Climate Policy, Prudence, and the Role of Technological Innovation[1]

Carolyn Fischer, Senior Fellow, Resources for the Future, Washington, DC; Fischer@rff.org

Thomas Sterner; University Fellow RFF; Professor of Environmental Economics; University of Gothenburg; PO Box 640 40530 Gothenburg; Sweden
Thomas.sterner@economics.gu.se
Tel +46 31 7861377
Fax +46 31 7861326

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Abstract

We study how uncertainty about climate change severity affects the relative benefits of early abatement and a portfolio of research and development (R&D) in lowering future abatement costs. Optimal strategies depend on the curvature of the functions for marginal benefits and particularly for marginal abatement costs (MAC)—that is, prudence. Greater (less) convexity in MAC implies greater (less) emphasis on early abatement in response to uncertainty. R&D may change the shape of the MAC curve and the need for additional early abatement. With competing technologies, uncertainty’s influence on the optimal R&D portfolio is more complex. Whether investment in a particular technology should increase depends on whether uncertainty increases the incentives for early abatement; whether investment lowers *marginal* costs for that technology; whether R&D lowers the *slope* of that technology’s marginal cost function; and the shape of that technology’s marginal cost function. We illustrate, focusing on the role of backstop technologies.

Key Words: climate change, uncertainty, early abatement, R&D, prudence

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Climate Policy, "Prudence," and the Role of Technological Innovation

Introduction

The ultimate goal of climate policy is to stabilize greenhouse gas (GHG) concentrations at a level that is sustainable both ecologically and economically. However, the determination of this level is difficult due to the uncertainties in geophysical and ecological sciences as well as in the costs of de-carbonizing economies (e.g., Heal and Kriström 2002). Thus, the policy problem for planning long-term reductions in carbon emissions is complicated by uncertainty (see also Dietz and Stern 2008).

Two types of policy tools are important to deal with climate change. First are policies that encourage abatement directly, such as carbon taxes or tradable emissions permits, and possibly instruments to encourage non-fossil energy or conservation. Second, as heavily emphasized in the Stern Review (2006), are technology policies that focus on bringing down the costs of reducing carbon emissions. Examples include research and development (R&D) investments in new technologies for energy supply or improvements in energy efficiency. Importantly, the two types interact because the presence of abatement incentives increases the returns to R&D in reducing the cost of technologies, and the costs of the technologies determine how much abatement can be afforded. Because carbon dioxide (CO_2) is essentially a stock pollutant, policies to manage long-term concentrations have flexibility in timing. If more abatement is done early, then less will have to be done in the future to reach any given target. R&D investment lowers the costs of reducing emissions in the future. There is currently considerable disagreement about how much the global community should spend on early abatement versus

R&D for future technologies. The Kyoto protocol emphasizes abatement while some other initiatives, such as the U.S.-sponsored Asia-Pacific partnership, put more emphasis on R&D.

When the future target is uncertain, both activities facilitate the adoption of more ambitious targets and thus help reduce the expected costs of future abatement, adaptation, and damages; furthermore, certain kinds of R&D may also help to reduce the degree of uncertainty in these costs. In this paper, we explore the effects of climate and emissions target uncertainties on an optimal portfolio of R&D and emissions reduction strategies. We consider R&D trade-offs among different types of technologies, as well as trade-offs between the research program and current abatement.

Many studies have addressed the interaction between optimal innovation and abatement strategies when policy targets are certain. Some address the effect of induced technical change (ITC) on the timing of abatement (Wigley et al. 1996; Goulder and Schneider 1999; Goulder and Mathai 2000) or on the costs of attaining a climate target, including the opportunity costs of R&D (e.g., Goulder and Schneider 1999; Popp 2004; Gerlagh 2006). We are concerned with the effect of uncertainty on these interactions.

Commentaire [CF1]: more discussion here of literature on uncertainty; include irreversibility arguments. Ulph & Ulph 1997, Kolstad 1996

Several climate modelers conduct sensitivity analysis of abatement effort, timing, and/or costs with respect to atmospheric targets. However different models produce different results. For example, van der Zwaan and Gerlagh (2006) find that the timing of emissions reduction effort in their model is nearly independent of target uncertainty. Keller et al. (2004) find that uncertainty about climate sensitivity and threshold-specific climate damages can decrease optimal abatement in the near term. On the other hand, Roughgarden and Schneider (1999) deduce that uncertainty about climate damages acts to increase optimal carbon taxes.

Several researchers have pointed to the critical role of backstop and alternative energy technologies in influencing different model outcomes and in driving technology policies for climate. Weyant and Olavson (1999) emphasize the need to recognize heterogeneity in technology options, noting that incremental changes in individual technologies do not necessarily result in incremental aggregate changes, because innovation in a less competitive technology may allow it to cross a competitive threshold, leading to rapid diffusion—and further incentives for innovation. Chakravorty et al. (1997) show that technical change in backstop technologies, not in conventional fossil fuel technologies, is the driver of changes in carbon emissions. Popp (2004) finds that adding an alternative (backstop) technology to the model generates larger welfare gains than the presence of induced technological change. A recent model comparison study by Edenhofer et al. (2006) reveals that induced technological change in combination with backstop technologies leads to dramatically lower predicted costs of reaching GHG concentration targets. Popp (2006b) identifies the incorporation of backstop technologies into climate models, particularly those of the top-down variety, with R&D-based induced technical change as a major future research need.

We use a general theoretical model to explore the interactions among uncertainty, early abatement, and R&D in a portfolio of different kinds of technologies. Our goal is to complement the diverse climate modeling literature by developing basic intuition, which will help us understand how specific choices in representing technologies and technological change influence results under uncertainty. While others have engaged in somewhat similar efforts using stylized forms of individual technologies (see e.g., Baker et al. 2006), we explicitly consider multiple technologies and employ general functional forms. We take a social planner's approach and abstract from questions of how to induce innovation, which have received much attention in the literature (Jaffe et al. 2003; Fischer et al. 2003; Fischer and Newell 2008; Carraro et al. 2003), questions of spillovers (Jaffe et al. 2005; Fischer 2008; Goulder and Schneider 1999; Popp 2006a), and how to incorporate these aspects into climate policy models (reviewed by Gillingham et al. 2008). We also abstract from uncertainty over the outcome of research (addressed in Biglaiser and Horowitz 1995; also recently reviewed in the context of climate models in Baker and Shittu, 2008), and focus instead on how target uncertainty affects the potential returns to R&D and early abatement. We also specifically address the role of backstop technologies versus conventional technologies.

