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Boiled frogs and path dependency in climate policy decisions

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29.1 Introduction

Formulating a policy response to the threat of global climate change is one of the most complex public policy challenges of our time. At its core a classic public-good problem, mitigating anthropogenic greenhouse gas emissions is likely to be very costly to any nation that undertakes it, while all would share the benefits. This dynamic creates a temptation to free-ride on others' efforts. This will require coordination among nations and the development of new institutional capacities. The heterogeneity across nations adds complexity; the costs of reducing emissions will not be the same, nor will the benefits of avoiding climate change. Another troubling characteristic is the enormous uncertainty involved, both in the magnitude of future climate change, and therefore the value of avoiding it, and in the costs of reducing emissions. The long timescales of the climate system, decades to centuries, add a final dimension to the policy dilemma. Given the stock nature of greenhouse gases, which build slowly over time, should we delay mitigation activities until some of the uncertainties are reduced? Or wait until technology improves to the point that mitigation is less costly?

We need not decide today on the amount of emissions reductions for all time. Given the degree of uncertainty, it would not make sense. Over time, we will revise the level of policy activities to respond to new information and changing conditions. The relevant question is how much greenhouse gas emissions abatement should be undertaken today. However, the choice of the "right" level of stringency does depend on our current expectations of what we will do later.

Given the policy question – how much effort to exert today when we can learn and revise in the future – and given some of the salient characteristics of the problem – uncertainty, sequential decision over time – a sensible choice for an analytical framework is that of decision analysis. Decision analytic tools have been developed to provide insight into precisely this kind of decision problem.

A number of studies have explicitly modeled the policy decision as a sequential choice under uncertainty, and allowed for learning and adaptation in policy over time (Hammitt *et al.*, 1992; Nordhaus, 1994a; Manne and Richels, 1995; Kolstad, 1996; Ulph and Ulph, 1997; Valverde *et al.*, 1999; Webster, 2002). The general result from all of these studies is that, given the ability to learn and adapt later, the optimal choice for the initial decision period is to undertake very little or no abatement activity. There are several reasons for this result. First, greenhouse gases are stock pollutants, which build up slowly in the atmosphere. This means that there is time to address the problem over the next century and that the impact of reductions in the next decade or two is relatively small. The second reason is that the uncertainty in future climate change is sufficiently large that if there is the ability to reduce this uncertainty and respond within a few decades, it is better to wait. Third, most of these models assume that technological options continue to be developed and improve over time, so that the cost of responding will fall over several decades. Finally, the use of a discount rate to reflect the opportunity cost of capital necessarily implies that policy costs in the near term will be weighed more heavily than either costs later or benefits later, which further biases the optimal choice to be one of waiting.

Human-induced Climate Change: An Interdisciplinary Assessment, ed. Michael Schlesinger, Haroon Kheshgi, Joel Smith, Francisco de la Chesnaye, John M. Reilly, Tom Wilson and Charles Kolstad. Published by Cambridge University Press.

In this paper, I begin by exploring an apparent paradox. A common approach in modeling climate policy and other long-term problems is to simplify to a two-period decision, in which the first period represents "today" or the near term, and the second period represents "later" or further in the future, perhaps after some uncertainty has been reduced. As discussed below, typical results from such models suggest that very little or no reduction in greenhouse gas emissions in the near term is optimal. If the problem turns out to be serious, fairly stringent reductions are undertaken in period 2. Even without resolution of uncertainty, more stringent abatement is optimal in the latter period because of the other reasons outlined above. The dilemma is as follows. Suppose we apply this approach in 2005 and find that very little reduction is warranted for the next 10 years. Suppose we then follow this strategy, and then in 2015 we again apply a two-period model. Will that model not also recommend doing little or nothing, because of the same factors described above? Are we doomed to repeat this cycle, until it is "too late" in terms of avoiding climate impacts? I dub this problem the "Boiled Frog dilemma."[1]

In the next section, I describe the numerical modeling system, and explore the Boiled Frog dilemma using a variety of two-period and three-period decision trees. In the traditional application of decision techniques, I will demonstrate that there is no Boiled Frog. In Section 29.3, I will demonstrate an alternative formulation of the decision model that captures the intuition behind the Boiled Frog problem, namely path dependency in political systems. The final section discusses the implications both for climate policy and for research.

