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Abstract

Both climate change and technical change are uncertain. In this paper we show the importance of including both uncertainties when modeling for policy analysis. We then develop an approach for incorporating uncertainty of technical change into climate change policy analysis. We define and demonstrate a protocol for bottom-up expert assessments about prospects for technologies. We then describe a method for using such assessments to derive a probability distribution over future abatement curves, and to estimate random return functions for technological investment in different areas. Finally, we show how these analytic results could be used in a variety of energy-economic models for policy analysis.

JEL classification: D81;O32; Q54; Q55; Q58

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

1 Introduction

Much of the work investigating the relationship between environmental policy and technical change has considered deterministic technical change in response to deterministic environmental damages. Both technical change and environmental damages (especially in relation to climate change), however, are uncertain. In this paper we review some papers that indicate the importance of incorporating uncertainty in technical change and uncertainty in climate change. We then develop an approach for incorporating uncertainty in technical change into policy analysis. In particular, we address three key issues: (1) both technical change and climate change are uncertain; (2) the decision problem is dynamic; and (3) the uncertainty in technical change is endogenous.

Understanding the relationship between technical change, climate change, and policy is important on a number of different levels. First, assumptions about technical change can have major impacts on optimal near term abatement (we define abatement as a reduction in emissions below a business-as-usual reference case). For example, optimistic assumptions about technical change lead to climate change "solving itself" (Popp, 2006). If technical change is assumed to result from focussed R&D expenditure, this usually implies slightly lower abatement in the near term, since R&D expenditures and abatement expenditures are substitutes (Goulder and Mathai, 2000); if technical change is assumed to result from learning by doing, this usually implies more abatement in the near term, since this leads to more technical change (Goulder and Mathai, 2000; Grubb, 1996). Second, assumptions about technical change impact the optimal policy instrument (Montero, 2002). Third, the success (and welfare impacts) of technology policy, including direct government R&D, R&D subsidies, and technology standards, clearly depends on understanding the relationships between technical change, climate outcomes, and policy.

We argue that explicitly including uncertainty in both technical change and in climate damages is important for understanding the relationship between technical change, climate change, and policy. First, we note that there is considerable uncertainty on both fronts. Regarding climate damages, in

Nordhaus (1994a) we see that expert assessments of the probability of a catastrophe range from less than 1% to greater than 35%. Regarding technical change, it is clear that no one can predict exactly which technologies will be successful and widely adopted in the future. Second, the type of technologies used in the future will depend on both technical change and climate damages. Incremental improvements in solar energy, for example, will have only a small impact on the economy if climate change damages turn out to be mild, inducing only small amounts of abatement. These improvements, however, will have widespread impacts on the economy if climate damages turn out to be severe, thus inducing a high level of abatement. On the other hand, incremental improvements in the efficiency of coal-fired electricity generators will have a significant impact on the cost of abatement if damages are relatively small, but virtually no impact if damages are severe, since it is unlikely that coal will be efficient in that scenario. In Section 2 we discuss a number of papers that include endogenous technical change and/or uncertainty. These papers taken as a whole indicate that optimal policy is different – especially in the presence of endogenous technical change – when uncertainty is taken into account.

Incorporating endogenous uncertainty in technical change has been challenging for three reasons. First, technical change involves a finite set of idiosyncratic technologies, whose detailed features affect how they can be deployed in future scenarios. Characterization of uncertainties about a varied range of technologies require subjective judgments that have simply not yet been solicited. Second, it is generally challenging to incorporate bottom-up data into top-down models. Third, there are computational challenges to modeling endogenous technical change.

Our framework for incorporating uncertainty in technical change into climate policy models, presented in Section 3, addresses these challenges as follows. First, we present a protocol for assessing probabilistically the level of future success that will result from R&D on various technologies. Second, we focus on translating bottom-up technological detail into the impacts on the marginal abatement cost curve (MAC). In Baker et al. (2006) we illustrated that the variety of assumptions about technical change in analytical and top-down models lead to a variety of impacts on the MAC; and, furthermore, that this variety of impacts has implications for policy analysis. Focusing on the MAC has the benefit of putting a number of diverse technologies on an even footing; being easily implemented in theoretical models; and being usable for parameterization in more detailed top-down economic models. Third, we provide a method for constructing (random) functions that relate R&D expenditures to probabilistic technical success. Thus, our framework provides a method for modeling *endogenous* uncertainty. That is, the probability distribution over outcomes depends on how much is invested and in which technologies. For example, it seems reasonable that the probability of achieving a given level of technical success will be higher if more resources are invested toward that goal. There may be some probability of technical change even with no investment, but most people would put the probability considerably higher if money is spent on a goal, and most likely, the probability will increase with increased expenditures. This idea has not been widely incorporated in the climate change literature. In Section 4 we discuss how our framework provides tools to incorporate such endogenous uncertainty into a variety of models, and therefore improve the state of policy recommendations. We conclude in Section 5.

2 Uncertainty in Technical Change and Climate Damages

In this section we review papers in the climate change literature that include technical change and uncertainty. We first cover a number of papers that discuss technical change in a deterministic world; and a selection of papers that include uncertainty in climate damages but no endogenous technical change. We go on to the main focus of this section, which are papers that include both uncertainty and endogenous technical change. We divide these papers into three groups: papers with (1) climate uncertainty only; (2) technological uncertainty only; and (3) climate and technological uncertainty combined.

There is a growing body of work on endogenous technological advance in the context of climate change. This literature covers technological change that is in some way induced by policy, generally by the indirect effect on market actors, but also as a control variable. On the modeling front, this literature includes, among others, Buonanno et al. (2003), Goulder and Mathai (2000), Goulder and Schneider (1999), Manne and Richels (2004), Nordhaus (2002), Popp (2004),(2006), Schneider and Goulder (1997), Sue Wing (2003), and van der Zwaan et al. (2002). On an empirical front, this literature includes Newell (1997), and Newell et al. (1999). For surveys of the literature see Clarke and Weyant (2002), Jaffe, et al. (2001), Gillingham et al. (2006), Grubb et al. (2002), Loschel (2004), and Clarke et al. (2006a, 2006b).

There is a large body of research that considers the impacts of uncertainty and learning on optimal near-term abatement levels (See for example Baker, 2005a ; Gollier, 2000; Karp and Zhang, 2006; Keller et al., 2004; Kolstad, 1996; Manne, 1996; Pizer, 1999; Ulph & Ulph, 1997; Webster, 2002).