Our results relate to the literature on "*prudence*" as defined by Kimball (1990), in which an agent is "prudent" if and only if the third derivative of the utility function is positive, carrying the opposite sign of the second derivative. In our framework, prudence is related to the curvature of cumulative marginal abatement costs (MAC), although that is not the only factor. We find that the effects of target uncertainty on early abatement depend in large part on the concavity or convexity of MAC, which can depend on the availability and characterization of a variety of abatement technologies, including backstops. Furthermore, R&D may change the shape of the MAC curve, and thereby the need for additional early abatement in response to uncertainty. With competing technologies, the impact of uncertainty on the optimal R&D portfolio is more complex than with a single, stylized technology. Whether investment in a particular technology should increase depends on the interaction of multiple factors: whether investment lowers *marginal* costs for that technology; whether R&D lowers the *slope* of that technology's marginal cost function; and whether the marginal cost function for that technology—as well as the cumulative MAC function—is concave or convex. We illustrate our results with a simple two-technology case and relate these results to the array of functional forms typically used in climate policy models.

General Model of Abatement Target Uncertainty

The essence of the problem can be captured by a two-period model that represents actions taken early on and actions performed in the second period when uncertainty has been resolved. Although the cost function is assumed to be certain, the damages due to emissions are uncertain. Consequently, the target amount of total abatement T is also uncertain.[2]

Abatement can be achieved by using various technological options. Let A_t^i be abatement with technology *i* at time *t*, and let K_t^i be the state of knowledge in that technology at that time. The cost of each type of abatement $c^i(.)$ in each period is a function of abatement and of the state of that technology: $c^i(A_t^i, K_t^i)$, where $c_A^i > 0, c_{AA}^i \geq 0, c_K^i < 0,$ and $c_{KK}^i > 0$. We will refrain from assuming a sign for $c_{AK}^i = c_{KA}^i$; it is commonly assumed that innovation lowers marginal costs, but it is possible that some improvements can raise costs on the margin, while lowering total costs. Investment *I* in cost-reducing technical change comes at a current cost of $f^i(I_t^i)$ for technology *i*, where $f_I^i > 0$ and $f_{II}^i \geq 0$. In our two-period model, we normalize $K_1^i = 0$ and $K_2^i = I_1^i = K^i$.

[2] CO_2 assimilates slowly from the atmosphere and for simplicity we treat it as a pure stock pollutant.

To distinguish between individual and collective abatement, let $T_t \equiv \sum_i A_t^i$ be total abatement in a given period and $T \equiv T_1 + T_2$ be the total abatement target, equal to cumulative abatement over both periods. The benefits of abatement *B*(.) are a monotonic, nondecreasing, and weakly concave function of total abatement ($B_T \geq 0, B_{TT} \leq 0$) and also a function of an uncertain parameter, ε. Abatement in the second period can also be thought of as the difference between the ultimate target and the abatement performed in the first period: $T_2 = T - T_1$. Whereas first-period abatement lowers costs in the second period by reducing the required level of effort, investment in technology lowers the cost of achieving any level of effort. Target abatement is resolved in the second period, balancing marginal costs and benefits after they are known; when damages are not perfectly elastic, the target itself will depend on both first-period emissions and second-period costs.

The planner's problem is to maximize the benefits of abatement and research, net of the costs of these activities, in expectations. Let V_2 be the net benefits in the second period, when the benefit function is known:

$$V_2(\mathbf{K}, T_1, \varepsilon) = \max_{\mathbf{A}_2} \left\{ B(T_1 + \sum_i A_2^i, \varepsilon) - \sum_i c^i(A_2^i, K^i) \right\} \quad (1)$$

Let V_1 be the expected discounted net benefits of both periods, maximized with respect to the vectors of abatement and investment for each technology:

$$V_1 = \max_{\mathbf{A}_1, \mathbf{K}} \left\{ \delta E[V_2(\mathbf{K}, T_1, \tilde{\varepsilon})] - \sum_i c^i(A_1^i, 0) - \sum_i f^i(K^i) \right\} \quad (2)$$

Starting in the second period, after information is revealed, the abatement decisions are characterized by the following complementary slackness conditions for all *i*:

$$A_2^i \geq 0, \quad c_A^i(A_2^i, K^i) \geq B_T(T, \varepsilon) \tag{3}$$

That is, for any technology being used, the marginal abatement costs equal the marginal benefits. From this set of conditions, assuming there is a unique solution at which Eq. (3) holds for all *i*, we can define second-period abatement as an implicit function of the first-period variables and the uncertain term: $A_2^i(T_1, \mathbf{K}, \varepsilon)$, and thereby $T_2(T_1, \mathbf{K}, \varepsilon)$.

In the first period, the first-order conditions for action are

$$A_1^i \geq 0, \quad c_A^i(A_1^i, 0) \geq \delta E\left[\frac{\partial V_2(\mathbf{K}, T_1, \tilde{\varepsilon})}{\partial A_1^i}\right] = \delta E[B_T(T_1 + T_2(T_1, \mathbf{K}, \tilde{\varepsilon}), \tilde{\varepsilon})] \tag{4}$$

and

$$K^i \geq 0, \quad f_K^i(K^i) \geq \delta E\left[\frac{\partial V_2(\mathbf{K}, T_1, \tilde{\varepsilon})}{\partial K^i}\right] = -\delta E[c_K^i(A_2^i(T_1, \mathbf{K}, \tilde{\varepsilon}), K^i)] \tag{5}$$

Eq. (4) states that marginal abatement costs in the first period are equalized with the discounted value of the expected marginal benefits. Note that, because the target will be optimized in the second period, the impact of early abatement on changes in the equilibrium target does not affect the choice of first-period abatement.

Eq. (5) states that, if investment in knowledge for technology *i* occurs, then the marginal abatement costs will be equalized with the marginal reduction in expected total costs, discounted to the current period. This cost reduction is positive—and therefore, the investment incentive is also positive—as long as the technology is expected to be in use with some positive probability.