29.2. The modeling system and the Boiled Frog

There is a wide spectrum of models that can be used to project the impacts of greenhouse gas emissions and resulting climate change as well as the economic costs of constraining those emissions. These range from very simple approximations to very large sophisticated models that require weeks on a supercomputer for a single simulation. The advantage of the more complex models is that they represent many of the non-linearities and complexities that make climate change a cause for concern. On the other hand, solving the dynamic optimization problem under uncertainty requires some simplification to make the analysis feasible. The approach used here is to fit reduced-form models to a climate model of intermediate complexity and to use a relatively detailed computable general equilibrium model of the global economy The reduced-form models are then embedded within a decision tree framework to solve for optimal decisions.

[1] This name derives from the apocryphal advice for cooking a live frog: if you drop a frog into boiling water, it will jump out. If you put a live frog in cool water and slowly heat over a stove, it will never jump out before boiling to death. Presumably the frog always believes it has more time, until it is too late. While this is apparently untrue, it provides a useful image for society's potential response to climate change.

29.2.1 *The MIT Integrated Global System Model*

The integrated assessment model used is the MIT Integrated Global System Model (IGSM) (Prinn *et al.*, 1999), augmented with a damage function related to change in global mean temperature. The economic component of the model, the Emissions Projections and Policy Analysis (EPPA) model Version 3 (Babiker *et al.*, 2001) is a recursive-dynamic computable general equilibrium model, consisting of 12 geopolitical regions linked by international trade, 10 production sectors in each region, and 4 consumption sectors. The climate component is a two-dimensional (zonal averaged) representation of the atmosphere and $\Delta T(t)$ (Sokolov and Stone, 1998). The climate model includes parameterizations of all the main physical atmospheric processes, and is capable of reproducing many of the non-linear interactions simulated by atmospheric general circulation models.

In order to choose one set of strategies as "optimal," a basis is required for comparing the costs of reducing emissions with the benefits of avoiding damages. I augment the EPPA mitigation cost model with the Nordhaus damage function (Nordhaus, 1994a). This damage function has been widely used (e.g., Peck and Teisberg, 1992; Kolstad, 1996; Lempert *et al.*, 1996; Pizer, 1999), and facilitates the comparison of results here with other studies. The Nordhaus damage function estimates the percentage loss of gross world product as a function of the global mean temperature change,

$$d(t) = \eta[\Delta T(t)]^{\pi} \tag{29.1}$$

where $d(t)$ is the fraction of world product lost because of climate damages in year t, and $\Delta T(t)$ is the increase in global mean temperature from pre-industrial levels. Consistent with previous studies, I assume that $\pi = 2$ and vary η as an uncertain parameter.

29.2.2 *Fitting reduced-form models*

Solving for an optimal sequential decision under uncertainty requires a large number of simulations of the numerical economic–climate model. Used directly, the IGSM requires too much computation time for this application, so instead I estimate a reduced-form version using least squares regression on a data set of 1500 runs. I derive simple non-linear representations of temperature change as a function of uncertain climate parameters and emissions from EPPA. These simpler functional forms replicate the results of the original IGSM to within a 1% error of the mean. The reduced-form models are used in all calculations below.

29.2.3 *The decision model*

I use the results from EPPA and the reduced-form fits of the climate model to frame a two-period sequential decision under uncertainty. The decisionmaker represents an aggregate decisionmaker for the world. The decisionmaker seeks to

Table 29.1 Strategy choices in each period: reduction below unconstrained emission growth rate (% per 5 years).

Case	Number of periods	Period 1 choice set	Period 2 choice set	Period 3 choice set
A	2	2010–2029: {0%, 2%, 4%, 6%, 8%, 10%}	2030–2100: {0%, 1%, 2%, 3%, 4%, 5%}	none
B	3	2010–2029: {0%, 2%, 4%, 6%, 8%, 10%}	2030–2049: {0%, 2%, 4%, 6%, 8%, 10%}	2050–2100: {0%, 1%, 2%, 3%, 4%, 5%}
C	2	2010–2029 Fixed at 0%	2030–2049 {0%, 2%, 4%, 6%, 8%, 10%}	2050–2100: {0%, 1%, 2%, 3%, 4%, 5%}
D	2	2010–2049: Fixed at 0%	2050–2069 {0%, 2%, 4%, 6%, 8%, 10%}	2050–2100: {0%, 1%, 2%, 3%, 4%, 5%}

Table 29.2 Impacts of period 1 strategy choice in 2030 (median growth case).