There is a selection of papers that investigate the impact of climate uncertainty on (deterministic) technical change. Van der Zwaan and Gerlagh (2006) use sensitivity analysis to compare the relative importance of energy savings and non-fossil energy use in a model with learning by doing. They find that energy savings first increases then decreases in importance as the stringency of the carbon target increases. Bosetti and Gilotte (2005) use a modified version of the DICE model and consider two alternative technologies for abatement – one persistent and one not persistent. They find that uncertainty in climate damages makes the less persistent technology more attractive. Baker et al. (2005) show that the socially optimal investment in alternative technologies increases with some increases in risk in climate damages, while the socially optimal investment in conventional technologies decreases. Baker (2005b) builds on the analytical results in the previous paper to show that in many cases abatement and alternative R&D act as "risk-substitutes": changes in risk that induce an increase in one, induce a decrease in the other. Specifically, alternative R&D tends to decrease in a Mean-Preserving Spread (MPS) that stretches the tail of the distribution; and increase in an MPS near the mean. Farzin and

Kort (2000) consider investment in abatement technology under a random carbon tax. Their work suggests that uncertainty in the magnitude of a carbon tax is more important than uncertainty about the timing. Baker and Shittu (2005) show that firms that can flexibly substitute from carbon to non-carbon energy may increase R&D into alternative technologies when the uncertainty surrounding a carbon tax is increased; otherwise firms will tend to decrease investment into R&D in an increase in uncertainty. These papers together suggest that including uncertainty in climate damages, particularly in the magnitude of climate damages, has a significant impact in models with endogenous technical change.

There is an emerging literature considering the interplay of technology and policy when technical change is uncertain. Baudry (2000) models a (fixed) new technology arriving at a random time, conditional on a fixed investment being made, and shows that there is a value to waiting for pollution levels to rise before investing in the new program. He does not investigate how the amount of uncertainty in the timing of the new technology impacts the result. Bohringer and Rutherford (2006) use stochastic programming to analyze the optimal policy mix between emission taxes and R&D for a given cumulative emissions limit when there is an "advanced" carbon free technology that may (or may not) become available at a future date. In this model R&D deterministically reduces the cost of both the current and the advanced carbon free technologies; but it does not impact the possibility or the timing of the arrival of the advanced technology. They find that in this framework R&D is an attractive substitute to emissions taxes. The emissions tax only rises when either the advanced technology arrives OR it becomes clear that the advanced technology is never going to arrive. That is, in the absence of the advanced technology, the emissions tax is very expensive. It is only used to either spur the usage of the advanced technology once it arrives; or as a last resort as it becomes apparent that the technology will not arrive. This suggests that the optimal carbon tax in the face of uncertain technical change is lower than if technical change is either deterministically available or deterministically unavailable.

Bosetti and Drouet (2005) also apply stochastic programming, using the RICE-FEEM model to consider uncertainty in the effectiveness of knowledge creation. They consider technical change through two avenues – a decrease in the output elasticity of energy and a decrease in the carbon intensity of energy. Technical change can be achieved through both investments in R&D and through Learning-by-Doing (LBD). They model uncertainty in the effectiveness of R&D to add to the knowledge stock; and the effectiveness of increased abatement to add to the stock of knowledge from LBD. Thus, similar to Bohringer and Rutherford (2006) above, the uncertainty is independent of R&D investments. They find that R&D expenditures are higher and abatement is slightly lower when they consider stochastic technical change as compared to a model in which they just use central values to approximate the effectiveness of learning. This result is particularly strong when the objective is to minimize the cost of reaching a pre-determined emissions concentration. This group of papers suggests that policy recommendations are different when uncertainty in technical change is modeled than when it is not.

Finally, in Baker and Adu-Bonnah (2005) we have combined uncertain technical change with uncertain damages to analyze the socially optimal portfolio of technology projects. Unlike the two papers above, R&D investment in this model impacts the probability distribution over the outcome of technical change. We found that the socially optimal investment in alternative technologies is higher for riskier projects than less-risky projects, where the opposite is true for conventional technologies. However, as we consider riskier climate damages, in terms of a higher probability of a great-depression-sized catastrophe, less-risky alternative technologies, and more-risky conventional technologies become more attractive. Thus, the relationship between uncertainty in technology and uncertainty in damages is complex, and has an impact on optimal policy.

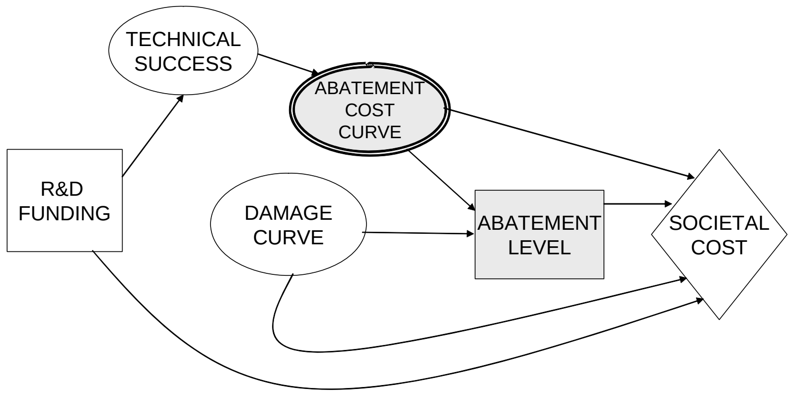

Figure 1: A two-stage model of decision making under uncertainty.

3 Framework

In this section we provide a framework for incorporating endogenous uncertainty in technical change into policy models. The framework has three key steps. The first is to gather data on potential uncertain technical change through probability assessments with experts in the appropriate field. The second step is to translate this raw, bottom-up data into impacts on the MAC. The third step involves representing this data in compact functional form so that it can be easily implemented in models and understood by policy makers. We start by describing a simple, conceptual model of dynamic decision making under uncertainty that informs the development of the framework.