We note that, by having only two stages and a resolution of uncertainty, there is no quasi-option value to delaying investment (or abatement) that might occur in a continuous-time model with ongoing uncertainty and irreversibilities. In our case, marginal costs in the first stage are merely equalized with the expected marginal benefits, and uncertainty influences those marginal benefits.

Let us express the cumulative abatement cost curve (*C*) in period *t* as the minimized costs for achieving a total amount of abatement T_t:

$$C(T_t, \mathbf{K}) \equiv \min\left[\sum_i c^i(A_t^i, K_t^i)\right], \quad \text{s.t.} \sum_i A_t^i = T_t$$

This function increases with total abatement and decreases with investments in a vector of technologies **K**. Although individual technologies might not be used, one may safely assume that some abatement will occur for positive marginal benefits. Thus, we can re-express the first-order conditions for abatement as a whole in the second and first periods, respectively, as

$$C_T(T_2, \mathbf{K}) = B_T(T_1 + T_2, \varepsilon) \tag{6}$$

which defines T_2 as an implicit function of the other variables, and

$$C_T(T_1, \mathbf{0}) = \delta E\left[B_T(T_1 + T_2, \tilde{\varepsilon})\right] = \delta E[C_T(T_2, \mathbf{K})] \tag{7}$$

In other words, the marginal costs of early abatement should be equalized with the expected marginal costs of achieving the remaining abatement target in the second period.

Portfolio Response to Uncertainty

Early Abatement

To explore the influence of greater uncertainty (in the Rothschild–Stiglitz sense of mean-preserving spreads in the distribution of potential targets) on optimal policy, one need only to return to the first-order conditions. From Eq. (7), it is clear that greater uncertainty will increase first-period abatement if, given any T_1,[3]

$$E[C_T(T_2(T_1,\mathbf{K},\tilde{\varepsilon}),\mathbf{K})] > C_T(T_2(T_1,\mathbf{K},E[\tilde{\varepsilon}]),\mathbf{K}) \qquad (8)$$

According to Jensen's inequality, this relationship holds if (and only if) the marginal abatement cost function is convex with respect to the uncertain parameter. Let Ψ denote this second derivative, assuming that the function is twice differentiable, so

$$\Psi \equiv C_{TTT}\left(T_{2,\varepsilon}\right)^2 + C_{TT}T_{2,\varepsilon\varepsilon} \qquad (9)$$

The sign of Ψ depends on (i) whether the *marginal* abatement cost function is concave or convex and (ii) whether second-period abatement is a concave or convex function of the uncertain parameter, which involves properties of both the cost and benefit functions.

From Eq. (6), given **K** and T_1, $T_{2,\varepsilon} = \dfrac{B_{T\varepsilon}}{C_{TT} - B_{TT}}$ and

$$T_{2,\varepsilon\varepsilon} = \left(B_{T\varepsilon\varepsilon} + (B_{T\varepsilon T} + B_{TT\varepsilon})T_{2,\varepsilon} - \left(C_{TTT} - B_{TTT}\right)T_{2,\varepsilon}{}^2\right) / \left(C_{TT} - B_{TT}\right).$$

From the second-order condition for abatement, $C_{TT} - B_{TT} > 0$, so the sign of $T_{2,\varepsilon\varepsilon}$ depends primarily on the third derivative of the cost function and the second-order derivatives of the marginal benefit function. Using these relationships, and noting that $B_{T\varepsilon T} = B_{TT\varepsilon}$, we can rewrite Eq. (9):

[3] We choose expected marginal costs rather than expected marginal benefits to allow a more straightforward evaluation of the case of threshold target uncertainty (i.e., perfectly inelastic marginal benefits). Otherwise, the two formulations are equivalent.

$$\Psi = \left(T_{2,\varepsilon}\right)^2 \left(\overbrace{C_{TTT}}^{(i)} \underbrace{\left(\frac{-B_{TT}}{C_{TT} - B_{TT}} \right)}_{\substack{T_{2,T_1} \\ +}} + \underbrace{C_{TT}}_{+} \left(\overbrace{\frac{B_{TTT}}{C_{TT} - B_{TT}}}^{(ii)} + \frac{\overbrace{B_{T\varepsilon\varepsilon}(C_{TT} - B_{TT}) + 2B_{TT\varepsilon}B_{T\varepsilon}}^{(iii)}}{B_{T\varepsilon}{}^2} \right) \right) \qquad (10)$$

In essence, the response of early abatement to greater uncertainty depends on the relative importance of three factors:

(i) the curvature of the MAC function (sign of C_{TTT}),

(ii) the curvature of the marginal benefits function (sign of B_{TTT} and size of B_{TT}), and

(iii) the effect of the uncertain parameter on the marginal benefits function.

To explore this relationship, let us consider some commonly used examples for the benefits function.

First, assume constant (but uncertain) marginal benefits, so that $B = (b + \varepsilon)T$. Then $B_{TT} = 0$, and all of the third derivatives of the benefit function are zero. Reducing (10) reveals $\Psi = 0$, implying that uncertainty has no effect on early abatement.

An uncertain threshold target is a case of perfectly inelastic linear marginal benefits. In this case, rather than focusing on the benefits function, we assume $T_2 = \overline{T} + \tilde{\varepsilon} - T_1$. Then $T_{2,\varepsilon} = 1$ and $T_{2,\varepsilon\varepsilon} = 0$, and from Eq. (9), $\Psi = C_{TTT}$.

The curvature of the MAC function remains a determining factor when marginal benefits are linear and decreasing, since $-B_{TT} > 0$. Furthermore, since $B_{TTT} = 0$, part (ii) of (10) is irrelevant. Part (iii) may depend on whether the source of uncertainty lies with the intercept or slope of the marginal benefits function and in the latter case, at what point the function pivots. (In the Appendix, we show that slope uncertainty *per se* does not affect early action, if the marginal benefit curve pivots around the expected target point.)