Reduction rate (% per 5 yrs)	CO_2 (GtC)	% change CO_2	Carbon price ($/tonne C)	Consumption	%Chg cons.
0%	12.5		0.0	5094.2	
2%	11.8	–5%	19.3	5091.8	–0.05%
4%	11.1	–11%	45.1	5087.9	–0.12%
6%	10.5	–16%	79.7	5082.1	–0.24%
8%	9.9	–20%	125.1	5073.3	–0.41%
10%	9.4	–25%	181.6	5060.8	–0.66%

Chg. cons. = change in consumption relative to the no policy (0%) case.

minimize the net present value of the total consumption losses. These losses result both from constraints on carbon emissions and from impacts of climate change. The stream of costs over time is discounted at a rate of 5%. The possible strategies represent choice over levels of emissions abatement only; other possible complementary policies of research, adaptation, and geoengineering are not considered here. In order to illustrate the point here about sequential decision, I make the simplification of aggregating the globe; in reality, climate policy will be determined by negotiations among sovereign nations. Also, I wish to explore the implications for overall level of effort, and not get into orthogonal questions of relative burden sharing. For this reason, I assume global trading of emissions permits between countries, and only examine the total global losses. One adjustment to account for equity concerns for developing nations is that the emissions reductions described below are cut in half for all developing (non-Annex I) nations between 2010 and 2040. After 2040, all policies apply equally.

The strategies are defined as the reduction required in the rate of growth of carbon emissions, relative to the unconstrained case. Thus, these policies will have differential effects depending on the region's reference growth path and will also vary with the (uncertain) rate of economic growth. Thus, "0%" means no emissions constraints at all, and "5%" means a 5 percentage point reduction in the CO_2 growth rate over that 5-year period, relative to the reference rate of emissions growth.[2] Smaller rates of reduction will result in slowed growth of CO_2 emissions while larger rates will actually reduce global emission over time.

Table 29.1 shows four different multi-period decision models that I explore here. Case A is the basic two-period model where the first period represents the 20 years from 2010–2029. Case B is a three-period model for comparison. Case C does not reduce emissions during 2010–2029 and defines a new period 1 from 2030–2049. Case D imposes no constraints for 40 years, from 2010–2049, choosing reduction rates for 2050–2069 and 2070–2100. To provide context for the relative stringency of these strategies, the impacts on several variables in 2030 are given in Table 29.2 for the period 1 strategies. To put these policy choices in more familiar terms, Table 29.2 lists the impacts of each possible first-period strategy by 2030 for the median productivity growth case, and the initial carbon price in 2010.

Based on previous work (Webster *et al.*, 2002, 2003), I consider five uncertain parameters that have the greatest impact on damage costs:

- Labor productivity growth rate (LPG): this parameter drives the overall rate of economic growth in EPPA.

[2] For example, if emissions grow 8% over the 5 years in the reference, then a policy of "5%" would limit emissions at the end of that 5-year period to be no more than 3% higher than the previous period.

Table 29.3 Distributions for uncertain quantities in decision model.

	Branch 1 ($P = 0.185$)	Branch 2 ($P = 0.63$)	Branch 3 ($P = 0.185$)
Labor productivity growth rate (relative to reference rates)	0.8	1.0	1.2
Temperature change (degrees C)	5th percentile	Median	95th percentile
Damage cost coefficient (%)	0.02	0.04	0.16