3.1 Conceptual Model

The conceptual framework is a two-stage model of sequential decision making under uncertainty and learning (See the influence diagram in Figure 1). In the first stage, the decision maker selects a set of technology R&D projects in which to invest in order to improve the abatement cost curve. The resulting future abatement cost curve is uncertain, depending on the success of the various projects. The climate damage curve is also uncertain. The second stage is at some future point in time after learning takes place, when the decision maker chooses a level of abatement that minimizes second stage costs, equal to the sum of abatement costs and damage costs. The first stage objective is to minimize the sum of expected second stage costs and R&D costs.

The value of any particular technology will depend on the eventual abatement level; the abatement level depends on both the marginal cost of abatement and the marginal damages. Thus, it is crucial to understand the impact of technology on the marginal abatement cost curve (MAC). Put another way, the effect of a single technology on societal cost is not inherent in the technology alone, but instead must be understood through the technology's effect on the MAC as it interacts with the eventual damage curve.

3.2 Expert Assessments of Technical Change

R&D poses a difficult problem. The results of investments are in the future and are often highly uncertain. The projects themselves are not very repeatable. Unlike the weather or stock prices, there does not appear to be a single stochastic process that underlies all R&D programs, or all energy R&D programs, or even all solar R&D programs. Thus we must forecast the future through "subjective" means, although forecasts may be informed by past experience, e.g., learning curves or experience curves can be fitted and used to project future incremental improvements in performance (IEA, 2000). Expert judgments about probability distributions are a key ingredient to understanding technical change.

Decision Analysis (DA) techniques are often used to quantify uncertainties in the form of subjective probabilities and probability distributions (Raiffa, 1968), and these techniques have been extensively validated (Winterfeldt and Edwards, 1986). These techniques involve recognizing and to the extent possible removing known psychological biases in judgment (Tversky and Kahneman, 1974), along with incorporating consistency checks and to the extent possible structuring the variables to be estimated in such a way that experts are left with cognitively simple assessment questions. Probability assessments are a main component of decision analytic practice. There have been numerous efforts, for example, to apply DA assessment techniques to characterize possible climatic conditions. Such efforts have synthesized the views of multiple experts, e.g., Nordhaus (1994a) , Morgan et al. (2001), Vaughn and Spouge (2002). Moreover, DA has been used widely in R&D portfolio management in the private sector (Clemen and Kwit, 2001; Keefer et al., 2004). Our previous work Keisler (2004) showed that R&D portfolio value can be substantially improved by improving estimates of project value.

Industry practice for R&D portfolio decision analysis has several standard steps (Sharp and Keelin, 1998). For each possible R&D project, analysts work with engineering experts to formulate a precise definition of success and then assess a subjective probability of success and an estimate of economic impact given that success is achieved. These quantities are assessed at one or more specified funding levels for each project. If a successful technology requires the resolution of a combination of several technical challenges, subjective probabilities are assessed for each of the challenges, and then overall probability of success is computed (rather than assessed directly). A separate model then calculates the value of a successful project, e.g., the profit per unit produced times the number of units produced. Finally, an efficient R&D funding frontier is identified by sorting projects in order of the ratio of their expected value to their R&D cost.

Our portfolio of technologies can be assessed in a manner similar to industry applications of decision analysis, with some unique challenges. A key complication in our problem is that climate change technology values are interdependent on each other and on the eventual realization of climate damages, so our approach must ultimately consider curves and not just scalar variables in order to "look at supply and demand interactions under uncertainty" (Marks, 2002). In analogous efforts, Whitfield and Wallsten (1989), Whitfield et al. (1996), and Winkler et al. (1995) demonstrated assessment methods for constructing stochastic response curves for health impacts resulting from lead exposure. Our assessment protocol is designed to address the four following issues.

1. Identifying which technologies to include in the portfolio for explicit assessment. We ask experts

in each of the major areas to name the technologies that are not deployed at all or not yet widely deployed, but could be deployed within 20-50 years; or technologies that are currently widely deployed but may be subject to considerable improvement.

2. Defining technical success unambiguously enough that experts can meaningfully estimate a probability of success *and* that we can determine the value of the key parameters needed to calculate the impact of the technology on the MAC. We ask experts what technical performance must be achieved before the R&D program could reasonably be considered a success, for example, a non-toxic compound must be discovered that will match current performance of a cadmium based photovoltaic materials, or a reliable wind tower platform must be built sufficiently far offshore for public acceptance while still using a variation of an existing lower-cost platform technology.

3. Defining funding scenarios where the funding is provided and expended on a national or worldwide level, rather than simply as a budget authorized by one unitary decision maker for the use of another. Our approach is to start by asking about what the current funding plans are, and then asking for a scenario (or two) which would provide a fair chance for the technology to be proven.

4. Engaging experts in a way that avoids potential psychological biases that are of special concern due to the issues being considered. For example, individual scientists will tend to self-select to work in areas they believe are promising. Furthermore, scientists face motivational biases, in particular, they commonly champion their areas in order to seek funding, or, alternatively, they might self-censor if their identities will be publicly associated with their assessments. Finally, experts may need to consider highly unlikely events, and events some distance in the future, and so it is especially important to help experts take a broad enough view that they don't over- or underweight these events. Peer review and use of multiple experts can reduce some of these biases. We preview questions with experts prior to interviews in order to alert them to potential

psychological biases and allow them to review sources in advance. During interviews we use common assessment techniques such as asking for both probability of success and probability of failure (to counter framing biases), and we use follow-up communications after interviews to further check consistency.

Ultimately, for each technology, we define a set of criteria (from which we derive parameters needed for MiniCAM to compute the impact on the abatement curve) that must be met for success and a baseline funding trajectory (and, possibly, trajectories for scaled up or scaled down funding). We then assess the probability that the funding trajectory will result in success. These assessments will ultimately be used to obtain a research productivity measure (e.g., expected impact per dollar invested). For a given relationship between cost, impact and probability, such a productivity measure is robust to minor variations in the specific definitions of funding and success. This enables us to interview one expert in depth in order to define the basis for assessment, but to efficiently solicit probabilities from multiple experts by using the same assumptions about funding and impact.

Using this process, we have piloted these assessments in three technology areas (solar power, wind power, and carbon capture and storage) and will be conducting more assessments in these and other areas. In each area so far, experts have found it relatively straightforward to identify the key dimensions and levels to define success (typically referencing their areas' technical literature). For example, in the area of post-combustion carbon capture and sequestration (CCS) for coal burning plants, success was defined as a technology which would result in *plant availability of 90%* with *derating of no more than 30%*, at *a cost of no more than \$25 per ton avoided*, and *usable on at least 50% of available coal*. We then translate these terms into the MiniCAM input parameters of *parasitic energy requirements*, and *additional capture cost* for a given *capture rate*.