Thus, when marginal benefits are linear but not constant, the shape of the marginal cost curve plays a decisive role in determining the impact of uncertainty on the optimal policy strategy. If the overall marginal abatement cost curve is convex within the range of potential outcomes, then greater uncertainty increases early abatement because expected MAC are higher than marginal costs at the expected mean abatement. In the case of linear MAC, uncertainty has no effect on early abatement. If, however, MAC are concave, as may be the case with sufficient backstop technologies, then greater uncertainty can decrease early abatement.

Of course, if marginal benefits are nonlinear, the relationship in (10) is more complicated, and the additional terms can exacerbate or mitigate the effect of the shape of the marginal cost curve. Convex marginal benefits tend to raise early abatement, whereas concave marginal benefits tend to lower it. Indeed, if the marginal abatement cost function is linear ($C_{TTT} = 0$), the nonlinearities in the marginal benefit function are decisive.

Thus, the shapes of the marginal benefits and the cumulative marginal abatement cost curves, representing all technological options, determine whether the optimal abatement path should become steeper or flatter in response to greater uncertainty about future abatement benefits. In general, the less convex the marginal abatement costs, the lower the need to conduct additional early abatement in response to uncertainty.

These results relate to the concept of "*prudence*" as used by Kimball (1990). In Kimball's study, an agent who maximizes expected utility exhibits prudence by responding to an increase in future risk by saving more today. This behavior occurs when an increase in risk raises the marginal value of wealth, which equals the expected marginal utility of future consumption. Using Jensen's inequality, Kimball shows that an agent is "prudent" if and only if the third derivative of the utility function is positive, carrying the opposite sign of the second derivative.

In an article on risk prevention, Eeckhoudt and Gollier (2005) demonstrate that, by this technical definition, prudence tends to have a negative impact on prevention, contrary to popular intuition. Because prudence favors the accumulation of wealth to face future risks, it induces agents not to spend money ex ante on preventive actions.

In our framework, prudence is related to the concavity of the marginal abatement cost curve, although that is not the only factor. As in the Eeckhoudt and Gollier (2005) case, technical prudence runs counter to notions of prudent behavior. With a concave MAC function and technical prudence, greater risk induces less prevention in the form of early action.

An important point to make is that these studies do not consider the possibility of endogenous prudence, such as the role of R&D in shaping future marginal abatement costs. In this case, R&D can then help reduce reliance on early action to the extent that it both lowers and flattens marginal abatement costs in future periods.

Uncertainty and R&D

The cost function shape is also important for determining the optimal R&D portfolio, but in this case, what matters are the total costs of a given technology rather than the marginal abatement costs of all technologies. In addition, the response of second-period abatement to cost changes matters.

Eq. (5) demonstrates that the value of additional knowledge (and thereby the optimal R&D resources spent) for technology *i* increases with uncertainty if

$$-E[c_K^i(A_2^i(T_1,\mathbf{K},\tilde{\varepsilon}),K^i)] > -c_K^i(A_2^i(T_1,\mathbf{K},E[\tilde{\varepsilon}]),K^i) \qquad (11)$$

The expression in Eq. (11) holds if the marginal benefits to knowledge investment are convex in the uncertain parameter, or if

$$\psi^i \equiv -c^i_{KAA}(A^i_{2,\varepsilon})^2 - c^i_{KA}A^i_{2,\varepsilon\varepsilon} > 0 \tag{12}$$

Whether this relationship holds in turn depends on the signs of both c^i_{KA} and c^i_{KAA} (whether R&D lowers marginal costs and the slope of the MAC curve for technology *i*) and also the sign of $A^i_{2,\varepsilon\varepsilon}$ (whether the additional use of abatement technology *i* in period 2 is increasing or decreasing under greater uncertainty).

From Eq. (3) and (6), assuming that an interior solution exists, a particular abatement technology will be deployed until its marginal cost is equal to overall marginal costs: $c^i_A(A^i_2, K^i) = C_T(T_2(T_1, \mathbf{K}, \varepsilon), \mathbf{K})$. From this relationship, we derive the implicit function for second-period abatement with technology *i*, given **K**, where $A^i_{2,\varepsilon} = C_{TT}T_{2,\varepsilon} / c^i_{AA}$ and

$$A^i_{2,\varepsilon\varepsilon} = \frac{1}{c^i_{AA}}\left(C_{TTT}(T_{2,\varepsilon})^2 + C_{TT}T_{2,\varepsilon\varepsilon}\right) - \frac{c^i_{AAA}}{c^i_{AA}}\left(A^i_{2,\varepsilon}\right)^2.$$

Consequently, the expression in (12) can be rewritten as

$$\psi^i = \frac{-c^i_{KA}}{c^i_{AA}}\Psi - \left(c^i_{KAA} + \frac{-c^i_{KA}c^i_{AAA}}{(c^i_{AA})^2}\right)(A^i_{2,\varepsilon})^2 \tag{13}$$

Thus, whether greater uncertainty increases optimal investment in a particular technology *i* depends on four components:

i) whether investment lowers *marginal* costs for that technology (the sign of c^i_{KA},);

ii) whether uncertainty increases the incentives for early abatement (the sign of Ψ,);

iii) whether R&D lowers the *slope* of that technology's marginal cost function (the sign of c^i_{KAA}), and

iv) whether the marginal cost function for *that* technology is concave or convex (the sign of c^i_{AAA}).

First, let us consider the common case in which R&D lowers marginal, as well as total, costs of abatement for each technology ($c^i_{KA} < 0$). In this case, whenever uncertainty induces more early abatement, it also encourages additional investment in all kinds of technologies. These results would be reversed if innovation reduced costs to a greater extent at low levels of abatement, making the marginal abatement cost curve steeper. Then greater uncertainty would tend to reduce optimal R&D. Meanwhile, a parallel shift in costs could mean that the expected gains to innovation are invariant to the degree of uncertainty, as with linear supply and demand for abatement.

In general, uncertainty means a greater emphasis should be placed on those technologies which have concave marginal costs and for which R&D decreases the slope of those marginal costs, especially if those technologies are likely to be used more heavily in the event of higher-than-expected marginal damages. In other words, a premium is placed on technologies that can help flatten the overall MAC curve. On the other hand, technologies with more convex marginal costs, because they become increasingly costly, are by nature going to be more limited in their scope for application and should receive less weight in the R&D portfolio when uncertainty over climate damages looms larger.

