

# Investment in Risky R&D programs in the Face of Climate Uncertainty\*

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## Abstract

We analyze how the socially optimal technology R&D investment changes with the risk-profile of the R&D program and with uncertainty about climate damages. We show that how technology is represented in the model is crucial to the results; and that uncertainty in damages interacts with uncertainty in the returns to R&D. We consider R&D that reduces the cost of abatement multiplicatively, and argue that this a good representation of R&D into non-carbon technologies; and R&D that reduces the emissions-to-output ratio, and argue that this is a good representation of R&D into fossil-fuel technologies. For R&D programs into non-carbon technologies, optimal investment is higher in riskier programs. Our empirical model indicates that the optimal investment in a risky program is about 3 1/2 times larger than in a program with certain returns. For R&D programs aimed at reducing emissions in fossil-fuel based technologies, our results show that, qualitatively, investment is higher in less-risky programs under most uncertain damage scenarios. Our empirical model shows, however, that the risk-profile of fossil-fuel based R&D programs generally has little quantitative impact on optimal investment. The exception is that when the probability of a catastrophe inducing full abatement is very high, investment is about twice as high in risky programs compared to programs with certain returns.

Keywords: Climate change; Technology R&D; Uncertainty; Environmental policy

# 1 Introduction

Policy makers are concerned with limiting the future cost of climate change. The economics literature has focussed on the optimal abatement path (e.g. [3][17][25][26][33][28][35][41][42]) and the relative merits of different abatement-related policy instruments for climate change or related environmental issues.<sup>1</sup> Policy makers in the U.S., however, have shied away from any emissions policy, and instead have focussed on technology policy.<sup>2</sup> In the face of uncertainty – about both eventual climate-related damages and technical success – it is unclear how much R&D is desirable and which categories of technologies should be targeted. Baker, Clarke, and Weyant [4] analyzed how socially optimal investment in broad classes of technology R&D was impacted by uncertainty in the damages from climate change. In this paper, we extend their model, considering two categories of technologies, and analyze how the optimal technology R&D investment changes with the risk-profile of the R&D program as well as with uncertainty about climate damages.

This paper is related to the literature on investment under uncertainty and stochastic dominance, as well as R&D portfolio problems. The classic investment under uncertainty problem considers how optimal investment is impacted by uncertainty in the environment, such as prices or demand (see [11][9]). This literature has also considered R&D programs with uncertain returns and has shown that there may be an option value to investing even when the program has an overall negative expected value, and that this option value may increase in the riskiness of the project [20][37]. Much of the stochastic dominance literature is focused on determining what kinds

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<sup>1</sup>See [1][6][7] for recent work comparing instruments for generic environmental regulation and [19][40] for an overview of instrument choice for climate change. See [12][14][18][23][29][30][34] for discussions of the impact of policy instruments on environmental technical change.

<sup>2</sup>See <http://www.doe.gov> for information on the Climate Change Technology Program.

of stochastic shifts in the environment induce more investment [2]. Another strand of the literature considers how the choice between risky prospects is related to the level of risk aversion [16][22].

In this paper we combine exogenous uncertainty in climate damages with uncertainty in R&D, for multiple technologies, to determine how the riskiness of the R&D program impacts the optimal level of investment in that program; and how this is impacted by uncertainty in the damages from climate change. We recognize that different R&D programs can have different levels of risk. Some programs are primarily aimed at incremental improvements, and tend to be low-risk: a larger investment leads to larger incremental returns with a great deal of certainty. Other programs are aimed at achieving breakthroughs, and tend to be high-risk: an increase in investment increases the probability of success. We define a breakthrough as technological change that will reduce the cost of abatement to near zero, for example a reduction in the cost of very low-carbon energy that makes it widely economically competitive with fossil fuel technologies, or a combination of efficiency gains and sequestration that would allow for near zero-emissions fossil-fuel based energy.<sup>3</sup> We model an investment in a risky R&D program as inducing a first order shift in the probability distribution over the possible outcomes of that program. We consider how an increase in the riskiness of a program impacts the optimal investment in a first order shift in the program.

This problem differs from classic R&D portfolio problems (See [24] for a review) because the effect of technological change is not inherent in the technology alone, but must be understood through the technology's effect on the marginal abatement cost curve (MAC) as it interacts with the eventual damage curve. For example, incremental improvements (as opposed to a breakthrough)

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<sup>3</sup>The main greenhouse gasses (GHG) are Carbon Dioxide ( $CO_2$ ), Nitrous Oxide, Methane, and CFCs. We will often refer to carbon, as it is the most economically important of the GHGs and the largest contributor to climate change.

in solar energy will only have widespread impacts on the economy if climate damages turn out to be severe, thus inducing a high level of abatement.

We present two alternative ways of modeling technical change – both common in the literature – and show that our results differ significantly for the two representations. For the first representation, technical change reduces the cost of abatement by a fixed percentage – it shifts the abatement cost curve down. We argue that this most closely represents investments into very low emissions technologies. For the second representation, technical change reduces the emissions-to-output ratio, leading to a rightward shift of the abatement cost curve. We argue that this most closely represents investments into reducing emissions in conventional, fossil-fuel based technologies. While the validity of these interpretations is an open empirical question, it is clear that the representation of technical change has serious impacts for the conclusions drawn.

When R&D shifts the cost curve down by improving alternative, zero-emissions technologies, optimal investment is significantly higher in riskier programs. Our empirical model indicates that the optimal goal in a risky program is about  $3\frac{1}{2}$  times more ambitious than in a program with certain returns, and that optimal investment is more than 12 times higher. For R&D programs that reduce the emissions-output ratio, our results show that, qualitatively, investment is higher in less-risky programs under most uncertain damage scenarios. Our empirical model shows, however, that the risk-profile of these R&D programs generally has very little quantitative impact on optimal investment. The only exception is that when the probability of full abatement is very high, investment is about twice as high in risky programs compared to programs with certain returns.

Investment in alternative R&D programs increases as the program gets riskier for the following reasons. Alternative energy is not widely competitive and is not likely to be after incremental

improvements, unless climate damages are very high. Therefore, incremental improvements in alternative energy are likely to have very little impact on the cost of abatement, unless climate damages are high. Therefore, the downside of investing in a risky program – that the program might fail, and society would lose out on the incremental improvements that could have been achieved by a less risky program – is limited. On the other hand, a breakthrough in alternative energy technologies would have a large impact on the economy, reducing abatement costs while leading to very high levels of abatement. Therefore, the upside of a risky program outweighs the downside, unless climate damages are very high. If damages are very high, the logic is reversed. High damages mean that alternative energy will be widely competitive, therefore incremental improvements will have a large impact, therefore the downside of a risky program is larger.

The logic is again reversed for conventional technologies, which are competitive when damages are mild or moderate, but not when damages are high. Thus, when the probability of a catastrophe is low alternative energy investments increase and conventional energy investments decrease in the riskiness of the program. When, however, the probability of a catastrophe is very high, the results may start to change.

The rest of the paper is organized as follows: In the next section we present two representations of R&D programs with their interpretations. In Section 3 we present a diagrammatic analysis of how the different R&D programs impact MAC, and thus, optimal abatement. In Section 4 we perform a simple analysis indicating when investment will tend to increase in risk. In Section 5 we present our computational model, based on the well-known DICE model, and our results. We perform sensitivity analysis over various damage scenarios, and then we perform sensitivity analysis over probability distributions over damages scenarios. We conclude in Section 6.

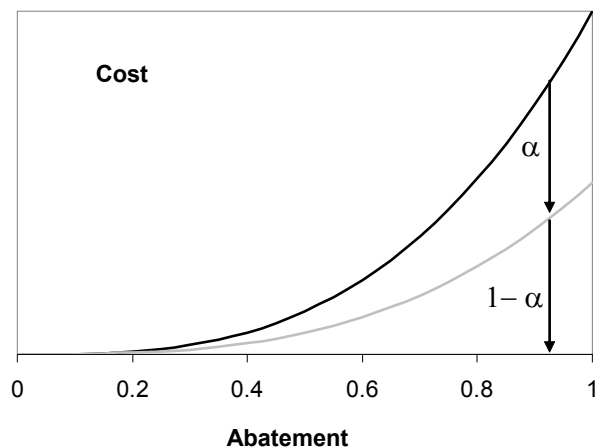


Figure 1: The impact on the cost of abatement of Alternative R&D.