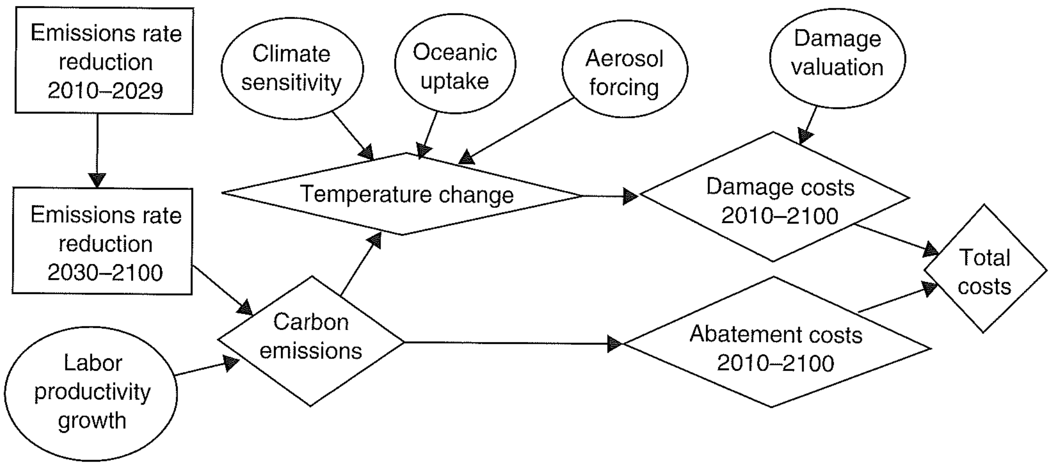

Figure 29.1 Influence diagram for standard two-period decision model.

Higher LPG results in higher carbon emissions and therefore higher temperature change and climate damages. (Webster *et al.*, 2002).

- Climate sensitivity (CS): this parameter determines the change in global mean temperature at equilibrium that results from a doubling of CO_2 (Forest *et al.*, 2002).
- Rate of ocean uptake (vertical diffusion coefficient, Kv): the 2D climate model parameterizes the mixing of both heat and carbon from the mixed-layer ocean into the deep ocean. A slower ocean will result in both higher carbon concentrations in the atmosphere and in more rapid warming (Forest *et al.*, 2002).
- Strength of aerosol radiative forcing (Fa): this parameter represents the uncertainty in the magnitude of radiative forcing from sulfate aerosols, which are negative (cooling) (Forest *et al.*, 2002).
- Damage valuation (DV): to reflect the large uncertainty in the valuation of climate change impacts, the damage coefficient η is uncertain (Nordhaus, 1994b).

The three uncertain climate parameters, CS, Kv, and Fa, are combined for each possible emissions path by performing a Monte Carlo simulation of 10 000 trials on the reduced-form climate models. The total resulting uncertainty in temperature change is then summarized by a three-point Tukey–Pearson approximation (Keefer and Bodily, 1983) using the 5th, 50th, and 95th percentiles. The climate parameter probability distributions are constrained by observations of twentieth century climate (Forest *et al.*, 2002; Webster *et al.*, 2003). When sampling from the climate parameter distributions, correlations are imposed of $\rho_{SK} = 0.004$, $\rho_{KA} = 0.093$, $\rho_{SA} = 0.243$, (where SK means correlation between sensitivity and Kv, SA between sensitivity and aerosol forcing, etc.) as consistent with twentieth-century observations.

The uncertainties in labor productivity and damage valuation are also represented in the decision tree with three-point discrete approximations (Table 29.3). The reference continuous distributions for these parameters are obtained from expert elicitation. The distribution for the damage valuation is taken from Roughgarden and Schneider (1999), based on the assessment by Nordhaus (1994b). The joint distribution of climate uncertainties, the labor productivity uncertainty, and the damage valuation uncertainty are assumed to be mutually probabilistically independent.

The basic two-period decision model is shown in Figure 29.1 as an influence diagram. Influence diagrams are a graphic representation of a sequential decision model. The rectangles represent the two decision points, 2010 and 2030, the circles represent the five uncertain parameters described above, and the diamonds represent the intermediate outcomes – carbon emissions, temperature change, damage costs and abatement costs, as well as the final outcome, total costs – of any decision path. Arrows pointing to decision nodes indicate the time ordering of decision and information. Arrows to outcome nodes indicate the