This analysis is useful for drawing intuition, but it has certain limitations, as we have ignored two kinds of interactions. One is that the extent of abatement with one technology may affect the marginal costs of abatement with another; for example, the effectiveness of carbon capture and sequestration is lower if the power plant has already reduced emissions by changing from coal to integrated gasification combined cycle technology. The second relates to the fact that these results are derived from considering small changes around an equilibrium. For a larger range of potential outcomes, however, these relationships may not all hold, partly because of the interaction with other technologies. The cost functions for individual technologies with respect to cumulative target abatement may be discontinuous because of the inequality constraints in the first-order conditions. For example, some targets may not generate sufficient emissions prices to trigger the use of certain technologies, whereas other targets may be so high that some technologies reach their limits of capacity or cost competitiveness. As a result, the effective cost function over the target range may be rendered more concave than the underlying cost function for abatement. Greater target uncertainty can then lower the expected costs of abatement from a particular technology by decreasing the expected reliance on that technology. Such is the effect of the availability of an adjacent technology: for example, a backstop limits the maximum abatement from conventional technologies so, to the extent that it makes use of the backstop more likely, uncertainty can lower the expected value of investments in conventional methods

Nor do we directly address all issues important for R&D investments. However, we can learn about their effects from the preceding analysis. First, research success involves its own uncertainty. Our framework clearly indicates that the key question is whether uncertainty raises or lowers the expected cost savings from research, given uncertainty about what the research expenditures will produce. If uncertainty raises the expected cost savings—such as by allowing for the possibility of some extremely successful outcomes—then R&D investment should increase as a response. If uncertainty instead increases the expected cost of succeeding, then R&D investment should fall. A balanced R&D portfolio will have to weigh the relative effects of research success probabilities and potential gains across different technologies.

Knowledge accumulation may not be driven solely by R&D. Still, intuition for the case of learning by doing can be derived from the R&D results. To the extent that abatement is a learning experience, abatement activities carry a dual purpose of reducing emissions and investing in knowledge. Thus, when greater uncertainty would call for increased R&D investment, it similarly would call for increased learning by doing, which implies increasing abatement in the first period. Thus, in the learning-by-doing case, the investment parameter is a proxy for the premium to additional abatement in the first period. Which effect dominates—increasing early abatement to invest in technological change or decreasing early abatement in anticipation of technological change—may be ambiguous (Goulder and Mathai 2000).

Numerical Example with a Backstop Technology

We explore some of these issues of the shape of the MAC curve by using a simple combination of two linear technologies: a conventional technology with upward-sloping marginal costs (superscript "*a*"), and a backstop technology with constant marginal costs (superscript "*b*"). To focus on the role of the cost function, we consider simple target uncertainty.

The intuition of this simple case is useful. Consider what happens in the absence of a backstop technology: the overall MAC curve is linear ($C_{TTT} = c^a_{AAA} = 0$), so $\Psi = 0$ and uncertainty would not affect early abatement. Furthermore, reducing (13), $\psi^a = -c^a_{KAA}(A^a_{2,\varepsilon})^2$, meaning R&D only increases in response to greater uncertainty if it lowers the *slope* of the MAC function for the conventional technology (i.e., pivots the curve downward, rather than merely shifting it). We will assume R&D causes a proportional reduction in costs, which means that greater uncertainty would shift the first-period policy toward more investment and less abatement because expected marginal costs then fall.

On the other hand, if the backstop were the only technology, then greater uncertainty in the threshold would have no effect on the desired investment, because a proportional cost reduction would result in a parallel shift in the marginal abatement cost curve ($\psi^b = 0$).

However, when both technologies are available, the R&D choice is trickier because two strategies must be balanced. For the regular technologies, the backstop serves to cap marginal abatement costs so that additional reductions do nothing to reduce cost variance in high-abatement states, as long as the backstop is used. Uncertainty can then reduce conventional R&D incentives if it reduces the likelihood the conventional technology will be the marginal technology. From the perspective of the backstop technology, having conventional technologies available means the backstop will come into play only in high-cost scenarios. In this case, if greater uncertainty increases the probability of using the backstop, it raises the expected marginal benefit of R&D to lower the cost of the backstop technology.

Combining these results implies that greater uncertainty tilts the overall policy portfolio toward developing technologies that are more likely to come into play in extreme outcomes. Furthermore, the optimal portfolio tends to call for diverting some resources from improving existing technologies when greater uncertainty limits their expected applicability. Finally, R&D can reduce the need for engaging in early mitigation to the extent that it reduces the convexity of the cumulative marginal abatement cost function.

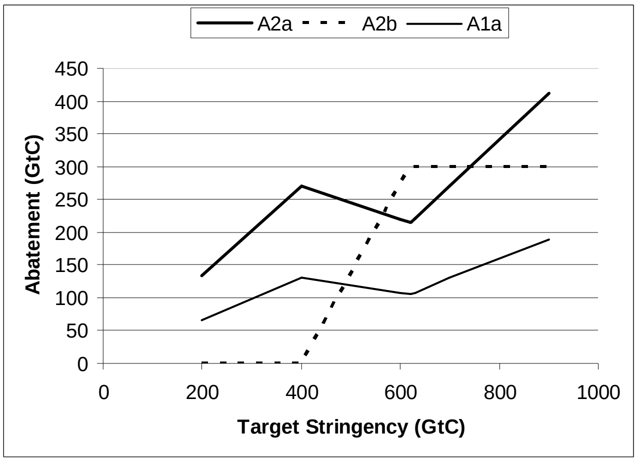
As we discuss later, most numerical climate policy models that do incorporate backstop technologies assume those technologies are not infinitely available (or substitutable), thus limiting the capacity for their replacement with conventional technologies. In our framework, when a backstop is available but has limited capacity, the marginal abatement cost curve is piecewise linear in three pieces: increasing, flat, then increasing again, The marginal cost function is concave at the first of these switch points and convex at the second. The effect of uncertainty on abatement and R&D in different technologies will depend on the interplay of all these parameters. When the backstop's applicability is limited, then there may be a range over which uncertainty increases and then decreases investment in the backstop (with the opposite effect on the conventional technology).

A study of scenarios with a range of abatement targets can give a sense of these results.

