et al. (2006a, 2006b) and Gillingham et al. (2007). While the papers covered in these surveys are largely deterministic, they indicate that technology development and deployment should be part and parcel of climate change policy evaluation.

There is some very recent literature investigating the optimal investment in energy technology R&D in the face of uncertainty. Some of these papers consider uncertainty in the climate damages (Farzin and Kort 2000, Baker et al. 2006, Baker and Shittu 2006, Baker 2009), while some other consider uncertainty in technological change (Bosetti and Drouet 2005, Bosetti and Gilotte 2007, Goeschl and Perino 2009), and at least one paper considers both (Baker and Adu-Bonnah 2008). However, all of these papers consider investment in one technology at a time, rather than a portfolio of technologies. While the conclusions of the papers vary, it appears that uncertainty in technological change has a quantitatively larger impact on optimal actions than does uncertainty in climate damages, and that the optimal investment in R&D is often much higher when uncertainty is explicitly included.

A few others have studied the impact of uncertainty on a *portfolio* of energy technologies. Gritsevskyi and Nakicenovic (2002) and Grubler and Gritsevskyi (2002) consider the question of how diversified the near term technology portfolio should be when the rate of technological learning is uncertain, and find that investment should be distributed across technologies that are in a cluster. Further, Grubler and Gritsevskyi (2002) indicate that optimal diversification increases with uncertainty in damages as long as increasing returns to scale are present. However, they consider technical change through the avenue of learning by doing, rather than through R&D.

Two studies that are closely related to our research are Blanford and Weyant (2007) and Blanford (2009). They consider the question of the optimal R&D portfolio when there is uncertainty in both technological change and climate damages, with a focus primarily on the drivers of diversification in the portfolio. They show that it is not enough to just consider the potential value of new technologies, but that the uncertain relationship between program funding and effectiveness is just as important. They provide a framework for considering spillovers between technologies, but don't operationalize it. One benefit to our approach is that we can explicitly examine the impact of increasing uncertainty on optimal investment. The key difference between the two approaches, however, is that we build our model on empirical estimates of the probability of success based on expert judgments, whereas they propose a theoretical probability model in which they assume decreasing returns to scale. This assumption allows them more freedom in two directions. First, they model a sequential decision problem in which R&D investments can be made in two periods, whereas we focus on a single near term decision only. They find, however, that the effect of possible future R&D decisions on near term decisions is small. Second, their decision variable, R&D expenditures, is continuous, where ours is modeled as an integer yes-or-no problem to be consistent with our elicited data and current decision framework.

2.2. Expert Elicitations

Past data on technological advance contains little information about future technological breakthroughs. In fact, a technological breakthrough, by its nature, is unique; and therefore we cannot use past data and relative frequencies to construct a probability distribution over success for future breakthroughs. Yet, current decisions depend on understanding the likelihood of such breakthroughs. For example, sound government technology R&D policy should consider the *likelihood of success* and the *impacts of success*, along with the total cost of a program, when making decisions (National Research Council 2007). When past data is unavailable or of little use, the alternative is to rely on subjective probability judgments (Apostolakis 1990). Expert elicitations are a formal method for gathering these judgments.

Decision analytic methods including expert elicitations (Howard 1988) have been applied productively to R&D in numerous industries, such as the automotive, pharmaceutical, and electronics industries (Sharpe and Keelin 1998, Clemen and Kwit 2001), as well as issues relating to societal decisions (Howard et al. 1972, Peerenboom et al. 1989, Morgan and Keith 1995). Most relevantly, National Research Council (2007) recommends that the U.S. Department of Energy use panel-based probabilistic assessment of R&D programs in making funding decisions. Thus, our analysis is built on a base of expert elicitations.

3. Theoretical Background and Motivation

In this section we start by providing our motivation for focusing on Marginal Abatement Cost Curves (MAC), i.e., curves that reflect the cost of reducing emissions by an additional ton. We then provide a very simple example that illustrates the importance of explicitly including damage uncertainty when choosing an optimal portfolio.

3.1. The Marginal Abatement Cost Curve

The value of a particular R&D program for a given technology depends on successful delivery and implementation of the technology, but also 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. On the other hand, 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.

It is particularly important to understand how new technologies will impact the MAC. In Figure 2 we illustrate how the impact of technical change on optimal abatement varies with technology and with the severity of marginal damages. The solid upward sloping line represents the original MAC, denoted by MAC_0. The two dashed lines represent different types of technical change. The horizontal lines represent two levels of marginal damages (MD), i.e. high and low. 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, while 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. However, both the impact of technology and the marginal damages involve significant uncertainty. Moreover, the uncertainties in both climate damages and in technical change are dynamic, in that society expects to learn more about each as time goes on. Our use of a two-stage stochastic programming model is aimed at capturing this stochastic dynamic structure.

3.2. Damage Uncertainty and Its Impact

We model uncertainty over climate damages as *parametric uncertainty* rather than what is sometimes called *dynamic stochasticity*. That is, we assume that a single value exists that represents the relationship between the stock of emissions in the atmosphere and the damages experienced by humanity, but that this value is unknown at this time. The alternate assumption, of *stochasticity* would imply that the value of the parameter changes over time. An example of such a parameter would be the temperature in San Francisco at 5 p.m, which will vary each day. While it is possible that climate damages vary in this way, there is no evidence upon which to base such an assumption. Thus, consistent with most of the literature on climate change, we model parametric uncertainty. Furthermore, we assume that there is perfect learning of the unknown parameter before the second stage. Previous work by Baker (2006), however, allows us to extend the results of perfect learning to the case of partial- or no- learning. This is discussed in the results section below.

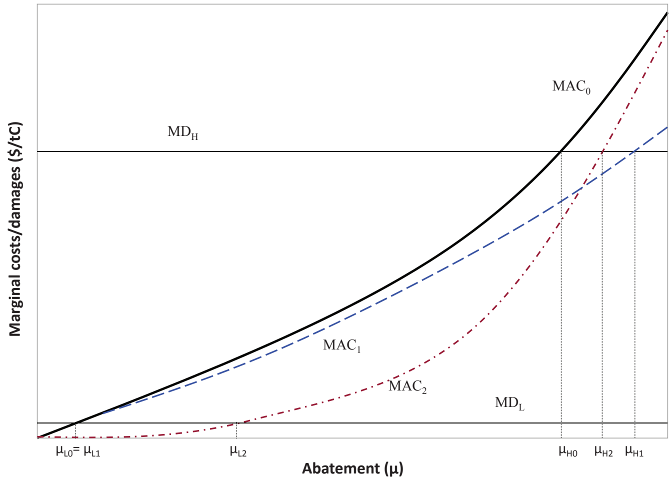

Figure 2 **Stylized representations of technical change impact on the MAC, and resulting optimal abatement levels.**

Explicitly modeling damage uncertainty is important. Previous work has shown that the optimal level of investment in a particular technology depends on the probability distribution over climate change damages (Baker et al. 2006, Baker and Adu-Bonnah 2008). Here we illustrate with a simple example that the *choice* of technology also depends on the probability distribution over damages.

For a given abatement level μ, let the baseline cost of abatement be $c(\mu) = \frac{\mu^2}{2}$ and the damages from climate change be $z(1-\mu)$, where z represents the level of damages. The baseline MAC is then $c'(\mu) = \mu$.