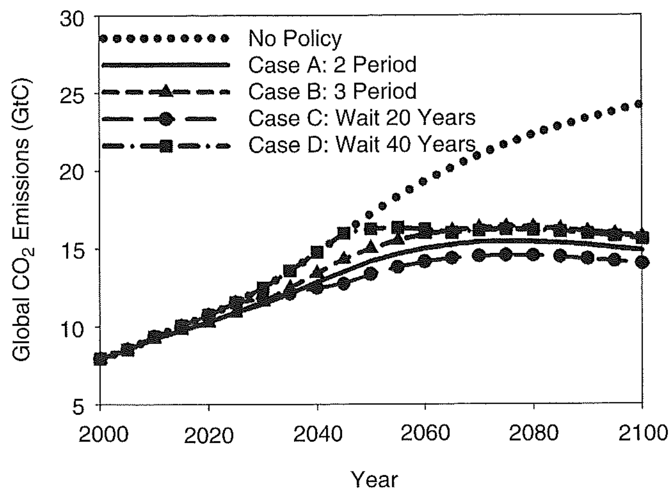

Figure 29.2 Optimal emissions paths for two- and three-period decision models.

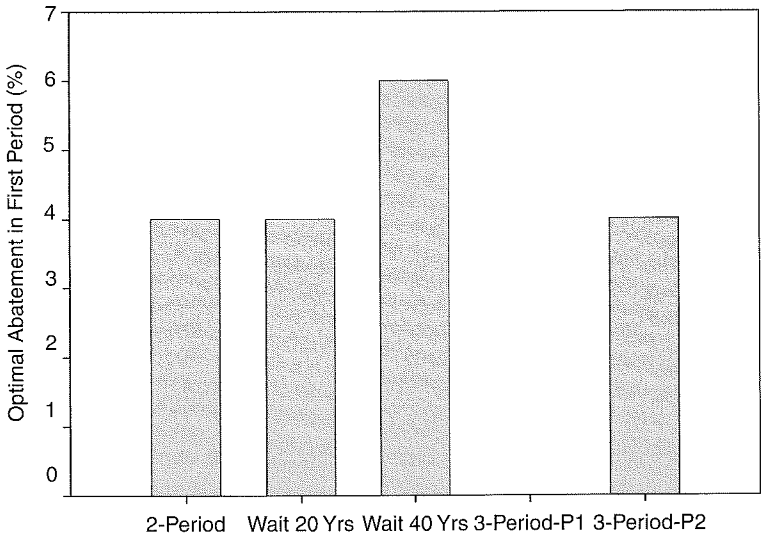

Figure 29.3 Optimal near-term abatement for two- and three-period decision models with resolution under uncertainty.

functional dependence; e.g., temperature change depends on the three uncertain climate parameters and on emissions. Figure 29.1 represents a situation with no resolution of uncertainty before the period 2 decision. The corresponding influence diagram for the case with learning before period 2 would add arrows from each uncertainty node to the 2030–2100 decision node.

I first show the results for each case where there is no resolution of uncertainty before the second-period decision. While this does not address the decision under uncertainty aspect, it does capture the other justifications for delaying abatement to the future: slow build-up of CO_2, technological change, and the discount rate.

Each of the decision models listed in Table 29.1 is calculated and solved for the optimal strategies in each period. The resulting global CO_2 emissions path under each optimal policy is shown in Figure 29.2. Note that the emissions from each two-period case closely approximate the three-period emissions. In other words, all cases are approximating the same continuous-time dynamic optimal path. The more flexibility in the model (i.e., more decision periods), the closer to the continuous-time optimal path the emissions will be. Waiting before imposing reductions does not cause the new period 1 choice to be less stringent; it is in fact more stringent to compensate for the delay.

Next, consider the situation in which uncertainty is revealed before the second-period decision in the two-period models or before the third-period decision in the three-period model. The optimal emissions paths are shown in Figure 29.2, and the optimal abatement strategy in the first period is shown in Figure 29.3. For the three-period model, the optimal decision in the first periods is 0% (no reduction) in period 1 and 4% in period 2. The two-period model, forced to choose one abatement level, has an optimal strategy of 4%. If the first decision period is delayed for 20 years with no abatement, the optimal strategy is 4%, and if delayed 40 years, the optimal strategy is 6%. The optimal abatement in the final period in all models is a probability distribution, since the optimal choice depends on what is learned.