Figure 1-Figure 3 show the results from a numerical simulation of the preceding model, revealing how optimal policy responds to increasing target stringency. The parameters are described and motivated in detail in the Appendix. The IPCC finds the climate sensitivity to a doubling of carbon dioxide in the atmosphere to range from 2 to 4.5 degrees centigrade; assuming damages are mostly temperature related, this factor introduces an uncertainty of roughly +/- 50% around a stock target. Plausible projections of emissions lead to a range of cumulative abatement targets between 200 and 900 Gigatons of carbon (GtC) for this century. We assume that a backstop is initially available at US$420/ton of carbon, approximating the cost of photovoltaic power, with a capacity constraint of 300 GtC in the second period. The key point of this exercise is to highlight the role of the changing slope in the marginal abatement cost function as the backstop enters into play and then reaches its capacity limits.

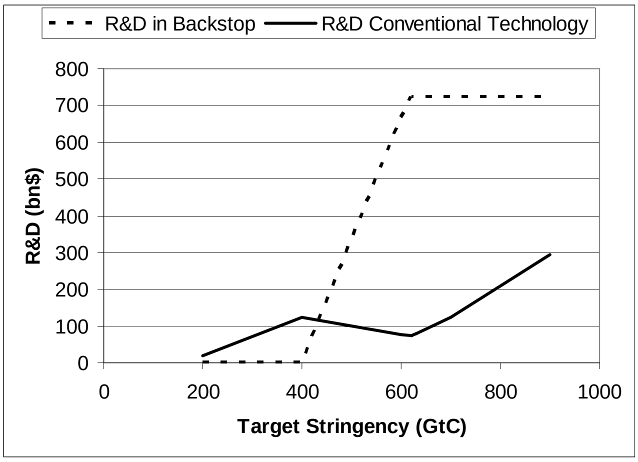
First, as the target becomes more stringent, conventional abatement in both periods increases initially and then declines as backstop use in the second period increases. This decline occurs because R&D shifts from the conventional technology to the backstop, changing the relative marginal abatement costs. However, after the backstop reaches its capacity constraint of 300 GtC, reliance on the conventional technology increases again.

Figure 1: Abatement by Type as a Function of Target Stringency



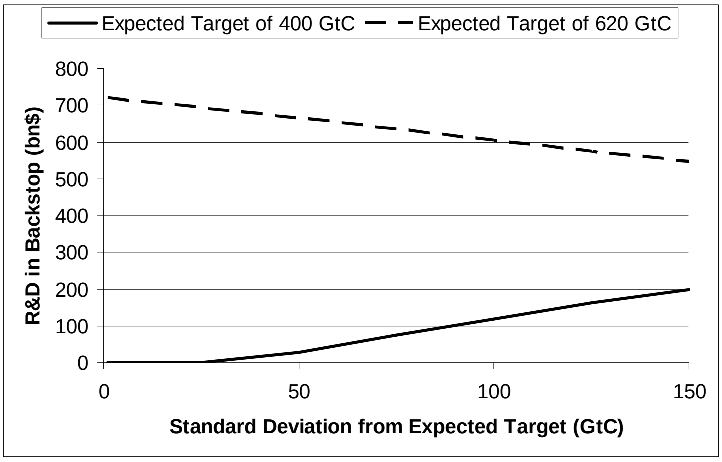
Next, Figure 2 shows that conventional R&D is crowded out as more stringent targets make R&D in the backstop technology more important. After investment in backstop R&D begins, the profitability of conventional R&D falls—until backstop capacity is reached, at which point R&D in conventional technology becomes more attractive again. The patterns for R&D in each technology are similar to those of abatement for each respective technology.

Figure 2: Investment Mix ($) with Different Climate Target Stringency (GtC)



These sensitivity analyses give indications of the effects of uncertainty, which are illustrated in Figure 3. Suppose, first, that the expected target is 400 Gt C, the cusp at which the backstop would be needed. As uncertainty broadens the range of potential targets from that point (by increasing the standard deviation of the target estimate), more scenarios incorporate the backstop, raising the expected gain from backstop R&D (see the lower, solid line in Figure 3). Meanwhile, the expected returns to conventional R&D decrease because costs are capped by the backstop and fall as low-target scenarios become more probable. However, if the simulation starts with an expected target of 620, then uncertainty has the opposite effect: increasing the spread of possible targets means lowering the expected value of the backstop (because its capacity is maxed out in more situations) and raising the expected value of lowering conventional technology costs (see the upper, dashed line in Figure 3). For an even larger range of uncertainty, the effects may be somewhat ambiguous because each cost curve has convex and concave components.

Figure 3: Effect of Target Uncertainty on Backstop R&D



Discussion: Prudence in Climate Policy Modeling

In this paper, we have focused on the effects of uncertainty about the severity of climate change on the benefits of early abatement and of R&D investment. We have shown that the effects depend on several factors, including the shape of the cumulative marginal abatement cost curve, or "prudence." When that curve is convex, an increase in benefit uncertainty implies the need for more early abatement, whereas with a concave MAC curve, uncertainty shifts the focus somewhat away from early action. We find that the extent of prudence is shaped by the characteristics of the technologies and their response to R&D; this aspect of prudence has been ignored in previous studies, in which the utility function is generally fixed. In the climate policy case, the national or societal marginal abatement cost curve represents a sequence of technological options. Backstop technologies can flatten out the curve and R&D that lowers those costs further changes the shape of the curve over the relevant range of potential abatement requirements. Prudence thus interacts with R&D, shaping the optimal portfolio of investments; those investments, in turn, shape the extent of prudence and the desirability of early action. Thus, given the vast uncertainty in the emissions targets needed for climate stability, key empirical questions for climate policy aim at revealing the true shape of the future marginal abatement cost curve and the technological options that compose it.

In climate policy modeling, however, little attention seems to have been paid to the third derivatives of the cost function. Most economic models addressing the R&D and abatement path question start with a particular functional form and derive results from it. Few economic models, if any, actually combine R&D with a diversity of technological options.