Consider two technologies with the same R&D cost, one that *pivots* the MAC by $\alpha = \frac{4}{9}$ to give a new MAC of $\tilde{c}'(\mu) = \frac{4}{9}\mu$; and another that *shifts* the MAC by $h = 0.15$ to give a new MAC of $\bar{c}'(\mu) = \mu - 0.15$. Given this simple formulation, optimal abatement under the pivot technology is $\mu_{\alpha z} = \frac{z}{\alpha} = \frac{9}{4}z$ and optimal abatement under the shift technology is $\mu_{hz} = z + h = z + 0.15$ (both limited to a maximum of 1). Let mean damages be $\bar{z} = 0.3$. At this damage level the total social cost (damages plus abatement) is the same under either of the technologies, i.e. they have equivalent value. Now consider a mean-preserving spread (MPS) where the random damage parameter Z is equal to $z_l = 0.1$ or $z_m = 0.5$ with equal probability. In this case, the pivot technology is strictly preferred to the shift technology as it has a lower expected total social cost. However, consider a different MPS, where $Z = z_l = 0.1$ with probability 27/29 and $Z = z_h = 3$ with probability 2/29. In this case the shift technology is strictly preferred to the pivot. In Figure 3, we illustrate this example.

The reason for the change in optimal choice is as follows. When damages are below the mean of $\bar{z} = 0.3$, the shift technology is better than the pivot, and above $\bar{z}$ the opposite is true[1]. Under low damages, $z_l = 0.1$, the optimal level of abatement is about the same under the two technologies, i.e. the MD low curve in Figure 3 crosses both MACs at about the same place. However, the cost of abatement is lower for the shift, i.e. the area under the shift curve is smaller than the area under

[1] That is, when $z < 0.3$, $c(\mu_{zh}; h) + D(\mu_{zh}; z) < c(\mu_{z\alpha}; \alpha) + D(\mu_{z\alpha}; z)$

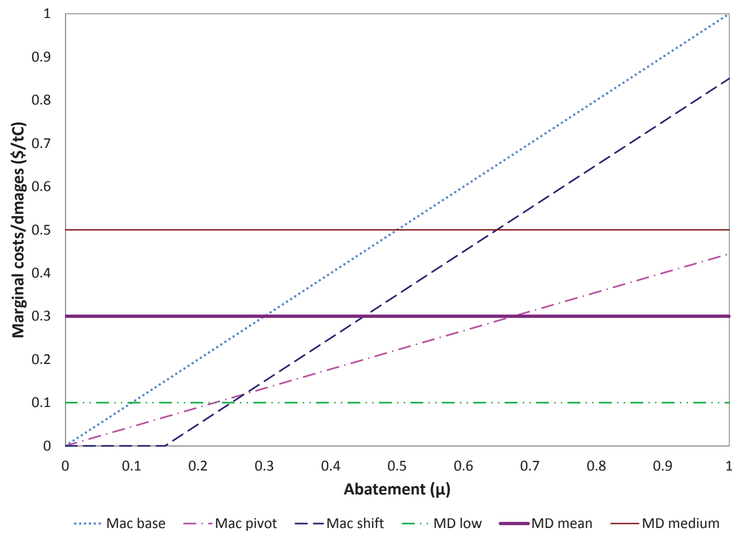

Figure 3 **Illustrative MACs and marginal damage curves.**

the pivot curve. Under the medium damage case, $z_m = 0.5$, optimal abatement under the pivot is equal to 1 (there is a corner point solution). The first MPS favors the pivot, because there is a small difference between the two technologies when damages are small, but a large difference when the damages are higher. On the other hand, the second MPS has a very small probability of very large damages (not shown in the figure). The pivot technology is much better in the high damage case, but the probability is so low that it favors the shift technology.

This analysis illustrates that in general (1) the optimal portfolio may depend on the risk in the climate damages, and (2) it does not change monotonically in risk. Therefore, it is crucial to do sensitivity analysis over the probability distribution of damages to determine if such behavior holds under currently available technology and climate change information.

4. Deriving Uncertain Marginal Abatement Cost Curves

4.1. The Technologies

In this paper, we focus on a subset of potential energy technology projects, which might include hydrogen, biomass, geothermal, hydro, wind, solar thermal, or energy conservation, along with solar photovoltaics (PV), carbon capture and storage (CCS), and nuclear. We used the following criteria in choosing which technologies to focus on. First, we concentrate on the electricity generation sector, since this sector produces the largest portion of greenhouse gasses, and is predicted to become even more important under climate policy regimes. This removes hydrogen, liquid fuels from biomass, and energy conservation from our list. Second, we wanted to focus on uncertainty, thus we consider technologies that have the possibility of breakthrough. This removed hydro, wind, electricity from biomass, and solar thermal from contention, as these technologies are most likely to profit from engineering advances related to scale and reliability, rather than breakthroughs related to scientific discovery. Finally, as mentioned in the introduction, we chose technologies that have a large resource base. Hydro, wind, and biomass are all limited by their resource base, and geothermal has a very uncertain resource base. Thus, we focus on solar PV, CCS, and nuclear in this paper. Baker et al. (2008), Baker et al. (2009a) and Baker et al. (2009b) describe expert elicitations on these three major energy technologies. Here we briefly describe the potential research directions that we evaluated.

Solar photovoltaic cells turn the energy in sunlight into electricity. We consider three research directions for this technology: Purely organic solar cells; a search for better inorganic semiconductors, which we label Inorganic; and Third Generation Concepts, including highly efficient technologies involving new cell architectures, quantum dots and multi-junction cells.

Carbon capture and storage refers to the process of capturing the CO_2 generated by fossil-fuel electricity plants before it is released into the atmosphere and storing it either underground in aquifers or in the deep ocean. We consider the three main categories of CCS corresponding to three points in the process: Pre-combustion carbon capture; a specific alternative combustion technology called chemical looping; and post-combustion removal.

For nuclear power, we consider improvements on the current Light Water Reactors (LWR); and also two more radical directions: High Temperature Reactors (HTR) and Fast Burner Reactors (FR). Both of these have the advantage of higher efficiencies and potentially lower waste.

The products of the expert elicitations, which are described in detail in Baker et al. (2008, 2009a, 2009b), include explicit definitions of endpoints for each technology, and probabilities of achieving those endpoints for given funding levels. We report the relevant results as an online supplement, where the pivoting and shifting impacts of the technologies on the MAC are summarized.

4.2. Computational MACs using MiniCAM

Our next step was to determine how the technologies would impact the MAC, if they achieve the defined endpoints. Specifically, we derive MACs for the year 2050 under different assumptions about technological pathways. We consider each of the technologies on their own, as well as all combinations of technologies to model interactions. Our baseline MAC assumes no CCS, solar PV at around 14 cents/kWh, and current nuclear technology at about 4.7 cents/kWh in 2050. Our analysis extends the work in Baker et al. (2008, 2009a, 2009b) by considering the interaction between the technologies.

The analysis was conducted using the MiniCAM [2] integrated assessment model, which integrates an economic model with a climate model. It looks out to 2095 in 15-year timesteps through a partial-equilibrium model with 14 world regions that includes detailed models of land-use and the energy sector (Brenkert et al. 2003, Edmonds et al. 2005). Assumptions for technologies other than the specific ones considered were based on the version of MiniCAM used in the Climate Change Technology Program (CCTP) MiniCAM reference scenario (Clarke et al. 2008).

The benefit of this step is that we are able to get a simple, yet sophisticated representation of the implementation of the different technologies. It is clear that the implementation of the technologies will depend on a myriad of factors, including not only their own technical characteristics, but the costs and characteristics of competing technologies, regional resource constraints, and enabling technologies such as electricity storage. MiniCAM, while only a single model with a specific set of assumptions, takes all these things into consideration.