## 2 Technical Change and R&D

We represent technical change as an impact on the abatement cost function, and give an interpretation about what different assumptions mean. We define abatement as a reduction in emissions below business-as-usual. In the next two Subsections, we present the description and interpretation of technical change found in Baker, Clarke, and Weyant [4]. In Subsection 2.3 we present our model of uncertainty in the outcome of R&D.

### 2.1 Alternative R&D

Figure 1 illustrates technical change that pivots the abatement cost function downward by a fixed percentage, denoted by  $\alpha$ . This representation is found in a number of papers, including Goulder and Mathai [18], Montero [30], Fisher et al. [14], and Parry [34]. The original cost of abatement is  $c(\mu)$  where  $\mu$  measures abatement in terms of the fractional emissions reduction. Let quantities

associated with the new technology be marked with a  $\tilde{\cdot}$ . The new cost function, which allows for proportionally lower costs of abatement for all abatement levels, is given by

$$\tilde{c}(\mu, \alpha) = [1 - \alpha] c(\mu) \tag{1}$$

Note that a shift of  $\alpha$  has a small absolute impact on the lower part of the cost curve, and a large impact as abatement nears 1. We argue that this program should be interpreted as primarily reducing the cost of low-carbon, alternative energy sources, such as wind, solar, or nuclear. For example, a reduction in the cost of photovoltaic cells combined with the development of low-cost hydrogen or battery technologies (to carry electricity to applications such as transportation) would reduce the cost of reaching zero emissions, but would also reduce the costs of achieving small decreases in emissions because these technologies could be cost-effectively deployed in smaller, niche markets. We will call this program ARD (for Alternative technology R&D).

## 2.2 Conventional Technology

Figure 2 illustrates technical change that decreases the emissions-output ratio by a proportional amount  $\alpha$ . This is another common representation of R&D, found in Farzin and Kort [13] as an alteration to the production function, and in Buonanno, Carraro, and Galeotti [8], Nordhaus [32], and Gerlagh and Van der Zwaan [36] as a reduction in the emission-output parameter. The new cost function is related to the original cost function through the following relationship:

$$\tilde{c}(\mu, \alpha) = c\left(\frac{\mu - \alpha}{1 - \alpha}\right) \tag{2}$$

For any given level of output and inputs, technical change reduces the emissions (by a fixed percentage) needed to achieve that output. Therefore, technical change has the largest effect on the higher-emitting portions of the abatement cost function; it has no effect on zero-carbon technologies (since they have no emissions to reduce) and therefore on the costs of moving all the way to a zero-emissions world. This technology is best interpreted as representing carbon capture and sequestration; we have shown in other work, however, that the qualitative results tend to be similar for increases in efficiency of fossil fuel technologies such as Natural Gas Combined Cycle (NGCC) electricity generation [5]. We term this program CRD (for Conventional technology R&D).

In Figure 2  $\alpha = .5$ , implying that the "After R&D" technology will capture 50% of society's carbon emissions. Thus the cost of reducing emissions by up to 50% is zero. If society wants to achieve still higher abatement it will be necessary to first substitute toward lower-carbon technologies (following the original abatement cost curve), and then use the new technology to capture half of the remaining emissions. For example, in order to achieve a reduction of 80%, society must first substitute toward lower-carbon technologies in order to reduce emissions by 60%; and then the new technology will capture half of the remaining emissions. Thus, the cost of reducing emissions by a total of 80% is equal to the before-R&D cost of reducing emissions by 60%.

The right-hand panel shows that CRD increases MAC over some regions. We see in the left-hand panel that the cost of abatement is everywhere (weakly) lower after R&D; however, the cost of full abatement remains unchanged. This is because in order to achieve full abatement society will substitute away from conventional, fossil-fuel burning technology. Thus, the slope of the cost curve is steeper after R&D over the higher range of abatement. Since conventional technology has improved, the jump from conventional to alternative energy is now greater. Thus the *marginal cost*

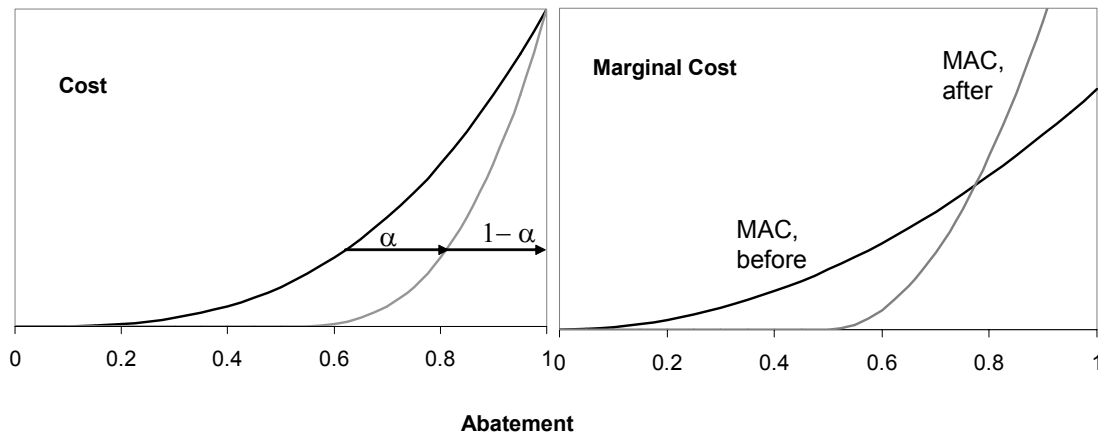


Figure 2: The impact of Conventional R&D on the cost (left-hand panel) and the marginal cost (right-hand panel) of abatement.

of abatement is greater after R&D for higher abatement (above 75% in this case). This phenomenon will exist whenever there is a ladder approach to abatement, with progressively cleaner technologies substituting for dirtier ones as abatement gets higher.<sup>4</sup> An investment into one technology on the ladder will increase the marginal cost of abatement for higher levels of abatement, since higher levels of abatement will require society to substitute away from the improved technology.

### 2.3 Representing Risky R&D

We represent the investment in R&D through a target amount of technical change,  $\bar{\alpha}$ . This represents the amount of technical change that would be achieved in a deterministic program; and the expected value of technical change achieved in a risky program. For example, investment might be aimed at reducing the cost differential between solar PVs and NGCC by 10%, on average. In a risky program, the actual cost reduction achieved may be higher or lower than 10%. We assume

<sup>4</sup>See [15] for an example of sulphur dioxide abatement.

that there is a one-to-one relationship between the amount of the investment and the target amount of technical change; and that the target amount increases as the investment increases.

We assume that an investment in R&D will result in one of three outcomes: the target amount of technical change, total failure, or a breakthrough. For purposes of exposition, we define a breakthrough as technical change which will allow for full abatement at no ongoing cost ( $\alpha = 1$ ). In fact, all but one of the analytical results remain the same for a less radical breakthrough,  $\alpha = \alpha^H < 1$ .<sup>5</sup> We do assume, however, that this breakthrough cannot be achieved in a deterministic program:  $0 \leq \bar{\alpha} < \alpha^H$ .

In the ARD program, a radical breakthrough  $\alpha = 1$  would represent major improvements in wind and solar along with batteries and electricity distribution that would allow non-carbon energy to be widely economically competitive with carbon energy. In that case, emissions will drop to zero with virtually no further investment. In the CRD program, a radical breakthrough would represent establishing carbon capture and sequestration which would allow for zero-cost<sup>6</sup> sequestration of 100% of emissions. A less radical breakthrough would allow for zero-cost sequestration of a portion of the emissions equal to  $\alpha^H$ .

The probability distribution over these three outcomes depends on the target amount of technical change, which in turn depends on investment in R&D. Given an investment of  $g(\bar{\alpha})$  the

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<sup>5</sup>See Section 4.2 for the exception. See author for analysis.