It takes some effort to list the different sources and users of research funding. For CCS, we focused on U.S. funding and estimated that approximately \$15M was spent on pure research for 2006. Once this is done, it is not difficult for experts to identify reasonable trends in the current trajectory and whether these will be sufficient to cover most of the potential work in the area. For CCS, we defined a baseline scenario where government funding starts at current levels and doubles in real terms over the next ten years after which it remains level for five years and then terminates. Because most of the interesting avenues receive funding under this scenario, we didn't add another, but for a different technology (organic solar photovoltaics) current funding trends leave many efforts unfunded and we felt it was necessary to also define an increased funding scenario for comparison.

Much of our effort has gone into structuring the sequence of challenges and tasks that must be completed for each technology. With post-combustion CCS, for example, our experts said the technology would succeed if any of six promising methods (a: metal solvents, b: alternative solvents, c: cryogenics, d: stimulus, e: amine-based membranes, and f: ammonia-based membranes) under investigation would lead to the targeted levels of performance. We determined that methods a and b were strongly correlated, as were methods e and f. The actual assessment of numeric probabilities was not so difficult here, as we were able to compare target levels to current levels - it can also help to calibrate by looking at analogous advances. Given the assumed funding trajectory and the definition of success, experts estimated the probability of success with $(a \text{ or } b) = 0.70, c = 0.35, d = 0.40, (e \text{ or } f) = 0.20$. We then calculated the probability that at least one of these methods would work as $0.91 = 1 - (1 - 0.70) * (1 - 0.35) * (1 - 0.4) * (1 - 0.2)$. Our experts then confirmed that this was essentially a high-probability, incremental improvement technology. For other technologies, we structured different paths to success.

Overall, this adaptation of standard decision analytic assessment methodology provides a more rigorous and data-driven basis for broader simulation models involving this segment of the economy.

3.3 The Impact of Technical Change on the Marginal Cost of Abatement

In order to make the raw data useful in theoretical models and portfolio optimization models we must translate technology-specific information into a metric that can be compared across technologies. As shown in Baker et al. (2006), the crucial point is how technical change impacts the MAC. Our framework employs a technologically-detailed integrated assessment model (MiniCAM) to translate the raw data into impacts on the global abatement cost function.

MiniCAM is a global IAM that looks out to 2095 in 15-year timesteps. It is a partial-equilibrium model, with 14 world regions that includes detailed models of land-use and the energy sector. MiniCAM explicitly represents a range of electricity-generating technologies including various generations of nuclear power, multiple fossil generating technologies, solar and wind power, and electricity from biomass. The model is specifically designed to represent the forces that drive the availability of, and interactions between, technologies.[1]

Technology characteristics in MiniCAM are inputs to the model; the model does not include learning curves or other approaches to induced technological change. Electricity technology efficiencies and non-energy costs are specified for each model period. These technology characteristics are generally assumed to improve over time to capture technological advance.

To produce MACs for a particular set of technology assumptions, the following approach can be used. MiniCAM is run to meet a series of increasingly stringent carbon price pathways. For each of these pathways, MiniCAM produces an associated emissions level in each of its 15-year time steps. For each time step, the associated relationship between prices and abatement levels relative to a no policy case traces out an abatement cost function. Figure 2 is an example of a reference and a high technology MAC.

A number of methodological and conceptual issues must be addressed to develop these cost functions.

[1] See Brenkert et al. (2003) and Edmonds et al. (2005) for more discussion of the model.

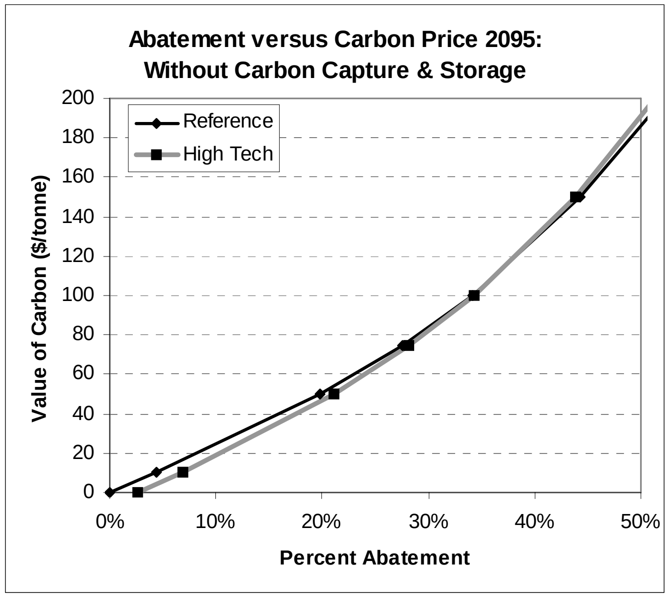

Figure 2: The marginal cost of abatement for a reference case and a high-tech case that includes higher fossil fuel efficiencies.

At a conceptual level, ability to abate in any period depends on actions that were taken in previous periods. For example, the more stringent was emissions policy in earlier periods, the lower will be the price of fossil fuels because less would have been used in previous periods. Similarly, the more stringent was emissions policy in previous periods, the greater will be the deployment of low-emitting capital, which provides abatement in the present period. Because of these conceptual issues, the abatement cost functions derived through MiniCAM are stylistic representations of marginal costs.

The interlinking of past and present raises the question of the appropriate emissions pathways to use for generating MACs in any period. The approach used for this analysis was to posit an emissions price that increases over time at the rate of interest (i.e., consistent with a Hotelling approach to resource extraction), but modified by the rate of ocean uptake. This approach is understood to be optimal in the climate context (see, for example, Peck and Wan, 1996). Another approach would be to posit a constant carbon value over time, but this approach is so inconsistent with economically optimal abatement that it was not deemed to be a meaningful alternative. Hence, the MACs generated from this exercise represent the relationship between carbon prices and abatement in a particular period given a carbon price that rises over time roughly in line with the discount rate.