When we combine these empirical curves with the elicited probabilities above, we have random MACs – a probability distribution over a discrete number of curves. However, working with random

[2] The full name of the model used for this analysis is Mini Climate Assessment Model. The current version of this model is known as the Global Climate Assessment Model (GCAM).

functions is challenging theoretically and computationally. So, in the next section we parameterize these functions to make them more tractable to work with and analyze the impacts based on these parameter values.

5. The Portfolio Model

5.1. Parameterization of the MAC

In this section we discuss how we produce a probability distribution over MACs for different levels of funding of different projects. We use the data generated by MiniCAM to estimate a smooth relationship between technical change and the impacts on the MAC. We observed from the empirical curves that the effect of technology on the MAC could be parameterized by two parameters, α measuring the pivot and h measuring the shift:

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

where the tilde represents the MAC after technical change parameterized by α and h, 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 constant h differs for each individual technology and technology combination. In order to make the parameterization portable to multiple models, we anchored the shift to the marginal cost of 50% abatement. For the individual technologies, we estimated the values for α and h from the empirical MAC curves using a least squares method. Specifically, we minimized the sum of the square of the percentage error between the estimator and the numerical MAC. Based on experimental analysis, we concluded that the pivot for the combined technologies is best represented by a multiplicative combination of the individual technologies: $\alpha_{CSN} = 1-(1-\alpha_C)(1-\alpha_S)(1-\alpha_N)$. The values for h for combinations of technologies were again estimated using the least square method. The values of α and h for each single technology are given in the online supplement.

In Figure 4 we graph the values of h and α for each individual technology and technology combinations. Note that nuclear, solar, and their combinations have relatively weaker pivots and stronger shifts than portfolios that include CCS.

5.2. Initial Non-convex model

Given a probabilistic representation of the MAC based on the distribution of the parameters α and h, we next consider the portfolio of technologies that would minimize the expected costs in this stochastic setting.

The overall goal of the climate change energy technology model is to minimize the sum of expected abatement costs and expected damages for a given R&D budget. The initial decision is to *determine a set of R&D projects to fund*. Each potential funded portfolio leads to a probability distribution over *successful* portfolios based on our expert elicitations. The second-stage decision is *how much to abate*, for a given damage and abatement cost curve.

We let the indices i and j represent the technology category (CCS, solar, nuclear) and the specific project within the category, respectively. Further, the index k represents the investment level. The key binary 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 $\mu \in [0,1]$, i.e. the fraction of emissions reduced below a business-as-usual level. This variable is conditioned on the

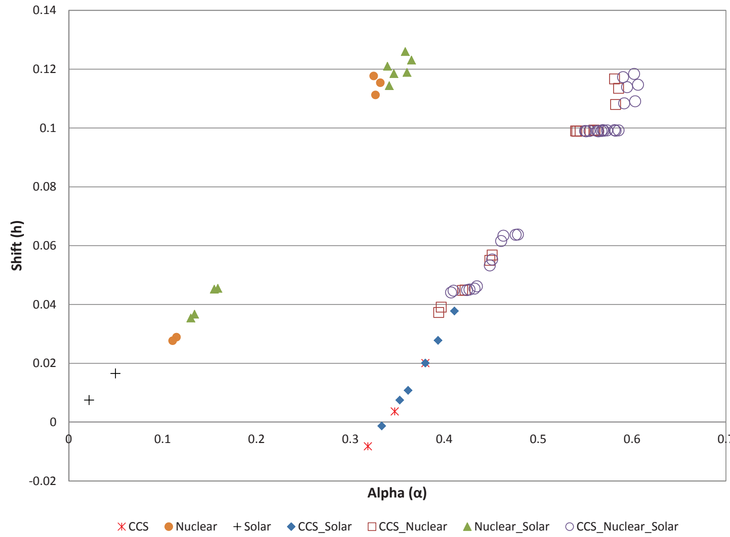

Figure 4 The shift and pivot of all technology combinations.

state of climate damages, represented by a random multiplier Z; and by the state of the invested technologies, represented by the random vector $\overrightarrow{\alpha}$. The objective is to minimize the expectation of the sum of abatement costs and damage costs as follows:

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

where $D(\mu)$ is a damage cost function. Note that the investment in a technology is made without information on technical success or climate damages, while abatement is chosen conditional on technical success and damages, i.e. it is a second stage decision. The investment decisions are constrained by the R&D budget B, and by the fact that a project can be invested in only at one level:

$$\sum_i \sum_j \sum_k f_{ijk} x_{ijk} \leq B \tag{3}$$

$$\sum_k x_{ijk} \leq 1, \quad \forall i, j \tag{4}$$

where f_{ijk} is the required level of investment for funding level k of project ij.

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 realization of the random vector $\overrightarrow{\alpha}$ is simply the product of the probability of the individual components of that realization.

According to our elicitation, the probabilities of success for individual projects depend on whether that project has been invested in or not, as well as the level of investment. We perform the following steps to define the input distributions of the model. First, we calculate the probability of each realization of $\overrightarrow{\alpha}$ using the probability of success if funded. For each funded project ijk there are three potential outcomes: failure, moderate success, or high success. We index these by $l = -1, 0, 1$. Then, for example, the probability P of the event that we get high success in organic cells and no success in anything else, given there is high funding, i.e. $k=2$, in organic solar cells $(i=S, j=1)$, is:

$$P = p_{S12,1} * \prod_{(i,j,k)\neq(S,1,2)} p_{ijk,-1} \tag{5}$$

where $p_{ijk,l}$ represents the probability that funded project ijk will result in outcome l.

Second, we define the outcomes so that they correctly match with the probabilities. Specifically, the outcome of each realization of $\overrightarrow{\alpha}$ is a vector with entries α_i, $i = C, S, N$, representing the amount of technical change in each category. We assume that only the best technology project in each category will diffuse in the economy. For example, if all solar projects are highly successful, we assume that the lowest cost technology will take over the market, giving solar a cost of \$0.029/kWh and $\alpha_S = 0.05$.[3] Let $\overrightarrow{\omega}$ be the state of the world, a vector containing the realized outcome of each project. Then we define the components of $\overrightarrow{\alpha}$ vector as follows:

$$\alpha_i(x;\omega) = \max_{j,k}\{x_{ijk}\alpha_{ijkl}\} \tag{6}$$

where α_{ijkl} is a parameter taken from the data in the online supplement. In this formulation, if we do not invest in technology ij, then $x_{ijk} = 0$. For example, consider again the event that there is high funding in organic solar cells and that we get high success in organic cells and no success in anything else. The realization of $\overrightarrow{\alpha}$ associated with this event depends on whether organic solar is funded at the high funding level or not. If $x_{S12} = 0$ then the outcome will be $\overrightarrow{\alpha} = (0,0,0)$; if $x_{S12} = 1$ the outcome will be $\overrightarrow{\alpha} = (.05,0,0)$. The outcome depends on the decision variable x_{ijk}, while the probability does not.

Between the technology categories, we assume that the pivots are multiplicative, but that the shifts are defined according to dependency relationships between the technologies. Based on these relationships, we define the total shift in the MAC, h as:

$$h = K(\mathbf{x}, \overrightarrow{\alpha}) \tag{7}$$

where $K(\mathbf{x}, \overrightarrow{\alpha})$ represents the shift value for the realized combination of technologies. For each possible combination of α values, these mappings are generated exogenously and included in the optimization model. This is further discussed in Section 5.3.