<sup>6</sup>In fact, the results are identical if we assume that there is a fixed cost for implementing the carbon capture and sequestration system.

probability distribution over the three possible outcomes is as follows:

$$\alpha = \left\{ \begin{array}{cc} \text{value} & \text{probability} \\ 0 & p[1 - \bar{\alpha}] \\ \bar{\alpha} & 1 - p \\ 1 & p\bar{\alpha} \end{array} \right\} \quad (3)$$

The parameter  $p$  determines the riskiness of the R&D program, with  $p = 0$  representing a no-risk program, and  $p = 1$  representing a high risk program. Increasing  $p$  results in a mean-preserving-spread [38] for any given  $\bar{\alpha}$ . The expected value of  $\alpha$  equals  $\bar{\alpha}$  for any  $p$ . Increasing  $\bar{\alpha}$  results in a first order stochastic shift for any given  $p$ . Note that  $p$  can be thought of as representing the proportion of a risky program in a portfolio containing both a safe and a risky program [22]. We will investigate how the riskiness of the program, represented by  $p$ , impacts the optimal level of investment in the program, represented by the optimal targeted amount of R&D  $\bar{\alpha}^*$ .

### 3 Optimal Abatement and Technical Change

Our basic framework is a two-stage, social planning model, in order to explore the socially optimal level of R&D. In the first stage, the decision maker chooses a level of investment in an R&D project in order to improve the abatement cost curve. The resulting future abatement cost curve is uncertain, depending on the success of the project. The climate damage curve is also uncertain. The second stage is at some future point in time after learning takes place, when society chooses a level of abatement that minimizes societal costs. The costs at that point are the sum of the

abatement costs and the damage costs. The objective is to minimize R&D costs together with second stage expected societal costs. Formally, the R&D decision problem can be represented as follows:

$$\min_{0 \leq \bar{\alpha} \leq 1} \left\{ g(\bar{\alpha}) + \mathbb{E}_{Z, \alpha(\bar{\alpha})} \left[ \min_{0 \leq \mu \leq 1} c(\mu; \alpha) + D(S - \mu; Z) \right] \right\} \quad (4)$$

where  $\bar{\alpha}$  is the target amount of technical change;  $g(\bar{\alpha})$  is the cost (including the opportunity cost) of implementing a program with target  $\bar{\alpha}$ ;  $\mu$  is second period abatement, measured as the fraction of emissions reduced below the business-as-usual level of emissions;  $\alpha$  is a random variable representing the realized level of technical change. Technical change impacts the abatement cost function  $c(\cdot, \cdot)$ . We assume that a breakthrough reduces the cost of abatement to zero:  $c(\mu; 1) = 0$ . The probability distribution over  $\alpha$  depends on the initial investment in R&D,  $\bar{\alpha}$ .  $S$  is the current stock of emissions in the absence of abatement;  $Z$  is the random variable that impacts damages; and  $D(\cdot)$  is the damage from global climate change. We make the standard assumptions that  $g(\cdot)$  and  $c(\cdot)$  are increasing and convex; and that  $D(\cdot)$  is increasing and convex in the stock  $s = S - \mu$ . Furthermore, we assume that both damages and marginal damages increase in  $Z$ : this assures that second stage optimal abatement is increasing in  $Z$ .

Abatement in the second stage is assumed to be optimal, and to depend on both technical success and climate damages. Formally, the optimal interior value of  $\mu^*(\alpha, Z)$  satisfies the first order condition

$$\frac{\partial c}{\partial \mu} = \frac{\partial D}{\partial s} \quad (5)$$

We may, however, have a corner point solution, where  $\mu^*(\alpha, Z) = 1$  and  $\frac{\partial c}{\partial \mu} < \frac{\partial D}{\partial s}$ . In particular,  $\mu^*(1, Z) = 1$  for all  $Z$ .

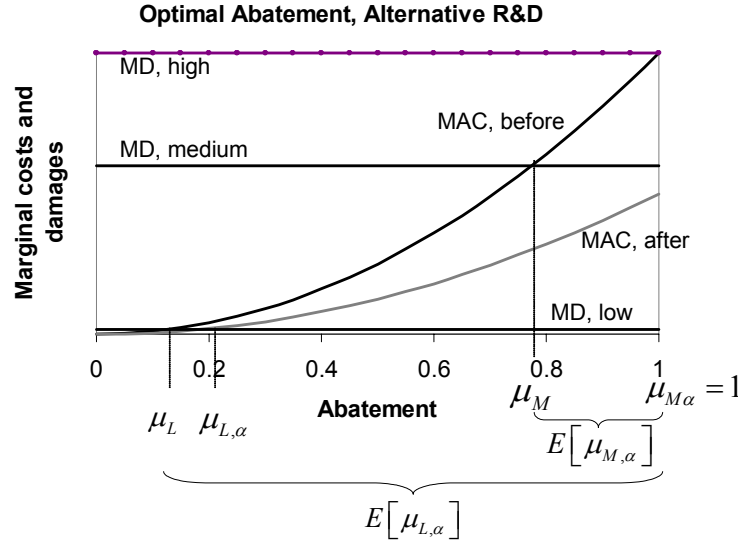


Figure 3: Marginal Cost of Abatement, before and after alternative R&D, with associated optimal abatement levels when Marginal Damages (MD) are low and medium. When MD are high, abatement is equal to 1 for all outcomes of R&D. The endpoints of the curly brackets show optimal abatement when R&D is a failure and a success; the point of the curly brackets points to expected optimal abatement when R&D is risky.

We are interested in comparative statics on the optimal level of targeted R&D,  $\bar{\alpha}^*$ . In particular, when does  $\bar{\alpha}^*$  increase in the riskiness of the R&D program? How is this relationship impacted by the riskiness in climate damages,  $Z$ ?

In this Section we present a simple diagrammatic illustration of how R&D impacts optimal abatement under each of the programs.

### 3.1 Alternative Technology

Figure 3 shows the marginal abatement cost curve (MAC) before and after technical change equal to a 50% reduction in costs, and the resulting optimal abatement. The upward sloping lines represent

the MAC before and after alternative R&D. ARD tilts the MAC downward. The three horizontal lines represent marginal damages in three different scenarios. Optimal abatement is chosen by equating marginal costs to marginal damages. When the marginal damages are greater than the marginal costs everywhere on the curve then optimal abatement is 1. Thus, if a breakthrough is achieved ( $\alpha = 1$ ), then abatement will be equal to 1 regardless of the damages. First consider low damages. This is representative of the base case damages for climate change.<sup>7</sup> We show three points related to low damages:  $\mu_L$ , optimal abatement in the absence of technical change;  $\mu_{L\alpha}$ , optimal abatement after technical change equal to  $\alpha = 0.5$ ; and  $E[\mu_{L\alpha}]$ , expected abatement when technical change is uncertain. If technical success is maximally uncertain ( $p = 1$ ), then an investment of  $\bar{\alpha} = 0.5$  will produce no technical change with probability 0.5 and will produce a breakthrough with probability 0.5, thus  $E[\mu_{L\alpha}] = 0.5 * \mu_L + 0.5 * 1$ . What we see is that the expected amount of abatement is quite a bit higher when R&D is risky than when it is certain:  $E[\mu_{L\alpha}] \gg \mu_{L\alpha}$ . This provides a rough intuition as to why investment in riskier R&D is higher when damages are low.

Now consider "medium" damages, that is a level of damage that does not induce full abatement under the original abatement cost curve, but does induce full abatement under the new cost curve. Here we see that the expected amount of abatement is less when R&D is risky than when it is certain. Again, this roughly indicates that investment in less risky R&D will be higher. Finally, consider high damages. In this case abatement is equal to 1 regardless of the outcome of technical change; expected abatement is also 1. Thus, it appears that the riskiness of the R&D would have

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<sup>7</sup>For example, Nordhaus' survey of expert opinion on climate change reports "best-guess" damages resulting from a 2.5C increase as between 1.9 and 3.6% loss of GDP [31]. A selection of integrated assessment models estimate damages between 1 and 2.5% of GDP [33] p. 70.