To interpret climate policy model predictions, one must understand how they incorporate carbon-free backstop technologies, determine long-run marginal abatement costs, and allow for technological change (see Edenhofer et al. 2006). The assumption of a true (nonscarce) backstop technology, producing a concave marginal abatement cost curve, is a more common approach for partial equilibrium models. In contrast, like the vast majority of the top-down climate models, general equilibrium models primarily evaluate a host of energy substitution options, including mix shifting and output substitution. However, the typical specifications using nested constant elasticity of substitution (CES) functions—even those with a carbon-free technology—necessarily imply convex marginal abatement costs. That is because the functional form assumes that some fossil energy sources are always desired, no matter how expensive they become, implying that removing carbon from the economy becomes increasingly costly.[4] In a meta-analysis of several major climate models, Fischer and Morgenstern (2006) find the marginal abatement costs (as a percentage from baseline) to be basically linear, which does imply convex marginal costs in terms of levels. However, only one of these models included a backstop technology, and the range of abatement may not have been stringent enough to evaluate significant curvature.

Indeed, few energy–economy models allow for the wholesale replacement of one technology with another. Those that do allow carbon-free technologies to enter as perfect substitutes for other energy sources employ techniques to slow their penetration, such as additional fixed factors of production or capacity growth constraints, resulting in MAC that are highly convex in the GHG concentration target.[5]

As a result of these techniques, convexity seems the dominant shape of the effective marginal abatement cost curves in most models. Furthermore, when technology-specific change is incorporated, it typically manifests itself as a percentage reduction in costs of that technology, which effectively lowers the slope of that technology's supply curve.[6] Therefore, we would expect most model results to show that target uncertainty should lead to more early action and more R&D in the relevant technologies. The question is, how accurate are the assumptions needed to close these models and allow for the reasonable computation of solutions?

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[4] In other words, if carbon-free technologies are assured a market niche even when they are more expensive, then coal and other fossil technologies also are assured a niche in the future, even when they become more expensive.

[5] Examples include the EPPA model, MERGE, and most bottom-up models.

[6] Some climate models assume technology lowers emissions intensity, or that knowledge substitutes for polluting factors in production, which can lead marginal abatement costs to rise at some point. See review by Baker and Shittu (2008).

Unfortunately, the true shape of these curves in the relevant range cannot easily be resolved by empirical studies because that range lies well outside what has historically been observed. In terms of true backstop technologies, the most-discussed candidates are carbon capture and storage (CCS), nuclear, and solar. Each have the possibility of being utilized at large scales, though location (and risk management) could be constraining factors.[7] Solar energy is particularly large in comparison to societal needs; current world energy use of commercial fuel is roughly 450 EJ/year, whereas the solar energy flow to Earth is 5.4 million EJ/year (World Energy Council 2007). Of course, a question that looms large for the more radical technologies is not just their ultimate capacities, but how rapidly these capacities can be tapped. Given the importance of backstop technologies, scientists and economists alike should pay greater attention to understanding and estimating the future costs and capacities. Climate policy modelers should heed these studies and consider how well their models are able to represent the dramatic shifts in energy technologies that some all-too-possible scenarios will require.

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[7] For example, the North Sea aquifer is capable of storing a hundred years' worth of European carbon emissions. If carbon could be stored stably in deep sea storage, the capacity would be quite large.

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Appendix

Linear Marginal Abatement Costs and Slope Uncertainty

Suppose that $B=(b+\varepsilon)T-a(T-\hat{T})^2/2$, where $\hat{T}$ is a pivot point. Then $B_T=b+\varepsilon-a(T-\hat{T})$, $B_{TT}=-a,\ B_{T\varepsilon}=1$, and $B_{TT\varepsilon}=B_{T\varepsilon T}=B_{T\varepsilon\varepsilon}=0$. Consequently, part (iii) is zero as well, and (10) reduces to $\Psi=\left(T_{2,\varepsilon}\right)^2\left(a/(C_{TT}+a)\right)C_{TTT}$, in which case the sign depends on that of C_{TTT}. Suppose, instead, that the uncertain component is the slope, not the level, of marginal benefits from abatement; in other words, $B=B_0+b(T-\hat{T})-(a+\varepsilon)(T-\hat{T})^2/2$. Then $B_T=b-(a+\varepsilon)(T-\hat{T})$, $B_{TT}=-(a+\varepsilon),\ B_{TTT}=0$, $B_{TT\varepsilon}=B_{T\varepsilon T}=-1$, $B_{T\varepsilon}=\hat{T}-T$, and $B_{T\varepsilon\varepsilon}=0$.

Consequently, evaluating at $T=\bar{T}$, $\Psi=\left(\dfrac{\hat{T}-\bar{T}}{C_{TT}-B_{TT}}\right)^2\left(C_{TTT}\left(\dfrac{a+\varepsilon}{C_{TT}+a+\varepsilon}\right)+C_{TT}\dfrac{2}{(\bar{T}-\hat{T})}\right)$. If the pivot point occurs at the expected level of total abatement (i.e., $\hat{T}=\bar{T}$), the expression reduces to zero, meaning slope uncertainty *per se* does not affect early abatement. However, if the pivot point is elsewhere, then there is effectively a combination of slope and intercept uncertainty, and the sign of part (iii) depends on the distance between that pivot point and $\bar{T}$.

Numerical Model Specifications

In this section, we present the model on which the figures and simulations in the text are based. We consider two technologies, each with linear marginal abatement costs (MAC). The conventional technology has upward sloping MAC, whereas the carbon-free backstop technology has flat MAC, but may be limited in its ultimate capacity. We consider the case of target (threshold) uncertainty, as opposed to uncertainty about some downward-sloping marginal benefits function.

The simulation model is intended to illustrate the theoretical section and is not intended as a “scenario.” The simplifications involved in modeling the future as two 50-year periods and all technologies collapsed into one conventional and one backstop make it inappropriate to strive for any precision; nevertheless, we use representative values as far as possible.

Let *a* denote the conventional technology and *b* the backstop technology. Consider the case of linear MAC that are shifted by research and development (R&D) investment:

$$c^a(A_t^a, K_t^a) = e^{-\rho_a K_t^a} \frac{c}{2}(A_t^a)^2 \qquad (\ .14)$$

In this case, R&D pivots the MAC curve downward, lowering costs of achieving any given level of abatement by ρ percent. By this assumption, R&D lowers marginal costs and flattens the conventional MAC curve, which the text notes is a determining factor in the results.