Given h, the abatement cost is:

$$c(\mu; \overrightarrow{\alpha}) = \prod_i (1-\alpha_i)\left[c(\mu) - hc(0.5)\mu\right] \tag{8}$$

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 (Nordhaus 2008):

$$c(\mu) = b_0\mu^{b_1} \tag{9}$$

[3] This is a simplifying assumption that derives from MiniCAM. It has a very large number of technologies and technology categories. Therefore, any particular technology, such as solar PV, is modeled as a single technology, using a single set of parameter values. We kept this convention for our analysis.

z_h	1 (no risk)	3 (med.risk)	14.6 (high risk)	14.6 (baseline)
$P(Z=0)$	-	0.666	0.931	0.245
$P(Z=1)$	1	-	-	0.737
$P(Z=z_h)$	-	0.334	0.068	0.018
μ^* if $Z=z_h$	46%	80%	100%	-

Table 1 Damage uncertainty

where b_0 and b_1 are parameters that are calibrated as discussed below. Moreover, the damage function is assumed to be quadratic, a common assumption in the literature (Tol 1995, Nordhaus 2008):

$$D(\mu) = M_0(Q - M_1\mu)^2 \tag{10}$$

where M_0, M_1 and Q are defined and calibrated as follows. The stock of emissions in the atmosphere Q 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 the 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 $M_0 = 2.74$, and took 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 was determined to be 0.597. The value of b_1 was set as 2.8, the value in DICE. Further, we set b_0 so that the optimal abatement is 0.46, which leads to a value of $b_0 = 10.4$.

We consider multiple cases for uncertainty over climate damages which are based on Nordhaus (1994). Four of these cases are shown in Table 1. In each case there are three possible realizations for the damages, either $Z = 0$, $Z = 1$, or $Z = z_h$ (which varies by case). The values for z_h for each case are shown in the top row, and the probability of each outcome in each case is shown in the body of the table. For example, in the baseline case $Z = 0$ with probability 0.245, $Z = 1$ with probability 0.737 and $Z = 14.6$ with probability 0.018. Each risk scenario has a mean $\bar{Z} = 1$. 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 an MPS of the no risk case (Rothschild and Stiglitz 1970), while the high risk case is an MPS of both the no-risk and medium risk cases. We also ran experiments using risk scenarios with means of $\bar{Z} = 3$ and $\bar{Z} = 14.6$. To put this in perspective, note that the highest damages that we consider, where $Z = 14.6$, are equivalent to a 20% loss in economic output given a 2.5°C increase in mean temperature.

5.3. Stochastic Programming Based Optimization

In order to formulate the problem as a two-stage stochastic programming model, we first expand our definition of ω and let $\omega \in \Omega$ represent a scenario consisting of possible values of the parameters α_{ijkl} and Z, and define p^ω as the probability of the scenario ω, calculated as described in Section 5.2. Since the scenario definition involves both the vector $\overrightarrow{\alpha}$ and the random parameter Z, we refer to the realized value α_{ijkl} as α^ω_{ijk} for consistency in the description of the formulation. Note, our convention is that realizations of random variables have ω as a superscript; whereas decision variables that are conditional on the realization have ω as a subscript. The overall stochastic optimization problem can then be expressed as follows,

$$\min_{\mathbf{x}\in\mathcal{X}} \sum_{\omega\in\Omega} p^{\omega}\{\prod_{i}(1-\max_{j,k}\{\alpha^{\omega}_{ijk}x_{ijk}\})(b_0\mu_{\omega}^{b_1}-c_{0.5}h_{\omega}\mu_{\omega})+Z^{\omega}M_0(S-M_1\mu_{\omega})^2\} \tag{11}$$

$$\text{s.t. } h_{\omega}=K(\mathbf{x},\overrightarrow{\alpha}) \quad \forall\omega \tag{12}$$

$$0\le \mu_{\omega}, h_{\omega}\le 1 \quad \forall\omega \tag{13}$$

where $\mathcal{X}$ represents the set of feasible investment decisions, as defined by (3)-(4). Note that problem (11)-(13) is the deterministic equivalent of the stochastic optimization problem (2). Also note that the multiplicative nature of the pivot terms in the cost function, i.e. the product $\prod_i(1-\max_{j,k}\{\alpha^{\omega}_{ijk}x_{ijk}\})$, results in the model being highly nonconvex.

To develop an equivalent convex formulation, we first let ϕ_i be a nonnegative variable such that it is equal to the value of $-\ln(1-\max_{j,k}\{\alpha_{ijk}\})x_{ijk}$ for $j,k\in\arg\max_{j,k}\{\alpha_{ijk}\}$. Note that these variables are defined for each scenario, but we leave out the index ω in these definitions for the clarity of presentation. Further, we define a new nonnegative variable $q=h+\mu$, and binary indicator variables δ_{ijk} and β_i to represent the modified problem structure. β_i corresponds to the case with no investment in technology i, while δ_{ijk} is an auxiliary variable used to indicate whether the corresponding set of constraints holds in the model. Further, for technology category i, δ_{ijk} identifies the funded project determining the value of α_i, which is the highest realized value among all funded project returns in that category. In addition, we let the random parameter $\bar{\alpha}^{\omega}_{ijk}$ represent $\ln(1-\alpha^{\omega}_{ijk})$, which is calculated outside the optimization. Finally, we define the set of variables $y^{\pi}_{i,i',i''}$ for all $i,i',i''\in\{C,N,S\}$, where π corresponds to a distinct combination of possible α_{ijk} values for the three technology categories. The variables y are used to denote the dependency relationships that apply to the shift parameter h in a given solution to the problem. We will refer to the combined set of y variables as y^{π}_{I}, and assume that a constant K^{π}_{I} is calculated exogenously for each possible combination.

With these definitions and modifications, the following equivalent formulation of the climate change energy technology R&D problem can be developed:

$$\text{Minimize} \quad \sum_{\omega} p^{\omega}[(e^{-\sum_i \phi_{i\omega}+\ln(b_0\mu_{\omega}^{b_1}-\frac{1}{2}c(0.5)(q_{\omega}^2-h_{\omega}^2-\mu_{\omega}^2))})+Z^{\omega}M_0(S-M_1\mu_{\omega})^2] \tag{14}$$

$$\text{subject to} \quad \sum_i\sum_j\sum_k f_{ijk}x_{ijk}\le B \tag{15}$$

$$\sum_k x_{ijk}\le 1, \quad \forall i,j \tag{16}$$

$$\phi_{i\omega}+\bar{\alpha}^{\omega}_{ijk}x_{ijk}+M\delta_{ijk\omega}\le M \quad \forall i,j,k,\omega \tag{17}$$

$$\phi_{i\omega}+\bar{\alpha}^{\omega}_{ijk}x_{ijk}+m\delta_{ijk\omega}\ge m \quad \forall i,j,k,\omega \tag{18}$$

$$\sum_j\sum_k \delta_{ijk\omega}+\beta_i=1 \quad \forall i,\omega \tag{19}$$

$$\phi_{i\omega}+M\beta_i\le 1 \quad \forall i,\omega \tag{20}$$

$$h_{\omega}-\sum_I y^{\pi}_{I\omega}K^{\pi}_I=0 \quad \forall\omega \tag{21}$$

$$y^{\pi}_{I\omega}=1\Leftrightarrow\sum_{i\in I}(\sum_j\sum_k \delta_{ijk\omega}\alpha^{\omega}_{ijk})=\alpha^{\pi}_I \quad \forall I,\pi \tag{22}$$