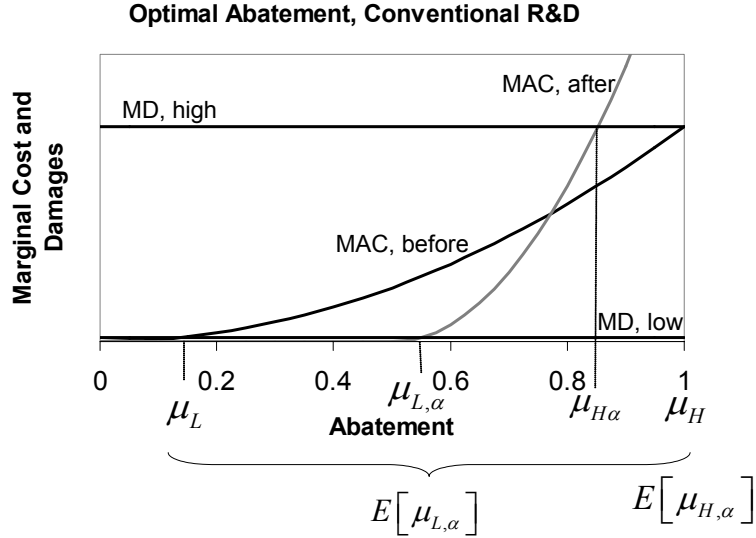


Figure 4: Marginal Cost of Abatement (MAC), before and after conventional R&D, and associated levels of optimal abatement, when Marginal Damages (MD) are low and high.

little impact.

### 3.2 Conventional R&D

Figure 4 shows the MAC before and after conventional R&D, and the resulting optimal abatement.

Again, we show optimal abatement in the absence of technical change, after technical change equal to  $\alpha = 0.5$ , and expected abatement when technical change is uncertain. When damages are low, optimal abatement is significantly higher after technical change, and expected abatement is about equal to certain abatement:  $E[\mu_{L\alpha}] \approx \mu_{L\alpha}$ . This roughly indicates that optimal R&D investment would be about the same under different risk-profiles. When damages are high, however, we see that optimal abatement decreases in R&D:  $\mu_{H\alpha} < \mu_H$ . This is a direct result of the increased MAC. Expected abatement under uncertain R&D, however, is equal to full abatement. This is

because if the technology fails, it is optimal to abate fully, and if there is a breakthrough, it is optimal to abate fully. This roughly indicates that investment will be higher in a riskier program when damages are high.

## 4 Analysis

In this section, we analytically investigate when investment into R&D increases in the riskiness of the program. Recall that an investment into R&D induces a first order stochastic shift, while an increase in riskiness implies a mean preserving spread. We start by discussing the results for given climate damages, and then briefly discuss how uncertainty in the damages impacts the results.

We re-write decision problem (4), suppressing the initial stock of emissions,  $S$ , and climate uncertainty  $Z$ , and applying the probability distribution for  $\alpha$  described in Subsection 2.3.

$$\min_{\bar{\alpha}} g(\bar{\alpha}) + p[1 - \bar{\alpha}][c(\mu^*) + D(\mu^*)] + p\bar{\alpha}D(1) + [1 - p][\tilde{c}(\mu^*; \bar{\alpha}) + D(\mu^*)] \quad (6)$$

where  $\mu^*$  represents optimal abatement in the absence of R&D and  $\mu^*(\bar{\alpha})$  represents optimal abatement given technical change equal to  $\bar{\alpha}$ . Note that the second term is the probability of failure  $p[1 - \bar{\alpha}]$  multiplied by the payoff given failure; the third term is the probability of a breakthrough  $p\bar{\alpha}$  multiplied by the payoff given a breakthrough; and the fourth term is the probability of achieving the mean technical change  $[1 - p]$  multiplied by the payoff given mean technical change. The expected payoff from an investment of  $g(\bar{\alpha})$  is a weighted average of the expected returns from risky R&D and the return from no-risk R&D. Applying the envelope theorem, the first order condition for

optimality of  $\bar{\alpha}$  is

$$g'(\bar{\alpha}) = p[c(\mu^*) + D(\mu^*) - D(1)] - [1 - p]\tilde{c}_2(\mu^*(\bar{\alpha}); \bar{\alpha}) \quad (7)$$

where the last term is referring to the partial derivative of  $\tilde{c}$  with respect to its second argument. The marginal benefits from investing in R&D are a weighted average of the marginal benefits to risky R&D (the quantity multiplied by  $p$ ) and the marginal benefits of no-risk R&D (the quantity multiplied by  $[1 - p]$ ). The marginal benefits from investing in R&D (the right-hand side of (7)), and therefore the optimal value of  $\bar{\alpha}$ , will increase in risk (as represented by  $p$ ) when

$$c(\mu^*) + D(\mu^*) - D(1) \geq -\tilde{c}_2(\mu^*(\bar{\alpha}); \bar{\alpha}) \quad (8)$$

That is, optimal investment in R&D will increase in risk when the marginal benefits to risky R&D (the left-hand side of (8)) are greater than the marginal benefits to no-risk R&D (the right hand side). So, the central question of this section is when does the inequality in (8) hold?

First, we note that the marginal returns to risky R&D (the left-hand side) is independent of the representation of R&D. This is because we have modeled a breakthrough in either program as reducing the cost of abatement to zero. Also, the marginal returns to risky R&D are constant in the targeted amount  $\bar{\alpha}$ . This is because an increase in the targeted amount simply moves probability from a failure to a breakthrough, thus the marginal returns are simply the difference in payoff between a failure and a breakthrough.

The marginal benefits to no-risk R&D are equal to the marginal cost savings due to technical

change, and thus they do depend on the representation of R&D. In the next two sections we discuss when condition (8) holds for the two representations of R&D.

#### 4.1 Alternative R&D

For the ARD representation the right-hand side simplifies to

$$-\tilde{c}_2(\mu^*(\bar{\alpha}); \bar{\alpha}) = -\frac{\partial}{\partial \bar{\alpha}} [(1 - \bar{\alpha}) c(\mu^*(\bar{\alpha}))] = c(\mu^*(\bar{\alpha})) \quad (9)$$

The marginal benefits to the no-risk program, are increasing in  $\bar{\alpha}$ . An incremental investment results in an incremental reduction in the cost of abatement. Abatement increases in R&D and cost increases in abatement. Thus, investment will increase in risk if

$$c(\mu^*) + D(\mu^*) - D(1) \geq c(\mu^*(\bar{\alpha})) \quad (10)$$

Whether this holds depends *directly* on  $\mu^*$  and  $\bar{\alpha}$ , which depend on  $Z$ , and  $g$ , the cost of producing R&D. First, when damages are very high, abatement will be full regardless of the outcome of R&D:  $\mu^* = \mu^*(\bar{\alpha}) = 1$ . This implies that the right hand side of (10) is equal to the left-hand side: the marginal benefits to R&D are independent of risk. In this case risk should have no impact on optimal investment in R&D. The benefits to the no-risk program are a certain reduction in the cost of full abatement equal to  $[1 - \bar{\alpha}]$ ; the benefits to the risky program are a full reduction in the cost of full abatement with probability  $[1 - \bar{\alpha}]$ , thus the expected reduction in cost is equal to  $[1 - \bar{\alpha}]$ .

Now, assume that damages are not so high. Specifically assume that  $\mu^* < 1$ , that abatement in

the absence of technical change is less than full. In this case, when  $\bar{\alpha} \approx 0$  then  $c(\mu^*(\bar{\alpha})) \approx c(\mu^*)$ , and the left-hand side is greater than the right-hand side. When  $\bar{\alpha}$  is high, so that  $\mu^*(\bar{\alpha}) \approx 1$ , then  $c(\mu^*(\bar{\alpha})) \approx c(1)$ . By optimality of  $\mu^*$  we know that

$$c(\mu^*) + D(\mu^*) \leq c(1) + D(1) \tag{11}$$

Therefore the left-hand side of (10) is less than the right-hand side.

This implies that when damages are low and the cost of producing R&D are high (inducing small amounts of R&D), then the marginal benefits to riskier R&D are greater than the marginal benefits to no-risk R&D. On the other hand, when damages are high and/or the cost of producing R&D is low, (inducing a relatively large amount of R&D), then marginal benefits are lower under risk than certainty. When full abatement is optimal given  $\bar{\alpha}$ , there is no environmental-side benefit to a breakthrough; there is, however, an environmental-side loss to a failure. This implies that optimal R&D investment is higher when returns are certain.