For the backstop technology, $c^b(A_t^b, K^b) = e^{-\rho_b K^b}\chi A_t^b$, with the additional constraint that the backstop has a maximum capacity $A_t^b \leq \hat{A}_t^b$. We consider cases in which the backstop is uneconomic or infeasible in the first period, so $T_1 = A_1^a$.

For R&D investment costs, we assume a simple quadratic function for technology *i*, implying linear marginal investment costs $f^i(K^i) = K^i + s_i(K^i)^2$.

For modeling simplicity, we consider the case of an uncertain target due to an uncertain catastrophic threshold $\tilde{T}$ resulting in a vertical marginal benefit curve. In the second period, uncertainty is resolved, and the total abatement target is determined by this threshold. Let *p* reflect the shadow value of carbon abatement at that threshold. That price is, in turn, determined by the equilibrium conditions at the optimum.

Substituting our functional forms into the first-order condition (Eq. 2 in the main text), we get

$$e^{-\rho K^a} c A_2^a = p, \quad A_2^a > 0 \qquad (.15)$$

and

$$\begin{aligned} &e^{-\rho K^b}\chi = p, \quad \hat{A}_2^b > A_2^b > 0 \\ &e^{-\rho K^b}\chi > p, \quad A_2^b = 0 \\ &e^{-\rho K^b}\chi < p, \quad \hat{A}_2^b = A_2^b \end{aligned} \qquad \text{(A.21)}$$

Let $A_2^* = e^{(\rho_a K_2^a - \rho_b K_2^b)}\chi / c$ be the level of abatement at which it is cheaper to switch to the backstop technology for further abatement. In this case, in the second period, we can express abatement by each technology as a function of the total target for that period, $T_2 = T - T_1$:

$$\begin{aligned} A_2^a &= \max\left[\min[T_2, A^*], T_2 - \hat{A}_2^b\right] \\ A_2^b &= \min\left[\max[0, T_2 - A^*], \hat{A}_2^b\right] \end{aligned} \qquad \text{(A.22)}$$

Then, the first-order conditions for the social planner reduce to

$$\begin{aligned} A_1^a &= \delta E\left\{e^{-\rho_a K_2^a} A_2^a\right\} \\ 1 + 2s_a K_2^a &= E\left\{\rho_a \delta e^{-\rho_a K_2^a} \frac{c}{2} (A_2^a)^2\right\} \\ 1 + 2s_a K_2^b &= E\left\{\rho_b \delta e^{-\rho_b K_2^b} \chi A_2^b\right\} \end{aligned}$$

With these five equations, and a distribution of *T*, we solve the system for $A_1^a, A_2^a, A_2^b, K_2^a, K_2^b$.

Simulation Parameters

Recognizing the limitations of this simplified model, we still attempt to parameterize it with values representative of the greenhouse gas abatement challenge.

The target value for emissions reductions, *T,* takes values between 200 and 900 gigatons carbon (GtC). Current emissions are around 7 GtC, and a linear interpolation of business-as-usual ("BAU") emissions data from Marland et al. (2003) would give close to 20 GtC/year, or 1300 GtC total emissions by 2100, which also corresponds to the median post SRES scenario of the Intergovernmental Panel on Climate Change (IPCC) fourth assessment report. Stabilization scenarios from Azar (2006) based on Wigley et al. (1996) and the IPCC indicate that, to reach targets of 550, 450, or 350 parts per million (ppm), emissions would have to stabilize, falling to 4 or almost 0 GtC/year by 2100. In our simulation, we consider two 50-year periods that together comprise this century. During this period, the total abatement necessary (compared with the BAU mentioned) is estimated by integrating under the emissions curves, which gives a total of 400, 630, and 1,000 GtC aggregate emissions reductions for 2000–2100 to meet the targets of 550, 450, and 350 ppm, respectively. Many authors focus on 550 or 450 ppm, thus the range of values analyzed for our target of 200 to 900 GtC covers the range generally discussed, such as in the Stern Review (2007).

The discount factor between the two periods was set to 50 percent ($\delta = 0.5$), corresponding to a discount rate of just under 1.5 percent per year.[8] Several other parameters were calibrated to give realistic marginal abatement cost figures, in line with those used in

[8] This is low but can be motivated by the arbitrary 100 year cutoff. It also corresponds well to the discount rate in the Stern Review where the pure rate of time preference of 0.1% combines with a unitary marginal elasticity of income and per capita growth rates to give a discount rate of 1.4%, Stern (2006)

Survey of Energy Resources (World Energy Council 2007). The cost parameters were set at c = 1.6 10^{-9} \$/ton^2 in the conventional abatement function and χ = \$420/ton C for the backstop technology, which is assumed to have a capacity constraint of 300 GtC in the second period (2050–2100). The cost parameter χ, shows the baseline abatement cost for the backstop technology in the year 2050 before the cost-saving effect of R&D. This number might appear high but the model is intended to deal with abatement that leads to the equivalent of emission reductions in the order of 80 – 100% in the year 2100. A backstop abatement cost of 420 \$/ton C corresponds to a 0.06 \$/KWh which is a common figure for photovoltaic power, see for instance Chakravorty et al (1997) or UNDP (2004). 0.06 \$/KWh corresponds to 700 \$/ton of C equivalent. The current price of oil is approximately 380 \$/ton C and hence the solar backstop would imply a price increase of 420 \$/TC). The parameter c is calibrated so as to give an illustrative mix of backstop and conventional abatement. Depending on the exact investments in R&D, the backstop becomes profitable after about 130 GtC of conventional abatement in the first period and 260 GtC of conventional abatement in the second one.

For both types of technologies, costs can be reduced by investments in R&D as described above. The parameters were calibrated to give a cost of R&D that is roughly equivalent to a range of values corresponding to between one and ten times the annual cost of R&D by member countries to the International Energy Agency (IEA) in 1980. The parameters were 0.0003 for ρ_a and 0.000306 for ρ_b ; 0.03 for s_a and 0.01 for s_b. The cost of R&D in the IEA in 1980 was 15 Billion \$ according to OECD (2006). Finally, the probability distribution for the target abatement is a normal distribution with a standard deviation of 125 GtC. The distribution is truncated to preclude negative targets and ensure a symmetric distribution.