3.4 Compact Representations

The step above will produce numerical before- and after- MACs. In this section we discuss ways to organize this data to make it easier to interpret and to implement in models. We start by discussing a method for parameterizing and categorizing the impacts of technical change on the MAC. We then discuss two methods for reducing the cognitive and computational requirements for analysis. The first method involves hypothesizing funding orders within each category; the second method builds on the funding orders to develop a returns-to-R&D-investment function (denoted RR function from now on) for each category. These simplifications have the benefit of making the problem computationally feasible, while at the same time providing an organization for the data which allows decision-makers to process it. Just as computers have difficulty processing 2^{30} portfolios, with over 2×10^{14} outcomes, the human mind cannot really grasp such a problem. People can, however, quickly and easily grasp a funding order. Similarly, an RR function provides a great deal of information in a way that is easy to grasp. Thus, even when the proposed two-stage decision structure is too limiting, the RR representation helps to clarify differences between portfolios.

3.4.1 Parameterize and Categorize

Here we present a simple method for representing the change in the abatement cost curve using one, or a combination of, 4 parameters – a shift down α_D, a shift right α_R, a pivot down α_{PD}, or a pivot right α_{PR}. A *shift* indicates that the entire cost curve is shifted to the right or down, and a *pivot* indicates that one end of the curve shifts down or right while the other end remains anchored. For example, assume that the original abatement cost curve can be represented as $c(\mu)$ where μ is the fraction of emissions abated

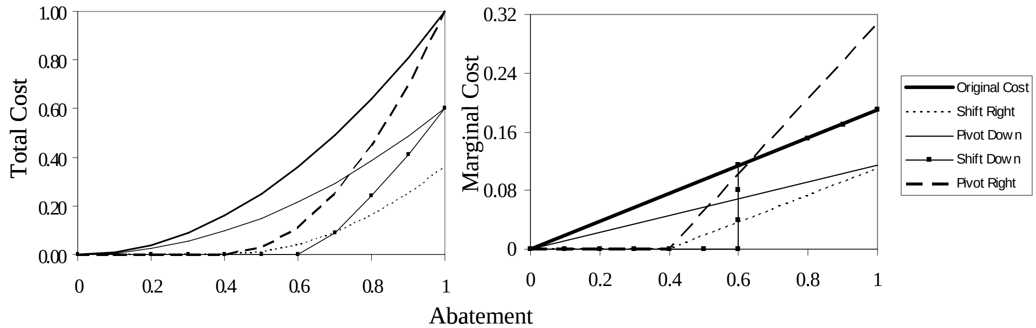

Figure 3: Potential shifts to the abatement cost curve (on the left) and the associated shifts to the marginal abatment cost curve (on the right).

below the business as usual level. Table 1 shows how each of the shifts can be represented in terms of both the cost curve and the MAC;[2] and Figure 3 illustrates each of the shifts, assuming $\alpha = 0.4$. Using numerical analysis, we can determine which parameter, or combination of parameters, best represents the observed impact on the MAC. If needed this framework can be extended to piece-wise shifts.

Type of Adjustment	Representation of Abatement Cost Curve	Representation of MAC
Shift Right	$c(\mu - \alpha_R)$	$c'(\mu - \alpha_R)$
Pivot Down	$(1 - \alpha_{PR})\, c(\mu)$	$(1 - \alpha_{PD})\, c'(\mu)$
Shift Down	$c(\mu) - \alpha_D$	$c\prime(\mu)$
Pivot Right	$c\left(\frac{\mu - \alpha_{PD}}{1 - \alpha_{PD}}\right)$	$\frac{1}{1-\alpha_{PR}} c'\left(\frac{\mu - \alpha_{PR}}{1 - \alpha_{PR}}\right)$

Table 1: Representation of shifts and pivots to the abatement cost curve and the MAC.

Technologies can then be categorized according to type of impact they have on the abatement cost curve. For example, all technologies that primarily pivot the curve to the right can be grouped together. We expect that the technologies will be grouped in intuitive ways, with, for example all the very low-carbon

[2]In each case except "pivot down" the cost of abatement is zero for $\mu \leq \alpha$.

technologies in one group and all increases in efficiency of carbon-technologies in another. Categorizing technologies in this way will allow for general insights (for example which technologies are the closest substitutes) and will allow for simplifications of the data that will allow us to implement it in models.

3.4.2 Funding Order Rule for Portfolio Selection

A funding order is a rule that assigns a rank to each technology within a cluster; technologies within that cluster are then funded in that order. We build on the funding orders described in this section to develop simple returns to R&D functions that can be used in theoretical and top-down computational models. Additionally, assigning a funding order has the benefit of greatly reducing the number of portfolios that need to be considered, thus providing a computationally feasible method for a portfolio analysis decision support tool. For example, consider 3 categories with 10 technologies per category, combined with just 2 possible climate outcomes. Without categorization we have 2^{30} fundable portfolios and over 4×10^{14} possible combinations of MACs and climate damages. Once a funding order has been established, we have only 11 possible portfolios in each category: the null portfolio, a one-project portfolio, a two-project portfolio, up to a 10-project portfolio. Using this method, we have only $11^3 = 1331$ portfolios and 17 billion outcomes. It is computationally feasible to evaluate 11^3 portfolios using Monte Carlo simulation.

Since our previous work has indicated that the risk-profile of R&D programs is important (Baker and Adu-Bonnah, 2003), we focus on this aspect. Consider technology i in category j. We represent the shift of this technology as α_{ij}, the probability of success as p_{ij}, and the investment cost as I_{ij}. We define the expected return per dollar as $EV_{ij} \equiv \frac{p_{ij}\alpha_{ij}}{I_{ij}}$. The funding orders can be parameterized by a risk-profile factor γ, ranging from -1, indicating a high risk portfolio, to 1 indicating a low risk portfolio. For a given value of $\gamma \leq 0$, the projects in category j are ranked in order of the following quantity:

$$(1 + \gamma)\, EV_{ij} - \gamma \alpha_{ij} \tag{1}$$

If $\gamma > 0$:

$$(1+\gamma)\, EV_{ij} + \gamma p_{ij}$$

For example, consider the four technologies described in Table 2. For $\gamma = -1$ (high risk) they will be funded in order 3,2,4,1; that is project 3 would be funded first, project 2 second, etc. For $\gamma = 0$ (mean-value) they will be funded in order 2,1,4,3; and for $\gamma = 1$ (low risk) they will be funded in order 1,2,4,3. Using this method, different funding orders can be compared to determine which is best for that category. For example, under a low-risk damage scenario society may be better off with a riskier alternative-energy portfolio and a less-risky conventional-energy portfolio.