Thus we predict that when damages are very high, risk will have little impact on optimal investment; when the cost of R&D and the magnitude of the damages are such that optimal investment in the no-risk program is very high, then investment will decrease in risk; when the cost of R&D and the magnitude of damages are such that optimal investment is low, then investment will increase in risk. In particular, when damages are low and the cost of R&D is high, optimal investment will increase in risk.

## 4.2 Conventional R&D

For the CRD representation the right-hand side of (8) simplifies to

$$-\frac{\partial}{\partial \bar{\alpha}} \tilde{c}(\mu^*(\bar{\alpha}); \bar{\alpha}) = -\frac{\partial}{\partial \bar{\alpha}} \left[ c \left( \frac{\mu^*(\bar{\alpha}) - \bar{\alpha}}{1 - \bar{\alpha}} \right) \right] = c' \left( \frac{\mu^*(\bar{\alpha}) - \bar{\alpha}}{1 - \bar{\alpha}} \right) \left[ \frac{1 - \mu^*(\bar{\alpha})}{[1 - \bar{\alpha}]^2} \right] \quad (12)$$

Clearly the marginal benefits from incremental CRD are quite different from the marginal benefits from ARD. The optimal value of  $\bar{\alpha}$  will increase in risk when

$$c(\mu^*) + D(\mu^*) - D(1) \geq c' \left( \frac{\mu^*(\bar{\alpha}) - \bar{\alpha}}{1 - \bar{\alpha}} \right) \left[ \frac{1 - \mu^*(\bar{\alpha})}{[1 - \bar{\alpha}]^2} \right] \quad (13)$$

Again, start by considering the case when damages are very high and  $\mu^*(\bar{\alpha})$  approaches 1. When this happens the marginal benefits to no-risk R&D (the right-hand side of (13)) will be very close to zero. This is driven by the fact that CRD has very little impact on the cost of abatement at high levels of abatement. The left-hand side, on the other hand, approaches  $c(1) > 0$  as damages get large. Thus, for large enough damages, condition (13) will hold, and investment will increase in risk. This result holds for a less radical breakthrough,  $\alpha = \alpha^H < 1$ , under the condition that optimal abatement given the breakthrough is less than 1:  $\mu^*(\alpha^H) < 1$ .<sup>8</sup>

We can also consider the impact of  $\bar{\alpha}$ . In the appendix we show that the marginal benefits to no-risk R&D increase in  $\bar{\alpha}$ . This indicates that the lower  $\bar{\alpha}$  is when the program is certain, the more likely it is to increase with risk; and vice versa. Thus, we expect investment to increase in

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<sup>8</sup>If damages are extremely high however, so that even given a (less radical) breakthrough it is optimal to abate fully (and therefore not use the new technology), then the marginal benefits to R&D, whether risky or not, are zero, and there will be no investment in CRD in either case.

risk as the cost of R&D increases.

The intuition is that CRD has very little impact when abatement is high, because at very high levels of abatement, fossil fuel technology will not be widely employed (unless there is a breakthrough). Thus, the payoff from an incremental improvement is limited when damages are high. This is especially true when the cost of R&D is high, leading to lower levels of  $\bar{\alpha}$ . An incremental investment in the risky program, however, has a significant payoff, since it increases the probability of a breakthrough. A breakthrough in CRD has the same impact as a breakthrough in ARD – it reduces the cost of abatement to zero, thus allowing for full abatement. So, as damages get higher, we expect that it is more likely for investment to increase in risk, and for this to be exacerbated when the cost of R&D is high. Furthermore, we expect the optimal investment in the no-risk CRD program to decrease in the risk of climate damages, since CRD has little benefit when damages are very low, and little benefit when damages are very high.

### **4.3 Impact of Uncertainty in Climate Change Damages**

In this section we illustrate the difficulty in analyzing the interaction between uncertainty in damages and uncertainty in R&D. We show that even under the simplest of assumptions, we cannot provide unambiguous results. The conclusions we draw from this are that 1) computational work is essential in determining these interactions, but that 2) it is crucial to perform sensitivity analysis over multiple representations of increasing risk.

What we would like to know is how increasing risk (in the Rothschild-Stiglitz sense [38]) in climate damages impacts the difference between the marginal benefits of risky and no-risk R&D. We will focus on ARD since it is simpler and more likely to give unambiguous results. Here we

represent the expected difference between the marginal benefits to risky and no-risk R&D, when  $Z$  is uncertain:

$$E_Z [c(\mu^*(Z)) + D(\mu^*(Z), Z) - D(1, Z) - c(\mu^*(\bar{\alpha}; Z))] \quad (14)$$

If increasing risk increases this difference, then risky R&D becomes relatively more attractive as damage risk increases; if risk decreases this difference then no-risk R&D becomes relatively more attractive as damage risk increases. Recall that the expected value of a function increases in risk if it is convex and decreases in risk if it is concave. Therefore, we investigate the convexity/concavity of the quantity inside the brackets in (14) with respect to  $Z$ . In order to illustrate the difficulties, we make extreme simplifying assumptions: damages are linear in  $Z$ ; costs and damages are quadratic in  $\mu$ ; and abatement is not constrained – it is possible to abate more than 100% of emissions, and in particular, it is possible to abate the entire stock of emissions. Specifically, the second period optimization problem given  $\alpha$  is

$$\min_{\mu} (1 - \alpha) \mu^2 + Z(S - \mu)^2 \quad (15)$$

The first order conditions tell us that

$$\mu^*(\alpha, Z) = \frac{ZS}{1 - \alpha + Z} \quad (16)$$

If  $\alpha = 0$ , then  $\mu^* = \frac{ZS}{1+Z}$ . If  $\alpha = 1$  then  $\mu^* = S$ . The quantity inside the brackets in (14) is equal to

$$\left(\frac{ZS}{1+Z}\right)^2 + Z\left(S - \frac{ZS}{1+Z}\right)^2 - 0 - \left(\frac{ZS}{1-\bar{\alpha}+Z}\right)^2 \quad (17)$$

This quantity is neither concave nor convex for any value of  $\bar{\alpha} < 1$ , implying that (14) is ambiguous in risk. If we constrain  $\mu \leq 1$ , the expression simply gets more complicated. Thus, under even the simplest assumptions the effect of risk is ambiguous: some increases in risk favor risky R&D, while other increases favor no-risk R&D. Thus, we turn to a computational analysis.

## 5 An Empirical Implementation

In this section, we investigate whether the qualitative predictions from the analytical model hold up by performing sensitivity analysis over different damage scenarios, and we investigate how uncertainty in the damages impacts the choice of a risky R&D program. Subsections 5.1-5.3 describe a modified version of the well-known DICE model in which we incorporate R&D and climate uncertainty.<sup>9</sup> Subsections 5.4 and 5.5 present the results of the model.

The application here is meant to augment more detailed, but deterministic studies. Along these lines, the approach includes a number of simplifications. R&D only occurs in the near-term (there is not a continuous R&D path) and climate uncertainty resolves at precisely the same time that the benefits from R&D accrue. And, at a more fundamental level, DICE itself is a very compact model of an enormously complex system.