$$q_{\omega}=h_{\omega}+\mu_{\omega} \quad \forall\omega \tag{23}$$

$$\delta_{ijk\omega}-x_{ijk}\le 0 \quad \forall i,j,k,\omega \tag{24}$$

$$\mathbf{x}, \mathbf{y}, \delta, \beta \in \{0,1\} \tag{25}$$

$$0 \le \mu, h \le 1; w, \phi \ge 0. \tag{26}$$

where α_I^π refers to the sum of the α values for the combination π, and M and m are upper and lower bounds based on the corresponding constraints. The objective function (14) in the above formulation is based on two reformulation steps. We replace the bilinear term $h\mu$ using the relation $q^2 = h^2 + 2h\mu + \mu^2$. The constraints (15) and (16) are the first stage constraints (3)-(4). The inequalities (17) and (18) ensure that the value of ϕ_i is equal to $\bar{\alpha}_{ijk}x_{ijk}$ if project ijk is selected and $j,k \in \arg\max_{j,k}\{\alpha_{ijk}\}$, while (19) is used to define β_i such that $\beta_i = 1$ if no investment is made in technology i. Similarly, (20) ensures that $\phi_i = 0$, if no investment is made in the technology. Based on exogenous parameters K_I^π, constraints (21)-(22) define the variable h as described in (12). The relationships enforced through constraint set (22) are not stated explicitly for the sake of clarity, but these relations are modeled using standard integer programming methods (Nemhauser and Wolsey 1999). Constraint (23) defines the variable q, and finally the inequality (24) ensures that a project can contribute to the portfolio only if it is selected.

Problem (14)-(26) is an integer program with a nonlinear objective function and linear constraints. Further the objective function is convex as we show below:

THEOREM 1. *Problem* (14)-(26) *is convex.*

Proof: See Appendix. □

Given the above result, the problem (14)-(26) 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 that occur in our case, we use sampling based procedures based on solving randomly sampled small scale instances to determine good or near-optimal solutions.

5.4. Solution Approach

To solve problem (14)-(26), we make use of the sample average approximation (SAA) method (also known as the sample path method), a Monte Carlo simulation technique that approximates a stochastic program by a set of smaller problems based on a random sample from the set of possible scenarios (Shapiro 2003, Linderoth et al. 2006). Letting $\omega^1, ..., \omega^N$ be an i.i.d. random sample of N realizations of the random vector ω, the SAA problem for (14)-(26) can be defined as:

$$\min_{\mathbf{x}\in\mathcal{X}} \{\hat{g}_N(\mathbf{x}) = \frac{1}{N}\sum_{l=1}^{N} G(\mathbf{x}, \omega^l)\} \tag{27}$$

where $G(\mathbf{x}, \omega^l)$ is the objective function (14) for realization ω^l. If v^* and $\hat{v}_N$ represent the optimal values of the "true" and SAA problems respectively, Kleywegt et al. (2002) show that $\hat{v}_N$ converges to v^* at an exponential rate as sample size N is increased. However, given that the computational complexity of the SAA problem increases exponentially with the value of N, it is typically more efficient to select a smaller sample size N, and solve several SAA problems with i.i.d. samples.

We solve M SAA problems with N samples in each, and use $\hat{v}_N^m$ and $\hat{\mathbf{x}}_N^m$, $m = 1, \ldots, M$, to refer to the optimal objective value and solution of the mth replication, respectively. Once a feasible solution $\hat{\mathbf{x}}_N^m \in \mathcal{X}$ is obtained by solving the SAA problem, the objective value $g(\hat{\mathbf{x}}_N^m)$ needs to be determined. While we determine these values exactly for problem (14)-(26), in general the value of a given solution can be approximated by the estimator

$$\hat{g}_{N'}(\hat{\mathbf{x}}_N^m) = \frac{1}{N'} \sum_{l=1}^{N'} G(\hat{\mathbf{x}}_N^m, \omega^l) \tag{28}$$

where N' is typically larger than N, as the computational effort required to estimate the objective value for a given solution is generally less than that required to solve the SAA problem. The quality of a solution $\hat{\mathbf{x}}_N^m$ is then computed through the optimality gap estimator $v^* - g(\hat{\mathbf{x}}_N^m)$, where $g(\hat{\mathbf{x}}_N^m)$ can be calculated exactly or estimated by (28), and v^* is approximated by

$$\bar{v}_N^M = \frac{1}{M} \sum_{m=1}^{M} \hat{v}_N^m \tag{29}$$

The sampling procedure can be terminated once the optimality gap estimate is sufficiently small or after performing all M replications, and the best solution among the SAA solutions can be selected using an appropriate criterion.

Effective implementation of the above sampling procedure requires that the SAA problems can be solved efficiently for relatively large values of the sample size N, and the candidate solutions are evaluated accurately. Problem (14)-(26) is especially suitable for such implementation, as it is relatively easy to evaluate the second stage objective function for given values of the $\mathbf{x}$ vector.

In the computations performed, depending on the instance, the values of N and M varied between 100-1000 and 100-250, respectively. Furthermore, as noted above, we calculated the values of candidate portfolios exactly through an algorithmic procedure, without the need for sampling. Hence, we could show numerically that the results obtained from the SAA method corresponded to true optimal portfolios.

6. Results and Policy Implications

6.1. Composition of Optimal Energy Technology R&D Portfolio

Our first finding is that the composition of the optimal portfolio is robust to different levels of damage risk, conditional on a budget. In Figure 5 we show the composition of the optimal portfolio at budget levels ranging between \$200 million and \$2000 million. These portfolios did not change under any of the risk scenarios in Table 1. On the other hand, we know from previous research (Baker et al. 2006, Baker and Adu-Bonnah 2008), as well as from the discussion in Section 3.2 , that in general damage risk can impact the optimal investment in technology. Thus, our result shows the value of incorporating actual data in the portfolio analysis. Specifically, in this case, the data leads 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, and even regardless of the mean of damages. That is, these technologies would be funded even if our objective were to minimize the consequences of the worst scenario. Similarly, these technologies would be funded even under the assumption of no learning about climate damages (which is equivalent in this case to deterministic damages). Hence, based on currently available data and expert opinion, we conclude that the optimal R&D investment is robust to uncertainty in climate damages.

Second, we see the effects of the problem having a “knapsack” structure. We see that solar, in particular, goes in and out of the portfolio at different budget levels. The solar projects are less