If there were a Boiled Frog situation, it would appear in the form of first period optimal strategies that are equally or less stringent after delays. But in fact, if the first decision is delayed longer, with or without resolution of uncertainty, the optimal strategy becomes more stringent, not less. There is no Boiled Frog in this model!

This result should not be surprising to those familiar with dynamic optimization. Nevertheless, there is still something that may trouble some who consider the prospects for making dramatic emissions reductions in the future when little is undertaken in the near term. Why do we fear that each generation will continue to pass responsibility on to the next, never addressing climate change until impacts are already severe? There is a basis for this suspicion, but it is not represented in the decision models above. The problem, path dependency in political systems, is the topic of the next section.

29.3 Hysteresis and path dependency in climate policy decisions

29.3.1 The political context and path dependency

In applying decision analytic methods to thinking about appropriate levels of global greenhouse gas emission reductions over the next century, the "decisionmaker" is a fictional entity created for analytical convenience. The reality is that policy responses will emerge from extremely complex multi-level, multi-party negotiations that will occur continuously over the century. At one level, the negotiations are between nation states, such as the 188 parties to the Framework Convention on Climate Change (UNFCCC, 1992). However, the positions at this level are driven by the competing positions and interests in the domestic politics of each of those countries. The system as a whole has been compared to that of a "two-level game" (Putnam, 1988).

The competing domestic interests and their resolution in the form of an official national position cannot be represented as a static preference function, but a highly fluid stream of positions that evolve and change over time. This is particularly the case over the time horizon, decades to centuries, relevant to climate change policy.

The contrast between the decisionmaker as modeled and the actual decision process requires that we closely examine the assumptions of the analysis method. One particular aspect of the political decision process is relevant to the discussion here: its ability to make radical shifts over time. Political scientists have long noted the tendency of political systems to exhibit path dependency, and have used this feature to explain a number of political outcomes (Lipset and Rokkan, 1967; Sewell, 1996; Levi, 1997; Pierson, 2000). The idea of path dependency is that once a particular course of action has been chosen, it becomes increasingly difficult over time to reverse that course. Policies tend to exhibit "lock-in", and while a legislature might from time to time create a new bureaucratic agency, it is exceedingly difficult to eliminate one. Pierson (2000) suggests that the phenomenon can also be thought of as increasing returns to scale within the political system.

An examination of previous studies of climate policy as a sequential decision under uncertainty reveals that the characteristic of path dependency is largely absent. On the contrary, in keeping with the conventional approach, the range of emissions reductions from which to choose is the same or similar in each decision period, with no explicit constraints on future decisions depending on previous periods. One notable example is Hammitt (1999), which represented path dependency in the sense that reduced emissions in one period will result in lower emissions in all future periods at no cost.[3] This is one important type of path dependency, although this interaction is represented in CGE models such as EPPA. The concept of path dependency explored here is a stricter form: constraints on the choice set conditional on previous choices.

The idea of path dependency is part of the underlying intuition that delayed emissions reductions make more drastic future reductions more difficult or less likely. We found no Boiled Frog effect in the previous section because the model assumed that all period 2 strategy choices were available regardless of the period 1 decision made. If we believe that this effect is a salient characteristic of the political process, it must be included in the model.

29.3.2 Modeling path dependency

A challenge in exploring this issue is *how* to represent path dependency in dynamic optimization models of the type used here. Ideally, this feature would be represented somehow in the underlying representations of the costs and benefits of each decision path. Since it is not, however, the goal here is to add a simple adjustment to the decision model that has the desired effect and that makes sensitivity analysis straightforward.

There are a number of possibilities. One simple approach would be to assume that since the relevant decisionmakers are choosing for the present only and have no control over future decisions, one could model those future choices as uncertainties rather than decisions. The difficulty with this approach is that probability distributions are then needed for future political choices, where these distributions are conditional on the period 1 strategy that was chosen. It is not clear on what basis one could design these distributions or from whom one could elicit them. A second approach is to instead retain future policy choices as decisions, but allow for the possibility that the options may be limited. Thus there is an additional

[3] Hammitt (1999) shows that the impact of path dependency on near-term optimal abatement is in the same direction as the results shown in this study.