### 5.1 The DICE Model

DICE is a global optimal growth model extended to include interactions between economic activities and the climate. The model covers the period from 1995 to beyond 2150 in ten-year periods. In

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<sup>9</sup>These subsections draw heavily from the description of the model in Baker, Clarke, and Weyant [4].

each period, output is divided between consumption and investment in new capital, consistent with the standard optimal growth framework. DICE adds to this framework by allowing for emissions of greenhouse gasses (GHGs) into the atmosphere as part of the production process. The accumulation of these GHGs affects welfare by increasing global temperatures, which, in turn, reduce production. In order to mitigate this effect, an abatement level can be chosen each period, which reduces emissions below what would otherwise occur for a given production level. While abatement has obvious benefits, it is costly, reducing the amount of output available for consumption or investment in every period. The objective of the model is to maximize the discounted sum of utility over time, where utility is based on consumption. The optimal abatement path reflects a balance between benefits and costs.<sup>10</sup>

Below are two equations from the model that are pertinent to the changes that will be made to incorporate R&D and uncertainty. (We do not present the full DICE model here. Readers unfamiliar with the DICE framework are encouraged to consult Nordhaus and Boyer [33] for a more thorough treatment.)

$$Q_t = \frac{1}{1 + \theta_1 T_t + \theta_2 T_t^2} \left[ 1 - b_1 \mu_t^{b_2} \right] A_t K_t^\gamma L_t^{(1-\gamma)} \quad (18)$$

$$E_t = [1 - \mu_t] \sigma_t A_t K_t^\gamma L_t^{(1-\gamma)} \quad (19)$$

Equation (18) shows the output relationship in the model. Output each period,  $Q_t$ , is based

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<sup>10</sup>Note that DICE uses a standard exponential approach to discounting with a discount rate of five percent. The use of different discount rates or different functional forms for discounting the far future changes the optimal level of R&D, but does not change the qualitative characteristics of our results.

on inputs of labor,  $L$ , and capital,  $K$ , modified by a general technological change parameter  $A$ . Abatement,  $\mu$ , reduces available output through the term  $[1 - b_1\mu^{b_2}]$ , where  $b_1 = .03$  and  $b_2 = 2.15$  are parameters of the model. Hence, the cost of abatement is  $c(\mu) = b_1\mu^{b_2}$  and the MAC is very close to a straight line (since  $b_2$  is close to 2). The accumulation of GHGs impacts production through the temperature effects in the term  $\frac{1}{1+\theta_1T+\theta_2T^2}$ , where  $\theta_1$  and  $\theta_2$  are parameters of the model. Equation (19) shows the emissions relationship of the model. Absent abatement, emissions each period,  $E_t$  are based linearly on unadjusted production,  $AK_t^\gamma L_t^{(1-\gamma)}$ , through the emissions-output ratio parameter  $\sigma$ . This parameter changes over time exogenously. Abatement reduces emissions by a fraction  $\mu$ .

## 5.2 Incorporating R&D

The R&D decision is made at the beginning of the first period, in 1995, before all other actions take place. The cost of R&D is given by  $g(\bar{\alpha})$ , where  $\bar{\alpha}$  represents the mean level of technological advance, as in above sections. These costs are subtracted from the initial capital stock as follows

$$K_1 = K - g(\bar{\alpha}) \tag{20}$$

The benefits of R&D, technological advance, accrue starting in 2045. Hence,  $c_t(\mu) = c_t(\alpha, \mu)$  for  $t \geq 2045$ , and remain unchanged for  $t < 2045$ , where  $\alpha$  represents realized technical change. (Recall that DICE includes exogenously specified general technological change affecting the parameter  $A_t$  in Equation 18. This remains in the model for all  $t$ .) As we discuss below uncertainty in climate damages is also resolved after 50 years. The time lag between effort and results is intended to

capture the idea that it takes time to transition from the results of R&D to the point of widespread technology deployment.

The lack of an opportunity for additional R&D after uncertainty is resolved is an important conceptual simplification of the model. It represents the idea that by the time uncertainty is resolved, it will take too long for additional R&D to bear fruit if quick action is needed. This simplification should be kept in mind when interpreting the model results. In particular, if a second decision were available, it would most likely put downward pressure on all of the types of near-term R&D.

We explore the programs discussed in Subsections 2.1 and 2.2 individually. For the alternative technologies program, the abatement cost function is modified to  $c(\mu) = [1 - \alpha] b_1 \mu^{b_2}$  and thus equation (18) is modified after 2045 to be

$$Q_t = \frac{1}{1 + \theta_1 T_t + \theta_2 T_t^2} \left[ 1 - (1 - \alpha) b_1 \mu_t^{b_2} \right] A_t K_t^\gamma L_t^{(1-\gamma)} \quad (21)$$

For the conventional technologies program, emissions from Equation 19 are multiplied by  $[1 - \alpha]$ , thus reducing the emissions-to-output ratio,  $\sigma$ :

$$E_t = [1 - \mu_t] (1 - \alpha) \sigma_t A_t K_t^\gamma L_t^{(1-\gamma)} \quad (22)$$

This is equivalent to the representation in Subsection 2.2.

The costs of R&D are given by  $g(\bar{\alpha}) = \frac{K\bar{\alpha}^2}{1-\bar{\alpha}}$ .<sup>11</sup> Along with simplicity, this functional form has

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<sup>11</sup>A reviewer pointed out that the implied marginal cost function for R&D has a zero intercept, which may be inconsistent with the general characteristics of labor supply curves, particularly those that use specialized labor as

two desirable qualities. First, it exhibits decreasing returns to scale in R&D. Second, it ensures that a deterministic investment in R&D will not bring about zero-cost full abatement: a breakthrough can only be achieved in a risky program. The constant  $K$  determines the capital intensity of the R&D investment. For example, if we consider the alternative technologies program with  $K = 1$ , in order to reduce the gap between the cost of non-carbon technologies and currently economic technologies by 10%, an investment of \$1.1 billion will be needed. On the other hand, if  $K = 15$ , achieving a 10% decrease in the gap would cost \$15.15 billion.

The probability distribution for  $\alpha$  depends on  $\bar{\alpha}$  as described in Subsection 2.3.

### 5.3 Incorporating Uncertainty in Climate Damages

The impact of a changed climate on human welfare is a fundamental uncertainty for climate change planning, whether for R&D or emissions policy. The less deleterious the implications of increased atmospheric GHG concentrations, the lower the appropriate near-term response. But this uncertainty has not been resolved to date, and, in fact, remains a matter of much debate.

In the DICE model, the impact on human welfare is captured as a translation of temperature increases into reduced production (see Equation 18 above), with the parameters  $\theta_1$  and  $\theta_2$  determining the degree of negative impact.

Uncertainty in climate damages is captured here by considering  $\theta_2$  to be a random variable with two possible outcomes,  $\theta^L$  and  $\theta^H$ , representing low damages and high damages. We take a stochastic programming approach, setting  $\theta_2$  equal to the standard value in DICE,  $\theta_2 = 0.0035$ , until 2045. At this point, learning takes place, and the world splits off into two paths.  $\theta_2$  may take

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does R&D.

on either the low-damage or the high-damage values,  $\theta^L$  and  $\theta^H$ , where the probability distribution maintains the standard value from DICE as the mean. The model is solved using GAMS/MINOS.

The use of discrete distributions to represent uncertainty presents fundamental conceptual challenges. The method chosen to approximate a continuous distribution with a discrete distribution may have serious ramifications for results.<sup>12</sup> Of particular importance, different discrete distributions derived from the same underlying continuous distribution may have fundamentally different uncertainty characteristics—one distribution may be a mean-preserving-spread of the other, therefore exhibiting more uncertainty. Additionally, some discretization methods will involve extreme values, while others will be more centered.

We use two-point distributions to underline these issues, and model increasing uncertainty using two distinct cases: (1) an “increasing probability” case and (2) an “increasing damages” case. Tables 1 and 2 below give the key values for each case. For the “increasing probability” case,  $\theta^H$  is held constant, but its probability is increased. The value of low damages,  $\theta^L$ , is adjusted to maintain a constant mean. Four scenarios are considered: a deterministic, and three uncertain scenarios. In each of these uncertain scenarios,  $\theta^H$  is set to .042, which implies a great depression sized loss of GDP (a 20% loss) for a 2.5° C increase in temperature. The probability of high damages for this scenario,  $p = .018$ , is calibrated from the estimates from Nordhaus and Boyer (2000), which in turn are based on an expert survey from Nordhaus (1994).<sup>13</sup> The third uncertain scenario assigns a probability of 8.3 percent to  $\theta^H$ . To put this in perspective, the average probability assigned by

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<sup>12</sup>See Smith (1993) for a discussion of the performance of four discretization methods.

<sup>13</sup>A group of experts were asked to assess the probability of a great-depression sized catastrophe (damages equal to about 20 percent of GDP) given a 2.5 C degree rise in temperature. Nordhaus combined the survey responses, then updated it with new information available since 1994, to get a probability of 1.8 percent. In our framework this implies that  $\theta_2 = .042$  with probability 1.8 percent.

the scientists in the survey by Nordhaus (as opposed to the economists) was 12 percent.