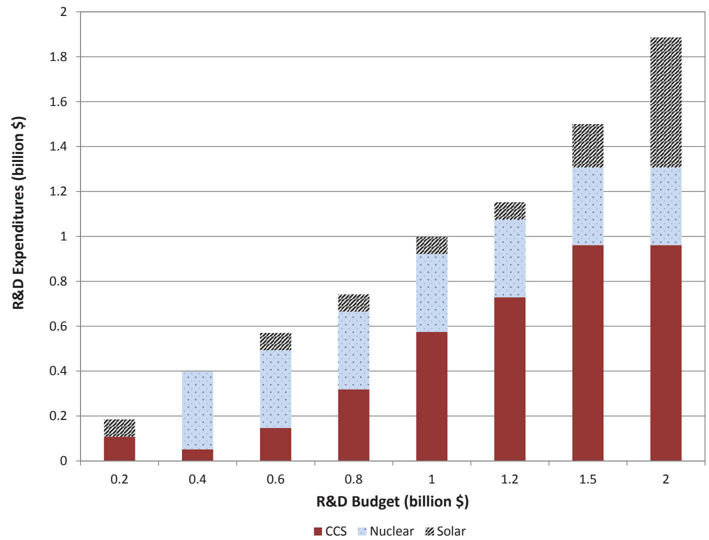

Figure 5 **Optimal portfolios.**

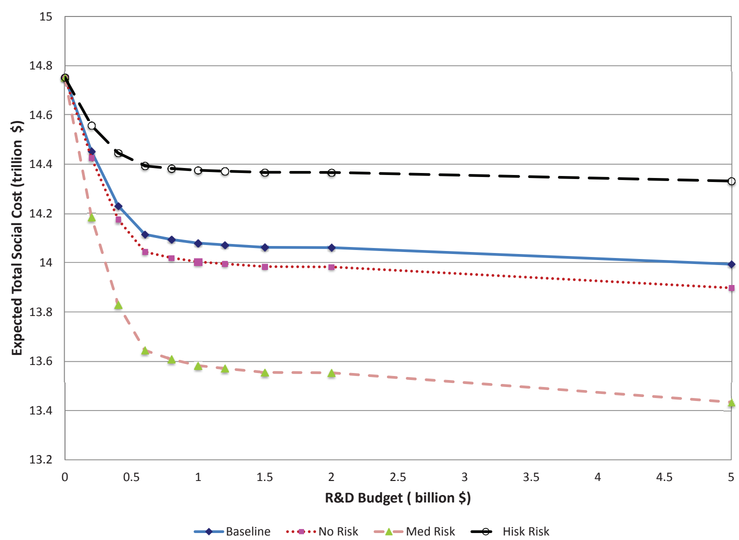

Figure 6 **Expected total social costs normalized according to the no-risk case.**

efficient compared to 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 in Figure 5, nuclear dominates the portfolio, since it has the highest budgets.

In Figure 6 we show how the expected total social cost is impacted by R&D investment, in the four risk cases defined in Table 1. The curves in the figure are normalized so that all cases appear on the same scale as the no-risk case.[4] Notice that there is an “elbow point” in each of the curves

[4] Total expected cost is lower under risk, since abatement is increased when damages are high (Baker 2009).

in Figure 6, where the cost savings from a bigger portfolio slows down considerably. This happens at a budget of \$600 million, which consists of a portfolio including a high investment in chemical looping, LWR, and inorganic PVs, along with medium level investments in the other two CCS technologies.

We pointed out above that the composition of the optimal portfolio at given budget levels is constant over a variety of different risk configurations. However, in Figure 6 we show that the *value* of R&D is impacted by the level of risk. First, R&D has the least 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 does not change the optimal level of abatement – it has no environmental-side effect. As a contrast, 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 more stringent abatement. In fact, when there is no risk our results show that the overall expected cost of abatement increases as the R&D budget increases – the optimal level of abatement increases enough that it outweighs the reduced cost of abating any given level. That is, the technology has a significant environmental-side benefit. Thus, it has overall more value.

We see, however, that the value of R&D is non-monotonic in risk, increasing significantly in the medium risk case, as we get both cost-side and environmental-side benefits. In this case, our results show that both expected damages and the overall cost of abatement decrease at higher budget levels.

In Figure 7 we illustrate this point. The figures show the baseline MAC, the expected MAC when the budget is \$600 million, and the marginal damages when the damage parameter $Z = 1$ and $Z = 3$. The left-hand chart shows the impact of technical change when $Z = 1$. In this case, 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, and it can be seen that the total abatement cost is slightly higher after technical change. The right-hand panel shows the impact of technical change when $Z = 3$. Optimal abatement increases from 80% to 100%, thus again there is an 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.

6.2. Optimal Level of R&D Investment

Money spent on R&D is considered to have a particularly high opportunity cost in the economy, perhaps up to 4 times as much as the out-of-pocket expense (Nordhaus 2002, Pizer and Popp 2008). Although the exact nature and amount of these opportunity costs is still an open question, we perform an analysis over a range of opportunity costs. We show results for the cases of no opportunity costs as well as total costs equal to 2, 4, and 8 times the net costs. The lower assumption would hold if "pork", i.e. money awarded by earmark for political reasons rather than based on scientific merit was minimal and only about 50% of new energy R&D was replacing other kinds of R&D (Popp 2006), while the highest assumption would hold if "pork" doubled the cost of R&D and all energy R&D replaced other kinds of R&D. We find the optimal portfolio under three risk cases and these four assumptions about cost. The results are shown in Tables 2 - 4. Investments

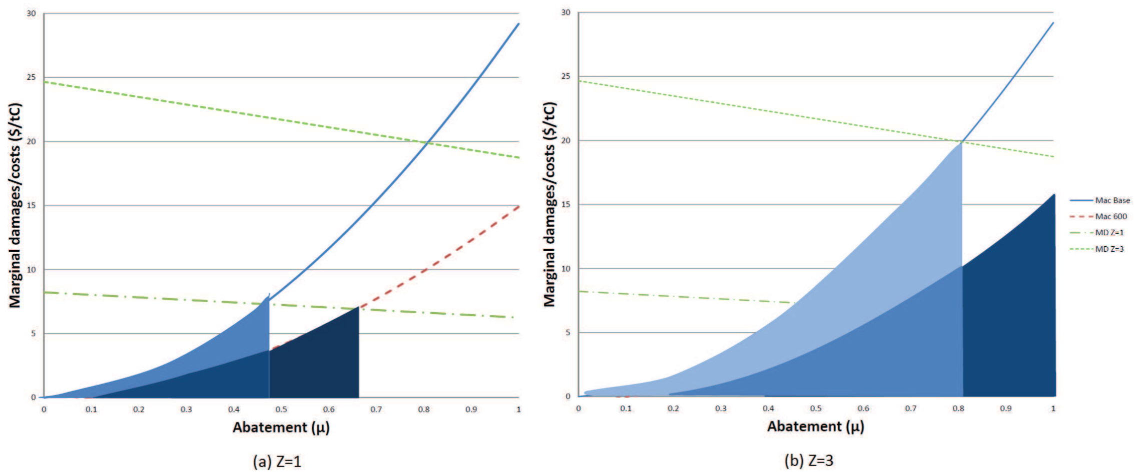

Figure 7 **Optimal abatement and total cost of abatement.**

Coef	Investments ($ million)									Tot. Inv.	Tot. Cost
	Pre C	Chem L	Post C	LWR	HTR	FR	Org.	Inorg.	3rd g	($bil)	($ tri)
1	386	56	519	346	3089	15443	830	77	386	21.132	13.863
2	386	56	519	346	3089	15443	830	77	386	21.132	13.885
4	386	56	519	346	3089	0	830	77	0	5.303	13.915
8	386	56	519	346	3089	0	116	77	0	4.589	13.936

Table 2 **Optimal portfolio as a function of the opportunity cost multiplier for no risk**

Coef	Investments ($ million)									Tot. Inv.	Tot. Cost
	Pre C	Chem L	Post C	LWR	HTR	FR	Org.	Inorg.	3rd g	($bil)	($ tri)
1	386	56	519	346	3089	15443	830	77	386	21.132	11.849
2	386	56	519	346	3089	15443	830	77	386	21.132	11.870
4	386	56	519	346	3089	4633	830	77	0	9.936	11.912
8	386	56	519	346	3089	0	830	77	0	5.303	11.935

Table 3 **Optimal portfolio as a function of the opportunity cost multiplier for medium risk**