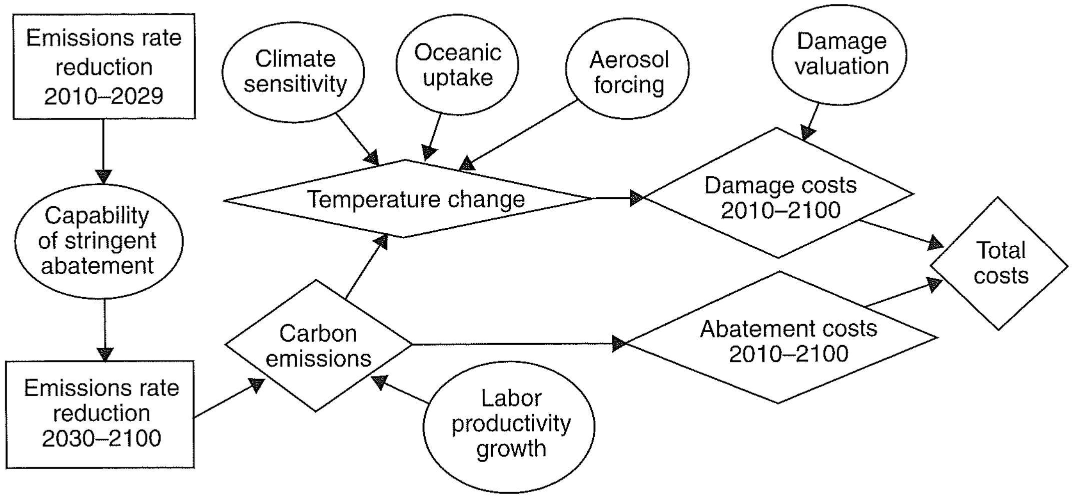

Figure 29.4 Influence diagram for decision model with hysteresis.

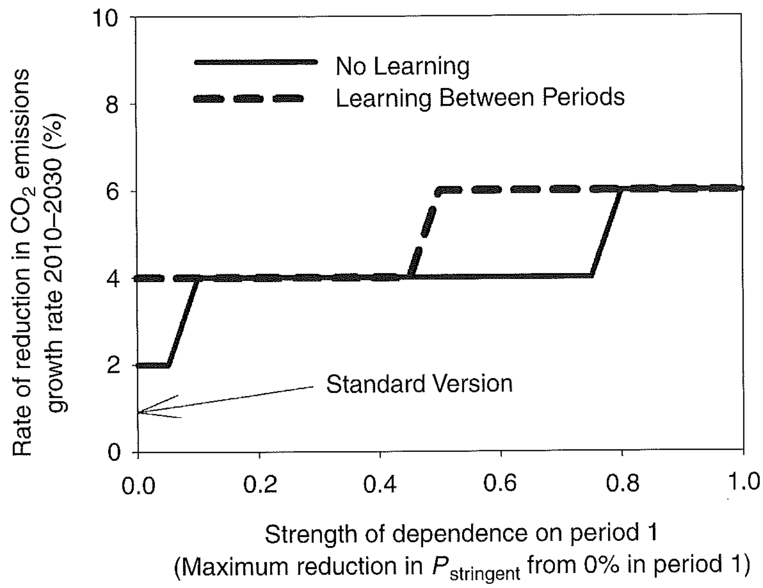

Figure 29.5 Optimal decision with path dependency.

uncertainty in period 1 over whether future decisions will have the full range of options to choose from. These constraints are then conditional on previous decisions. A third approach is to model the path dependency as an additional cost in the objective function to drastic changes in the level of stringency from previous periods, and which grows larger over time. This would have the same effect as the second approach, effectively ruling out some future options as non-optimal once the cost grew too large.

For analytical simplicity, this analysis uses the second approach of constraining future choice sets. Figure 29.4 shows how the influence diagram from Figure 29.1 changes for this variation (for the case without resolution of uncertainty). There is now an additional uncertainty node, "Capability of stringent abatement", which is resolved after period 1 but before period 2, and is influenced by the period 1 decision. This uncertainty determines the levels of emissions reductions that can be chosen from in period 2. There is some probability ($P_{\text{stringent}}$) that the full range of options from the original decision model is available to the period 2 decisionmaker. But now there is also the possibility, with probability $1 - P_{\text{stringent}}$, that only a limited range of emissions can be chosen from. In particular, the options no longer available are the most stringent reductions.