For the “increasing damage” case,  $\theta^L$  is held constant, and  $\theta^H$  is increased to capture increasing uncertainty. The probability of high damages is adjusted downward to maintain a constant mean. Four scenarios are considered in this case, labeled by the value of  $\theta^H$ . The scenarios were chosen to illustrate the non-monotonic response of optimal R&D to increasing uncertainty. The highest damage scenario here, with  $\theta^H = .1$ , implies about a 38 percent loss of GDP for a 2.5° C increase in temperature.

Probability of high damage	–	1.8%	5.0%	8.3%
Value of high damage $\theta^H$	0.0035	0.042	0.042	0.042
Value of low damage $\theta^L$	0.0035	0.0028	0.0015	0

Table 1: Parameters for the Increasing Probability scenarios

Probability of high damage	–	1.8%	1.3%	0.73%
Value of high damage $\theta^H$	0.0035 (1%)	0.042 (20%)	.057 (26%)	0.1 (38%)
Value of low damage $\theta^L$	0.0035	0.0028	0.0028	0.0028

Table 2: Parameters for the Increasing Damage scenarios. The values in parentheses in the second row indicate the percentage GDP loss given a 2.5C increase in temperature.

#### 5.4 Results for different damage scenarios

Figure 5 shows the results from the empirical model. On the left hand side is the alternative program; on the right hand side is the conventional program. The horizontal axis represents the % GDP loss given a 2.5° C warming. The vertical axis shows the optimal target amount of R&D,  $\bar{\alpha}^*$ . We see that for alternative technologies investment is much higher in the risky program when damages are low. Qualitatively, this is reversed for higher damages, but quantitatively the impact of risk is insignificant when damages are higher. For conventional technologies, the overall investment

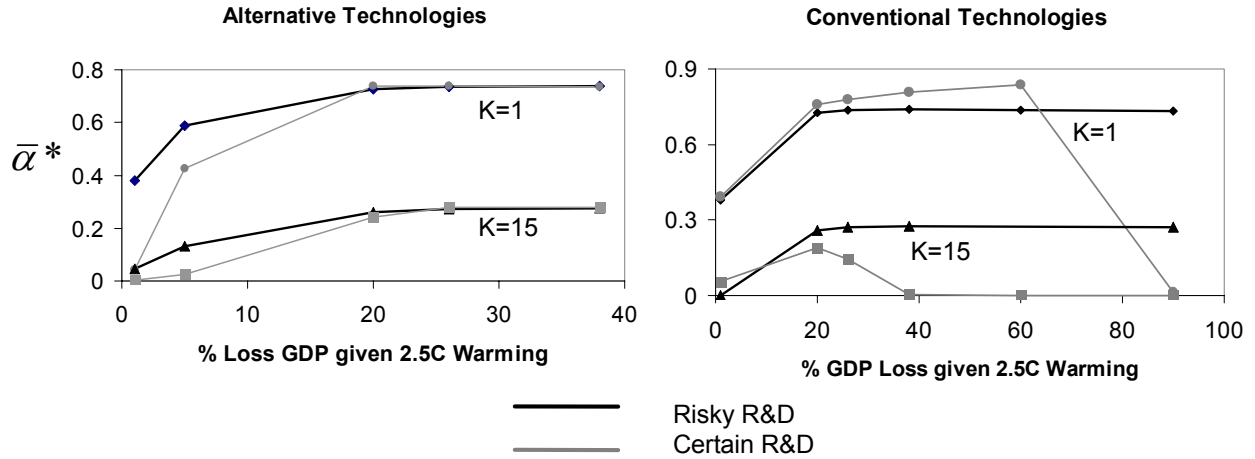


Figure 5: Optimal Investment in R&D when damages are deterministic. We represent the results for two values of the cost constant  $K$ . The two higher lines in each figure represent low-cost R&D; the lower lines represent high-cost R&D.

decreases in very large damages when the program is certain. This is because when damages are very high it is optimal for the economy to move to a no-emissions world. Unless there is a breakthrough, conventional technologies will always produce some emissions. Thus, in a certain world – a world without a breakthrough – there is no benefit to investing in conventional R&D if damages are very high. However, the level of damages at which the no-risk investment is maximized increases sharply as the cost of R&D decreases. Quantitatively, the difference between the no-risk and risky program is small, until the damages are very high, at which point investment in the risky program is significantly higher than in the no-risk program.

## 5.5 Results under uncertainty about damages

In this section we investigate the optimal investment in R&D under different probability distributions over the damages. As Lempert et al. [27] note, there is "deep" uncertainty about climate change, characterized by wide disagreement about appropriate models and the prior probability distributions of those models. One way to address this uncertainty is to determine how actions are impacted by various probability distributions. Thus, we do sensitivity analysis over the probability distributions discussed in Subsection 5.3 above. In each of the figures, a move to the right represents a mean-preserving-spread.

Figure 6 presents the results. The graphs on the left are for alternative R&D, on the right are conventional R&D; the graphs on the top represent increasing risk in term of increasing damages, on the bottom, in terms of increasing probability. The figures show the optimal target amount of R&D,  $\bar{\alpha}^*$ .

For ARD, investment is significantly higher in risky programs than in programs with certain returns, under all risk scenarios.<sup>14</sup> This is not surprising, given the results in figure 5, where we see that there is a big gap in between the two when damages are low, and very little gap when damages are high. Investments in the no-risk program begin to approach investment in the risky program only when the probability of a catastrophe gets large.

For conventional technologies, we get an almost opposite result. The risk-profile of the R&D program is unimportant, except when there is a very high probability of a catastrophe. Because, on average, damages are expected to be low, investment in the no-risk program tends to be fairly

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<sup>14</sup>When translated into dollar amounts, investment in the risky R&D program ranges from 12 to 115 times higher for  $K = 1$ ; and 30 to 2000 times higher for  $K = 15$ .

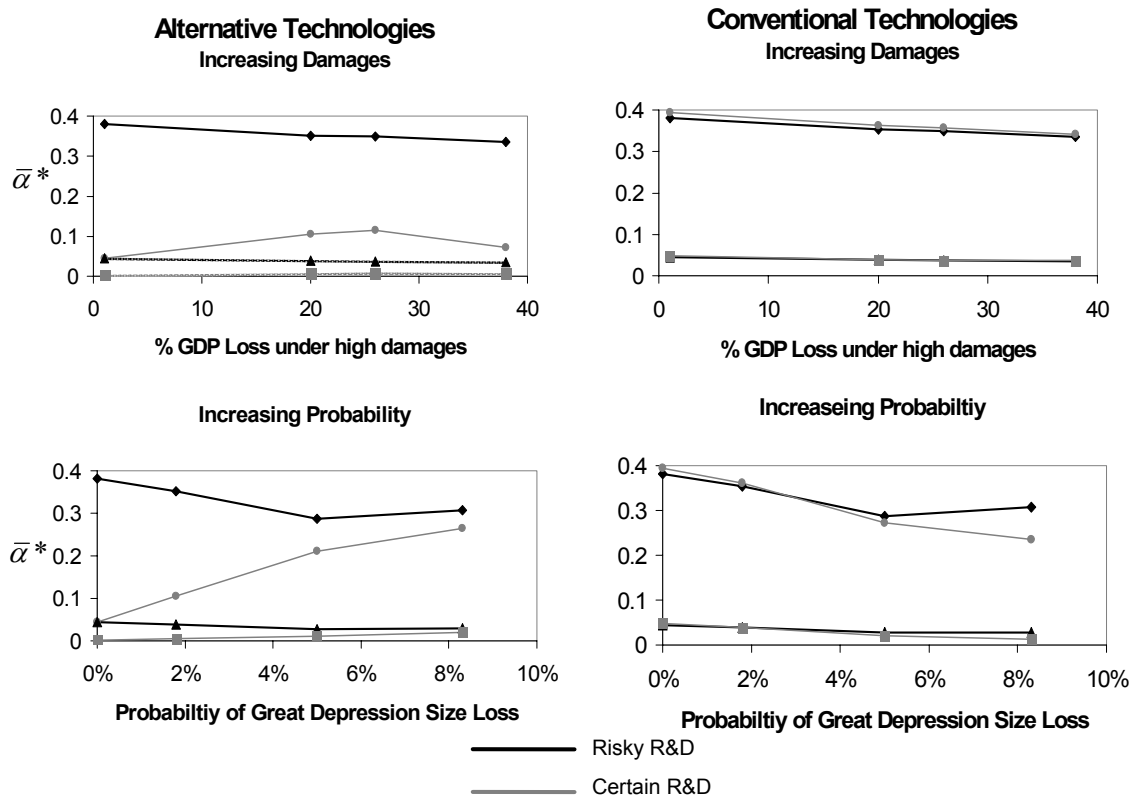


Figure 6: Optimal R&D under uncertainty about climate damages. The black lines represent R&D investment when the program is risky; the grey lines represent investment when the program is certain. The two higher lines in each graph represent investment when  $K = 1$ ; the lower lines when  $K = 15$ .

low. When  $\bar{\alpha}$  is low in the no-risk program, it has virtually no impact when damages are high; so the risky program has a higher payoff when  $\bar{\alpha}$  is low, and damages are high. When the probability of high damages gets high enough, investment in the risky program is higher than in the no-risk program.