Coef	Investments ($ million)									Tot. Inv.	Tot. Cost
	Pre C	Chem L	Post C	LWR	HTR	FR	Org.	Inorg.	3rd g	($bil)	($ tri)
1	386	56	519	346	3089	4633	830	77	0	9.936	10.339
2	386	56	519	346	3089	0	116	77	0	4.589	10.344
4	386	56	519	346	3089	0	116	77	0	4.589	10.354
8	386	56	519	346	1544	0	0	77	0	2.928	10.369

Table 4 **Optimal portfolio as a function of the opportunity cost multiplier for high risk.**

columns in each table show the optimal investment in each specific technology; total investment column shows the overall optimal net investment in R&D (that is, not including opportunity costs); and the total cost column shows the total expected social cost (including the opportunity cost of investment). It can be seen from the three tables that the optimal investment level varies in the risk of climate damages. These results are summarized in Figure 8. The pattern that emerges is consistent with the results in Figure 7, in which R&D has the highest value in the medium risk

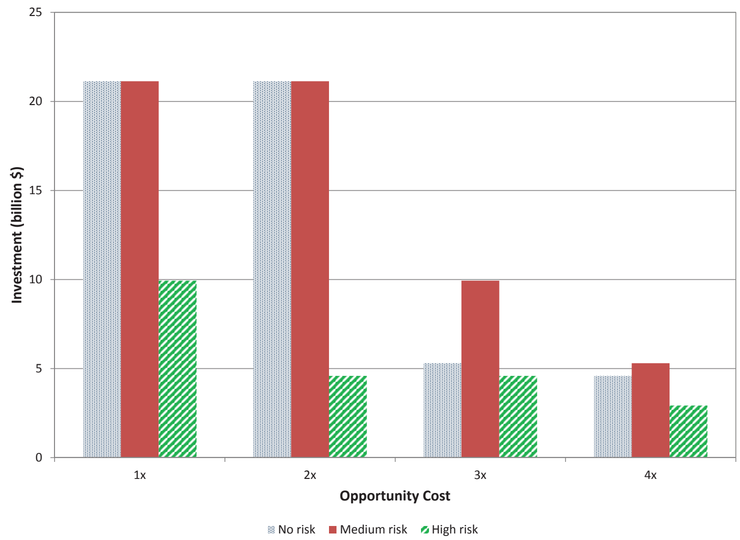

Figure 8 Bar chart showing optimal level of investment as a function of opportunity cost.

case and the lowest value in the high risk case. We see here that the optimal net investment in R&D is highest in the medium risk case and lowest in the high risk case. Notice that when the opportunity cost is low, the entire portfolio is funded under the no- and medium-risk cases.

Results from Baker (2006) allow us to extend these results to a case with partial learning. Baker (2006) shows that in decision problems that are linear in the random variable (Z in our case), the comparative statics of informativeness are the same as the comparative statics of risk. That is, given the high risk distribution from Table 1, the optimal investment in R&D would first increase with partial learning about damages, and then decrease with perfect learning about damages.

Consistent with our findings that the composition of the portfolio is robust to risk, it appears that the value of the individual technologies is not strongly effected by risk. If we read each table from top to bottom, we can see which technologies get reduced funding or leave the optimal portfolio as the opportunity cost gets higher. It appears that the first technology to be reduced is 3rd generation solar, followed by the Fast Reactor, followed by organic solar cells, and finally the HTR reactor.

6.3. Fixed Abatement Levels

As noted, R&D has the least value when technical change has no impact on abatement. Moreover, the most common type of analysis in the climate change policy literature consists of determining the value of investments in technology for fixed stabilization levels – this is equivalent to a fixed abatement path over time. Thus, we investigate how the optimal investment level changes if we fix the second stage decision, i.e. assume a fixed abatement level. Specifically, we consider three target abatement levels of 46%, 62%, and 80%. These values correspond to the optimal fixed abatement in the absence of uncertainty or technical change, the optimal fixed abatement in our R&D model without recourse, and a commonly discussed target abatement level. Note that the optimal R&D investment is not impacted by uncertainty in damages when abatement is fixed, as the payoff function is linear in Z when there is no recourse. In Figure 9, we show the optimal level of R&D expenditure under these three fixed abatement levels (assuming a 4x opportunity cost), and compare this to the optimal level of R&D expenditures in the model with recourse, under

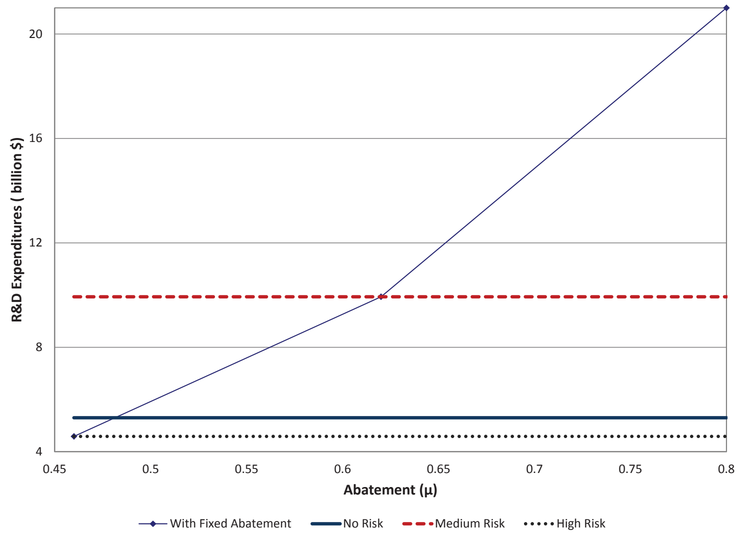

Figure 9 **Optimal levels of R&D expenditure under fixed abatement, compared with optimal expenditure under recourse for the three risk cases.**

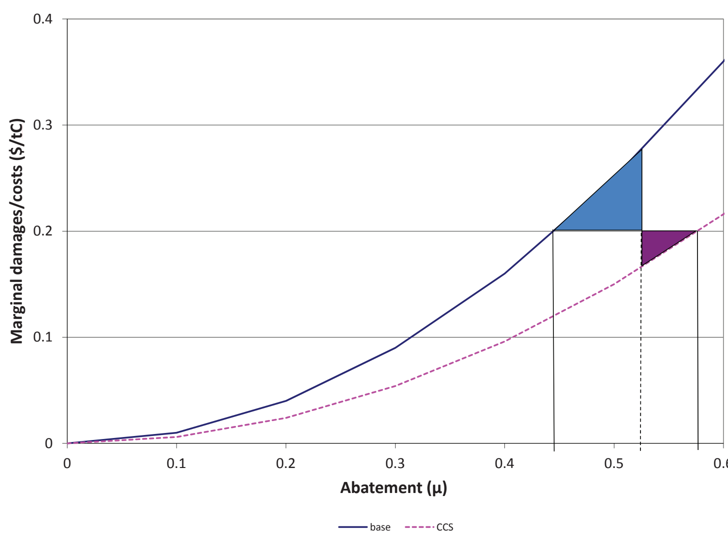

Figure 10 **Example case demonstrating the impact of fixed level of abatement.**

our three risk assumptions. We see from this figure that if the fixed abatement level is low, then technology may be undervalued compared to the true optimal case, whereas if the fixed abatement level is high, technology may be overvalued.