3.4.3 Random Returns to R&D Function

Technology	1	2	3	4
Investment Cost	1	2	3	2.5
Probability of Success	40%	20%	5%	18%
Shift, if successful	.04	.2	.65	.18

Table 2: A description of four technologies in one category.

The data and the funding orders described above are used to develop RR functions for each category and risk-profile. For each category and each risk factor we develop a random function

$$\alpha(I) = \left\{ \begin{array}{cc} \alpha_L(I) & p_L \\ \alpha_M(I) & p_M \\ \alpha_H(I) & p_H \end{array} \right\} \qquad (2)$$

where $\alpha(\cdot)$ is the shift in the abatement cost curve, I is the overall investment in the category, and p_r is the probability of function $\alpha_r(\cdot)$ attaining, $r = L, M, H$.

First, each curve is generated numerically. Given a funding order, we simulate a number of outcomes for each possible funding level. For example, consider the technologies described in Table 2, using the mean-value funding order. The possible levels of investment correspond to funding 0,1,2, 3, or 4

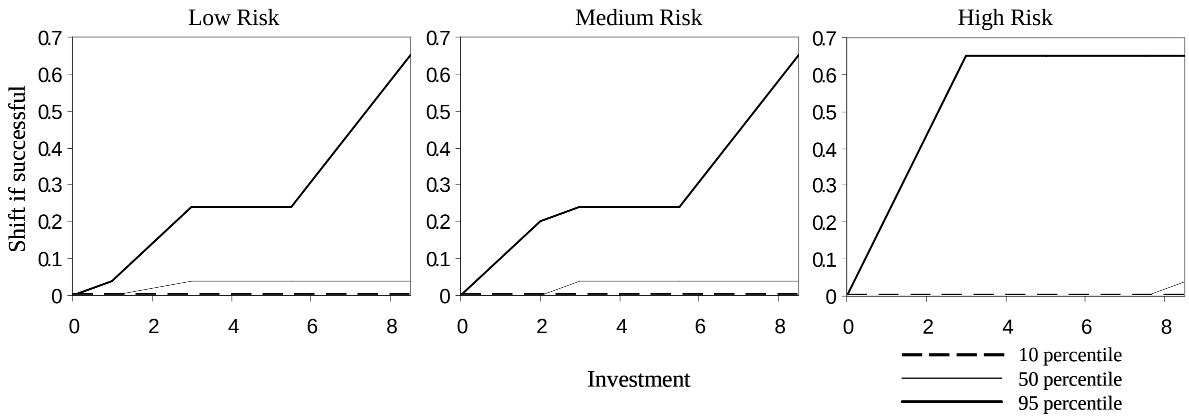

Figure 4: Random return curves showing shift in the abatement cost curve as a function of overall investment in a technology category.

technologies, and are equal to $I = 0, 2, 3, 5.5$, and 8.5 respectively. For each given investment level I, $\alpha_L(I)$ is set equal to the Lth percentile of the randomly generated values of α given an investment of I, α_M is the 50th percentile, and α_H the Hth percentile. The numerical curves have value as a visual way to compare different portfolios within the same category. Figure 4 illustrates the random return functions for low, medium, and high risk funding orders for the data in Table 2 using $L = 10$ and $H = 95$.

The numerical curves can then be approximated by functions for use in computational models. If the numerical curves appear to be of a similar family, then they may be described by one varying parameter, so that the uncertainty can be described with only one parameter. This has the benefit of reducing the outcome space considerably. Continuing the above example, there is only one random variable with 3 outcomes for each category; giving us a total of 54 possible outcomes (including the 2 possible damage outcomes). It is computationally feasible to use stochastic programming with this number of outcomes. If the curves do not appear to be of a similar family, however, then indicator random variables can be used to select the proper curve.

This approximation involves losing a considerable amount of detail. Even so, it provides a better basis for estimating random returns than the current state of the art. The simplicity of the parameterized curves will be useful for high-level analysis and provide a method for analyzing the optimal overall amount of investment into R&D (rather than using a portfolio-budget approach).

4 Applications of the Framework

The data and data structures derived from our framework will be applicable to theoretical economic models, to Integrated Assessment Models (IAMs),[3] and to portfolio analysis models. First, the raw data from the assessments in Section 3.2 can be used directly in bottom-up or technologically detailed top-down models such as MiniCAM. A common representation in top-down IAMs involves technical change impacting some parameter(s) within a CES production function (See for example Popp, 2004 and 2006; Gerlagh and van der Zwaan, 2003, 2004, and 2006 ; van der Zwaan et al., 2002; Farzin and Kort, 2000; Sue Wing, 2003; Goulder and Schneider, 1999; MacCracken et al., 1999; Manne et al., 1993; and Peck and Teisberg, 1999; Jacoby and Sue Wing, 1999; Gerlagh and van der Zwaan, 2006; Nordhaus and Boyer, 2000). The method described in McFarland et al. (2004) for translating raw, bottom-up data into impacts on capital, labor, and energy inputs can be extended to implement the raw data into these CES-based models, and the probabilities can be used for sensitivity or simple probabilistic analysis.

Second, our data structures will facilitate use of common portfolio techniques in a portable, managerially oriented decision support tool. Specifically, a two-stage decision model with simplified curves can be used to calculate expected values to identify an efficient frontier in terms of expected value versus cost; the funding order heuristic from 3.4.2 can be used to balance risk against return; and the parametric characterization of technologies' impact on the abatement curve can account for synergies

[3]These models integrate the science of climate change with the economic causes and impacts of climate change (Weyant, 1993 and 1999).

and dis-synergies. Planners at the firm level, the technology area level, or the national level can use similar models to answer questions about different facets of technology development.