The patterns for optimal investment as climate damage risk increases are complex. Baker, Clarke, and Weyant [4], under the assumption of certain returns to R&D, showed that optimal investment in conventional technologies tends to decrease in climate risk; and optimal investment in alternative technologies increases in the probability of full abatement; while all R&D programs tend to decrease under the increasing damages scenario. These results hold for the no-risk programs, but not for the risky programs. From these figures we can conclude that 1) increasing risk in climate damages has a smaller impact on riskier programs than on less risky programs and 2) the qualitative impact of increasing risk in climate damages can be different for risky and no-risk programs.

Finally, we note that for both ARD and CRD, the quantitative difference between the risky program and the no-risk program is large only when investment is higher in the riskier program. This combined with the fact that increasing risk in climate damages has a small impact on the optimal investment in a risky program, indicates that investing in riskier programs may be a more robust response to the deep uncertainty surrounding climate change than investing in less risky programs [21].

## 6 Conclusions

The level of investment in climate-technology R&D programs depends on how the program impacts the abatement cost curve and on the risk-profile of that program. For R&D programs that reduce costs proportionately (alternative energy programs), we have shown that optimal investment is significantly higher when the program is risky (when it has a high probability of both failure and a breakthrough) than when the returns are certain. The reason for this result is that an incremental decrease in the cost of alternative energy technologies will have a very small impact since it will not be likely to make the technology economically competitive; a breakthrough, on the other hand, will not only reduce the cost of abatement, but will have environmental-side benefits as well. One policy implication is that alternative energy R&D programs should be aimed at increasing the probability of a breakthrough. Moreover, this implies that there may be a rationale for government policy in alternative R&D programs, since the private sector is often regarded as excessively risk averse compared to what is socially optimal [10]. Finally, this result implies that investment should be significantly higher than would be shown under the assumption of certain returns.

Optimal investment into R&D programs aimed at reducing emissions in fossil fuel technologies tends to be independent of the risk profile of the program. Qualitatively, investment is lower for riskier programs, but this is not quantitatively significant. In fact, the only quantitatively significant impact is seen when the probability of full abatement is high, in which case riskier programs induce higher investment. This implies that conventional R&D programs should be aimed at increasing the expected amount of technical change: incremental improvements in fossil fuel technologies have a significant impact on the cost of abatement, so aiming for incremental improvements is optimal.

Moreover, there is less rationale for government involvement in conventional R&D programs, and deterministic studies should give a good approximation of the appropriate level of investment. However, as the probability of a catastrophe increases, investment in riskier programs increases relative to no-risk programs.

Each of the broad programs discussed in this paper are in fact made up of a multitude of individual projects. The risk profile of the overall R&D portfolio can thus be seen as a decision variable. In this light, the R&D portfolio aimed at reducing the costs of alternative technologies should optimally be tilted toward riskier projects; while the portfolio aimed at fossil fuels, such as efficiency and sequestration should be aimed at maximizing expected value, with little emphasis put on the risk of the program.

This model is a considerable simplification from real-world technology decisions. We have considered two broad categories of technical change, represented by different shifts to the abatement cost curve. We argue that they are broadly related to classes of technologies, but work needs to be done connecting the impacts of specific technical change on the marginal cost of abatement. In fact, the key conclusion of this paper is that it matters how technology is modeled, and so research must start connecting potential real-life R&D projects with their representations in models. We have not considered the history of any particular technology, nor are we commenting on the likelihood of a breakthrough in any particular technology. Rather, we suggest that work needs to be done on assessing the future potential of technologies, whether fossil or non-fossil based. Additionally, we use a simple, two-period model. Thus, this work is not commenting on the option value that is created by considering sequential investments in R&D programs. On the one hand, there is a value to waiting to learn more about climate change damages (which would put a downward pressure on

all R&D investments); on the other hand, there is a value to investing a small amount in a risky project in order to learn more about the probability of success (which would put upward pressure on risky technologies). This work is primarily considering the impact of the interaction between uncertainty in damages and uncertainty in R&D.

We are looking at the overall optimal level of R&D investment in the economy *in response to climate change*. We are not considering ancillary benefits or costs from the technical change. The DICE model includes autonomous technical change, both in growth in production, and in a decrease in the emissions-output ratio. Thus, the R&D considered here is additional to the assumed autonomous technical change. Furthermore, the rationale for government technology policy is the gap between the overall optimal investment and what is provided by the private sector. We have begun to address the question of the overall optimal investment; an investigation of private sector investment is an important area of future research. Finally, this work assumes that future decisions will be optimal, implying that a carbon policy is implemented eventually, after more information is revealed. If this is not true and future abatement is inoptimally low, that will tend to favor riskier ARD and less risky CRD; if future abatement is inoptimally high, the result is reversed.

## 7 Appendix

We show that the marginal benefits to no-risk CRD increase in  $\bar{\alpha}$ . From Subsection 4.2 the marginal benefits are:

$$MB \equiv c' \left( \frac{\mu^*(\bar{\alpha}) - \bar{\alpha}}{1 - \bar{\alpha}} \right) \left[ \frac{1 - \mu^*(\bar{\alpha})}{[1 - \bar{\alpha}]^2} \right] \quad (23)$$

The derivative of (23) with respect to  $\bar{\alpha}$  is

$$\frac{\partial MB}{\partial \mu} \frac{\partial \mu}{\partial \bar{\alpha}} + \frac{\partial MB}{\partial \bar{\alpha}} \quad (24)$$

$$\frac{\partial MB}{\partial \mu} = c'' \left( \frac{\mu - \bar{\alpha}}{1 - \bar{\alpha}} \right) \frac{1 - \mu}{[1 - \bar{\alpha}]^3} - c' \left( \frac{\mu - \bar{\alpha}}{1 - \bar{\alpha}} \right) \frac{1}{[1 - \bar{\alpha}]^2} \quad (25)$$

$$\frac{\partial \mu}{\partial \bar{\alpha}} = \frac{c'' \left( \frac{\mu - \bar{\alpha}}{1 - \bar{\alpha}} \right) \frac{1 - \mu}{[1 - \bar{\alpha}]^3} - c' \left( \frac{\mu - \bar{\alpha}}{1 - \bar{\alpha}} \right) \frac{1}{[1 - \bar{\alpha}]^2}}{SOC} \quad (26)$$

Where SOC is the second order condition for  $\mu$  to be optimal. Thus the first term in (24) is

$$\frac{\left[ c'' \left( \frac{\mu - \bar{\alpha}}{1 - \bar{\alpha}} \right) \frac{1 - \mu}{[1 - \bar{\alpha}]^3} - c' \left( \frac{\mu - \bar{\alpha}}{1 - \bar{\alpha}} \right) \frac{1}{[1 - \bar{\alpha}]^2} \right]^2}{SOC} \geq 0 \quad (27)$$

$$\frac{\partial MB}{\partial \bar{\alpha}} = c'' \left( \frac{\mu - \bar{\alpha}}{1 - \bar{\alpha}} \right) \frac{1 - \mu^2}{[1 - \bar{\alpha}]^4} + c' \left( \frac{\mu - \bar{\alpha}}{1 - \bar{\alpha}} \right) \frac{1 - \mu}{[1 - \bar{\alpha}]^3} \geq 0 \quad (28)$$

(27) and (28) imply that (23) is increasing in  $\bar{\alpha}$ .

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