In Figure 10, we illustrate the opposing factors that determine whether technology is under- or over-valued. We present an example involving a single technology and no uncertainty in damages. The two upward sloping lines are a baseline MAC and a MAC after success in a CCS technology. The marginal damages are assumed to be 0.2, and optimal abatement based on the baseline MAC is about 44.5%; while it is about 57% based on the MAC after technical change. If we assume that there is a 60% chance of technical success, the expected amount of abatement is about 52% as shown. If we use this expected abatement level instead of optimal abatement to evaluate technical change, there are two countervailing effects. On the one hand, we will miss the fact that optimal abatement should be higher when the technology is successful. This effect will cause technical change to be undervalued with fixed abatement. On the other hand, if the fixed abatement level is high compared to the optimal level given the baseline, technology will lead to a significant cost savings in meeting this level of abatement. This effect will cause technical change to be over-valued with fixed abatement. In Figure 10, the two shaded triangles represent the relative impacts of these two effects. Specifically, the smaller triangle shows the benefits from technical change that we fail to recognize when abatement is fixed. The larger triangle shows the extra benefits from technical change when abatement is fixed at 52%. With the parameters as given, the benefit from the R&D appears greater under fixed abatement than under optimal abatement. R&D is over-valued in this case.

Consider a different case, in which the probability of success of the technology is lower, say 30%. In this case the expected abatement level would also be lower, around 49%, and the sizes of the two triangles would be reversed. Thus, ignoring the 2nd stage decision would cause R&D to be under-valued.

If society focuses on a fixed abatement level that ignores the possibility of technical change, then R&D will be undervalued. On the other hand, if society focusses on a fixed abatement level that assumes technical breakthroughs will occur, then R&D will be over-valued. In order to properly and accurately value the role of R&D, abatement must be considered as a recourse decision.

7. Conclusion

In this paper we have gone beyond the previous theoretical analyses to present results from a data-based climate change energy technology R&D portfolio model. Our R&D portfolio model has provided a number of insights. First, while it is easy to show theoretically that the optimal portfolio can depend on the level of risk, we have found in our data-based model that the optimal portfolio is robust to climate damage risk. This is good news, since determining the probability distribution over climate change damages is very difficult. Moreover, the optimal portfolio is even robust to the mean of the distribution. That is, the optimal portfolios remain optimal even in a worst-case scenario, or in a scenario with no learning about climate damages. 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, while the portfolio at any given budget level is robust to risk, this is not true for the value of R&D. We go on to show that the optimal level of spending depends explicitly on the probability distribution around climate damages. Fourth, we see that R&D and technical change will not be valued correctly if future emissions levels are fixed, which is a commonly used modeling convention in the climate change literature. 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.

Here we acknowledge that this paper provides one specific approach to a very complicated problem. In our model, we have vastly simplified the economy and the climate into a single equation, in order to represent diversity in the technologies. Similarly, our objective function is to minimize the costs and damages from climate change. While this has been shown to be a pretty good approximation of maximizing social utility (Nordhaus 2008), it is clearly a partial equilibrium approach that may miss important interactions in the economy. In future work, the insights drawn from this paper may allow this same data to be implemented into a more complex and dynamic integrated assessment model, thus addressing some of these limitations. Moreover, there is some debate in the climate change literature on whether optimization is the correct approach. Some argue for a "precautionary" approach, and it is common to take a cost effectiveness approach, i.e. by taking a climate target as given and minimizing the cost of achieving it. We have argued above that this presents limitations. However, it does provide a reasonable alternative approach. In future work, our probabilistic data may be used to perform Monte Carlo type analysis in some of the technologically-detailed cost effectiveness models in order to gain different types of insights. We have included only a simple, two-stage model of parametric uncertainty with learning. In particular, our R&D programs are either successful or not. In future work it would be useful to consider staged investments more formally, although this presents a serious challenge in data collection. Finally, we have included only a subset of possible energy technologies. Future work should aim to include more technologies, as well as to integrate a wide range of data that is becoming available. From a modeling perspective, an alternative approach may involve the inclusion of risk aversion based components in the objective function, although prior research has shown this to be of limited significance. Another modeling extension is to consider gradual resolution of uncertainty over technological success and climate change, as opposed to our assumption that the parameter values representing these will be known with certainty before the second stage decisions. However, inclusion of gradual learning into the model is likely to have significant computational implications for the stochastic optimization problem.

Appendix. Proof of Theorem 1

Since the problem contains linear constraints, it suffices to show that the objective function (14) is convex in the decision variables. Note that this function consists of two components, an exponential term and a quadratic function of the variable μ. It is trivial to show that the quadratic component is convex.

For the exponential term, we know that the exponentiation of a convex function is convex. Thus, the problem reduces to showing that $g(h_\omega,\mu_\omega) = -\ln(b_0\mu_\omega^{b_1} - \frac{1}{2}c(0.5)(q_\omega^2 - h_\omega^2 - \mu_\omega^2)) = -\ln(b_0\mu_\omega^{b_1} - \frac{1}{2}c(0.5)((h_\omega + \mu_\omega)^2 - h_\omega^2 - \mu_\omega^2))$ is convex. Note that $g(h_\omega,\mu_\omega)$ is twice differentiable, and the Hessian $H_g(h_\omega,\mu_\omega)$ is given by:

$$\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$$

where we use the values listed in Section 5.2 for b_0, b_1 and $c(0.5)$ to obtain

$$\begin{aligned}
a_{11} &= \frac{2.22\mu_\omega^2}{(10.4\mu_\omega^{2.8} - 0.745(h_\omega+\mu_\omega)^2 + 0.745h_\omega^2 + 0.745\mu_\omega^2)^2} \\
a_{12} = a_{21} &= \frac{1.49(10.4\mu_\omega^{2.8} - 0.745(h_\omega+\mu_\omega)^2 + 0.745h_\omega^2 + 0.745\mu_\omega^2) - \mu_\omega(43.39\mu_\omega^{1.8} - 2.22h_\omega)}{(10.4\mu_\omega^{2.8} - 0.745(h_\omega+\mu_\omega)^2 + 0.745h_\omega^2 + 0.745\mu_\omega^2)^2} \\
a_{22} &= \frac{(29.12\mu_\omega^{1.8} - 1.49h_\omega)^2 - 52.42\mu_\omega^{0.8}(10.4\mu_\omega^{2.8} - 0.745(h_\omega+\mu_\omega)^2 + 0.745h_\omega^2 + 0.745\mu_\omega^2)}{(10.4\mu_\omega^{2.8} - 0.745(h_\omega+\mu_\omega)^2 + 0.745h_\omega^2 + 0.745\mu_\omega^2)^2}
\end{aligned}$$

Clearly, $a_{11} \geq 0$, as all of its components are nonnegative. Further, it can be shown through algebraic manipulation that $a_{22} \geq 0$ holds for the ranges $0 < \mu_\omega \leq 1$ and $0 < h_\omega \leq 1$. Similarly, $|H_g(\mu_\omega,h_\omega)| \geq 0$, as the determinant of the matrix is given by

$$\frac{61.92\mu_\omega^{4.8}(\frac{0.08h_\omega^2}{\mu_\omega^{2.8}} - \frac{0.31h_\omega}{\mu_\omega} - 1.71\mu_\omega^{0.8})}{(1.49h_\omega\mu_\omega - 10.4\mu_\omega^{2.8})^4} \tag{30}$$

Hence, $H_g(\mu_\omega, h_\omega)$ is positive semidefinite, and $g(h_\omega, \mu_\omega)$ is convex. It follows that problem (14)-(26) is convex.

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