Finally, the RR functions from Section 3.4.3 can inform the theoretical literature on environmental innovation, which often begins with assumptions regarding the impacts of technological advance on the cost or marginal cost of abatement (See e.g. Downing and White, 1986; Goulder and Mathai, 2000; and Fischer et al., 2003; Jung et al., 1996; Milliman and Prince, 1989; Montero, 2002; Parry, 1998). There has been only limited understanding—and virtually no formal exploration—of what kinds of technical change will lead to what kinds of changes in the abatement cost function (Baker et al., 2006). Our framework and the resulting random return functions will allow for better representation of technical change in such models, and an easy way of representing the uncertainty. For example, consider the model in Montero (2002). The cost of abatement is $C(q-e)$, where q represents the level of emissions absent abatement and e is the targeted level of emissions after abatement. An investment of K results in a new abatement cost function $kC(q-e)$ where $k = f(K)$. This technical change is equivalent to the pivot down in the table above. Thus, two benefits could be derived directly from our framework. First, the results in the Montero paper could be interpreted in terms of the actual technologies that cause the cost curve to pivot down. Second, one could examine explicitly the impacts of a random return on investment K, using the RR functions derived for the pivot down technologies. Moreover, other types of technical change could also be investigated using the base model. For example, if we wanted to explore the impacts of technical change that pivots the cost curve down, the new abatement function would be $C\left(\frac{q(1-k)-e}{q(1-k)}\right)$.

Similarly, the RR can be implemented directly in the simplest IAMs, such as DICE (Nordhaus, 1994b; and FUND, 1999), since they use an abatement cost function.

5 Conclusion

We have presented a literature review that implies that uncertainty in both the damages from climate change and in technical success impacts optimal policy. Thus, modelers need to find a way to implement both kinds of uncertainty in order to provide insights and specific policy recommendations. We go on to present a framework for incorporating uncertainty in technical change into policy analysis models. Our framework has three key steps, each of which provide different kinds of data or insights for use at different levels of policy analysis. The first step is a formal expert elicitation relating R&D investments to the probability of technical success. This raw, engineering-based data will be directly useful in more technologically detailed models. The second step is to translate the raw data into impacts on the marginal abatement cost curve. This step provides insights into how improvements in specific technologies interact with climate damages to impact abatement, and therefore the technologies likely to be in use. The third step is to translate the numerical MACs into compact representations that can be used in a variety of models. Specifically, we propose risk-based funding orders that can be used in decision analytic portfolio models; and random returns to R&D functions that can be used in models that use an abatement cost curve.

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References

Baker, E. (2005a). Uncertainty and learning in a strategic environment: Global climate change. *Resource and Energy Economics*, 27:19–40.

Baker, E. (2005b). Uncertainty and learning in climate change. *Operations Research*, Under Review.

Baker, E. and Adu-Bonnah, K. (2005). Investment in risky R&D programs in the face of climate uncertainty. *Energy Economics*, Under Review.

Baker, E., Clarke, L., and Shittu, E. (2006). Technical change and the marginal cost of abatement. *Journal of Environmental Economics and Management*, Under Review.

Baker, E., Clarke, L., and Weyant, J. (2005). Optimal technology R&D in the face of climate uncertainty. *Climatic Change*, Forthcoming.

Baker, E. and Shittu, E. (2005). Profit-maximizing R&D in response to a random carbon tax. *Resource and Energy Economics*, 28:160–180.

Baudry, M. (2000). Joint management of emission abatement and technological innovation for stock externalities. *Environmental and Resource Economics*, 16:161–183.

Bohringer, C. and Rutherford, T. F. (2006). Innovation, uncertainty and instrument choice for climate policy. Working Paper. http://rockefeller.dartmouth.edu/assets/pdf/Rutherford.pdf.

Bosetti, V. and Drouet, L. (2005). Accounting for uncertainty affecting technical change in an economic-climate model. Technical Report FEEM Working Paper 147, Fondazione Eni Enrico Mattei, Milan.

Bosetti, V. and Gilotte, L. (2005). Carbon capture and sequestration: How much does this uncertain option affect near-term policy choices. Technical Report FEEM Working Paper 86, Fondazione Eni Enrico Mattei.

Brenkert, A., Smith, S., Kim, S., and Pitcher, H. (2003). Model documentation for the MiniCAM. Technical Report PNNL-14337, Pacific Northwest National Laboratory.

Buonanno, P., Carraro, C., and Galeotti, M. (2003). Endogenous induced technical change and the costs of kyoto. *Resource and Energy Economics*, 25:11–34.

Clarke, L., Weyant, J., and Birky, A. (2006a). On the sources of technological advance: Assessing the evidence. *Energy Economics*, Forthcoming.

Clarke, L., Weyant, J., and Edmonds, J. (2006b). On the sources of technological advance: What do the models assume? *Energy Economics*, Forthcoming.

Clemen, R. and Kwit, R. (2001). The value of decision analysis at eastman kodak company, 1990-1999. *Interfaces*, 31:74–92.

Downing, P. B. and White, L. J. (1986). Innovation in pollution control. *Journal of Environmental Economics and Management*, 13:18–29.

Edmonds, J., Clarke, J., Dooley, J., Kim, S., and Smith., S. (2005). Stabilization of CO2 in a b2 world: Insights on the roles of carbon capture and storage, hydrogen, and transportation technologies. In Weyant, J. and Tol, R., editors, *Special Issue, Energy Economics*.

Farzin, Y. H. and Kort, P. (2000). Pollution abatement investment when environmental regulation is uncertain. *Journal of Public Economic Theory*, 2:183–212.

Fischer, C., Parry, I. W., and Pizer, W. A. (2003). Instrument choice for environmental protection when technological innovation is endogenous. *Journal of Environmental Economics and Management*, 45:523–545.

Gerlagh, R. and der Zwaan, B. V. (2004). A sensitivity analysis of timing and costs of greenhouse gas emission reductions. *Climatic Change*, 65:39–71.

Gerlagh, R. and der Zwaan, B. V. (2006). Options and instruments for a deep cut in CO2 emissions: Carbon capture or renewables, taxes or subsidies? *The Energy Journal*, 27(3).

Gerlagh, R. and van der Zwaan, B. (2003). Gross world product and consumption in a global warming model with endogenous technological change. *Resource and Energy Economics*, 25:35–58.

Gillingham, K., Newell, R., and Pizer, W. (2006). Modeling endogenous technological change for climate policy analysis. Draft, prepared for Resources for the Future(RFF) http://rockefeller.dartmouth.edu/assets/pdf/Gillingham.pdf.

Gollier, C., Jullien, B., and Treich, N. (2000). Scientific progress and irreversibility: An economic interpretation of the 'precautionary pricipal'. *Journal of Public Economics*, 75:229–253.

Goulder, L. and Mathai, K. (2000). Optimal CO2 abatement in the presence of induced technological change. *Journal of Environmental Economics and Management*, 39:1–38.

Goulder, L. H. and Schneider, S. H. (1999). Induced technological change and the attractiveness of CO2 abatement policies. *Resource and Energy Economics*, 21:211–253.

Grubb, M. (1996). Technologies, energy systems and the timing of CO2 emissions abatement: An overview of economic issues. *Energy Policy*, 25:159–172.

Grubb, M., Kohler, J., and Anderson, D. (2002). Induced technical change in energy and environmental modeling: Analytic approaches and policy implications. *Annual Review of Energy and the Environment*, 27:271–308.

Jacoby, H. and Wing, I. S. (1999). Adjustment time, capital malleability and policy cost. *The Energy Journal*, Special Issue: the Costs of the Kyoto Protocol:73–92.

Jung, C., Krutilla, K., and Boyd, R. (1996). Incentives for advanced pollution abatement technology at the industry level: An evaluation of policy alternatives. *Journal of Environmental Economics and Management*, 30:95–111.

Karp, L. and Zhang, J. (2006). Regulation with anticipated learning about environmental damages. *Journal of Environmental Economics and Management*, 51:259–279.

Keller, K., Bolker, B., and Bradford, D. (2004). Uncertain climate thresholds and optimal economic growth. *Journal of Environmental Economics and Management*, 48:723–741.

Loschel, A. (2004). Technological change, energy consumption, and the costs of environmental policy in energy-economy-environment modeling. *International Journal of Energy Technology and Policy*, 2(3):250–261.

MacCracken, C., Edmonds, J., Kim, S., and Sands, R. (1999). The economics of the kyoto protocal. *The Energy Journal, Special Issue: The Costs of the Kyoto Protocol: A Multi-Model Evaluation*, pages 25–69.

Manne, A. and Richels, R. (2004). The impact of learning-by-doing on the timing and cost of CO_2 abatement. *Energy Economics*, 26:603–619.

Manne, A. S. (1996). Hedging strategies for global carbon dioxide abatement: A summary of poll results - EMF 14 subgroup analysis for decisions under uncertainty. Energy Modeling Forum, Stanford University.

Manne, A. S., Mendelsohn, R., and Richels, R. G. (1993). MERGE: A model for evaluating regional and global effects of GHG reduction policies. Technical report, Electric Power Research Institute.

McFarland, J., Reilly, J., and Herzog, H. (2004). Representing energy technologies in top-down economic models using bottom-up information. *Energy Economics*, 26:685 – 707.

Milliman, S. R. and Prince, R. (1989). Firm incentives to promote technological change in pollution control. *Journal of Environmental Economics and Management*, 17:247–265.

Montero, J.-P. (2002). Permits, standard, and technology innovation. *Journal of Environmental Economics and Management*, 44:23–44.

Morgan, M. G., Pitelka, L. F., and Shevliakova, E. (2001). Elicitation of expert judgments of climate change impacts on forest ecosystems. *Climatic Change*, 49:279–307.

Newell, R. G., Jaffe, A. B., , and Stavins, R. N. (1999). The induced innovation hypothesis and energy-saving technological change. *The Quarterly Journal of Economics*, 114:941–975.

Nordhaus, W. D. (1994a). Expert opinion on climatic change. *American Scientist*, 82:45–51.

Nordhaus, W. D. (1994b). *Managing the Global Commons*. MIT Press, Boston.

Nordhaus, W. D. (2002). Modeling induced innovation in climate change policy. In Grubler, A., Nakicenovic, N., and Nordhaus, W. D., editors, *Technological Change and the Environment*, pages 182–209. RFF and IIASA, Washington D.C. and Laxenburg, Austria.

Nordhaus, W. D. and Boyer, J. (2000). *Warming the World: Economic Models of Global Warming*. MIT Press, Cambridge, MA.

Parry, I. (1998). Pollution regulation and the efficiency gains from technological innovation. *Journal of Regulatory Economics*, 14:229–254.

Peck, S. and Teisberg, T. (1999). CO2 emissions control agreements: Incentives for regional participation. *The Energy Journal, Special Issue: The Costs of the Kyoto Protocol: A Multi-Model Evaluation*, pages 367–390.

Peck, S. C. and Wan, Y. H. (1996). Analytic solutions of simple greenhouse gas emission models. In Ierland, E. V. and Gorka, K., editors, *Economics of Atmospheric Pollution*, page Chapter 6. Springer Verlag, Berlin.

Popp, D. (2004). ENTICE: Endognenous technological change in the DICE model of global warming. *Journal of Environmental Economics and Management*, 48:742–768.

Popp, D. (2006). ENTICE-BR: The effects of backstop technology R&D on climate policy models. *Energy Economics*, 28:188–222.

Sue Wing, I. (2003). Induced technical change and the cost of climate policy. Technical Report 102, MIT Joint Program on the Science and Policy of Global Change.

Tol, R. S. (1999). Kyoto, efficiency, and cost-effectiveness: Applications of FUND. *The Energy Journal, Special Issue: The Costs of the Kyoto Protocol: A Multi-Model Evaluation*, pages 131–156.

Ulph, A. and Ulph, D. (1997). Global warming, irreversibility and learning. *The Economic Journal*, 107:636–650.

van der Zwaan, B. and Gerlagh, R. (2006). Climate sensitivity uncertainty and the necessity to transform global energy supply. *Energy*, Forthcoming.

Vaughan, D. G. and Spouge, J. R. (2002). Risk estimation of collapse of the west anarctic ice sheet. *Climatic Change*, 52:65–91.

Weyant, J. P. (1993). Costs of reducing global carbon emissions. *Journal of Economic Perspectives*, 7:27–46.

Weyant, J. P. (1999). *The Costs of the Kyoto Protocol: A Multi-Model Evaluation. Special Issue of The Energy Journal.* The Energy Journal.

Whitfield, R., Biller, W., Jusko, M., and Keisler, J. (1996). A probabilistic assessment of health risks associated with short-term exposure to tropospheric ozone. Technical Report ANL-DIS-3, Argonne national laboratory.

Whitfield, R. G. and Wallsten, T. (1989). A risk assessment for selected lead-induced health effects:an example fo a general methodology. *Risk Analysis*, 9:197–208.