The critical aspect needed to capture the notion of path dependency, as described in the political science literature, requires that the range of available future actions *depends* on earlier choices. Unfortunately, the strength of this relationship is not known. Presumably, earlier actions have some influence on the set of future options, but there may be some random

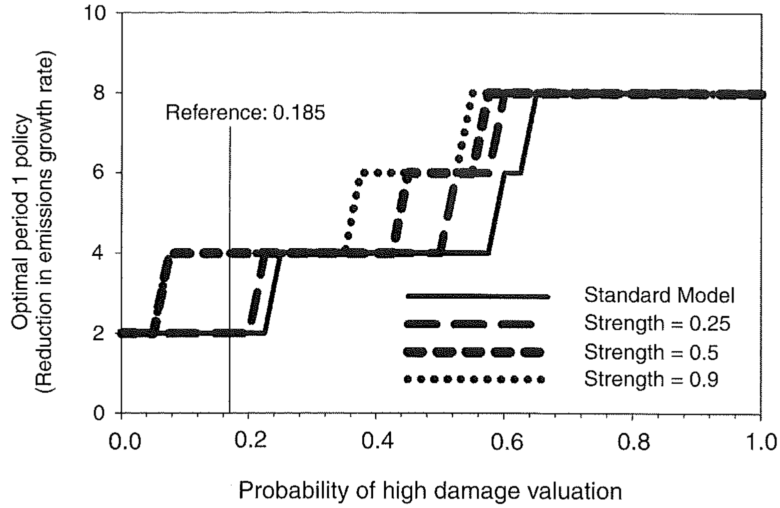

Figure 29.6 Sensitivity to damage uncertainty for varying degrees of path dependency (no learning between periods).

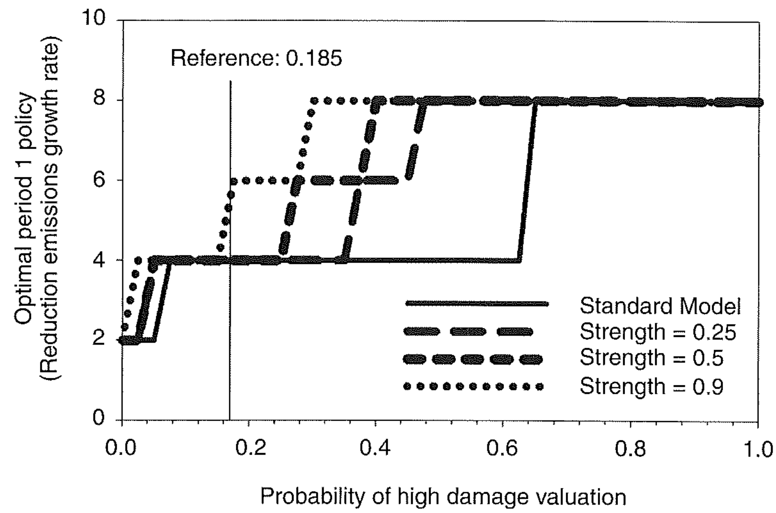

Figure 29.7 Sensitivity to damage uncertainty for different degrees of path dependency (complete resolution of uncertainty between periods).

stochastic element as well. I will use a simple formulation with extensive sensitivity analysis to explore the implications over a broad range of path dependency.

In this model of hysteresis, I define a second parameter H_{strength} as the maximum reduction in probability that stringent reductions are possible. I then calibrate a linear function of the first period policy such that no reductions (0%) will result in the maximum decrease in $P_{\text{stringent}}$ and the most stringent policy (10%) will result in no change ($P_{\text{stringent}} = 1.0$). All other strategy choices result in proportional reductions in $P_{\text{stringent}}$. Thus, when H_{strength} is zero, there is no hysteresis and the model is the same as in Section 29.2. When H_{strength} is unity, the probability of stringent action in period 2 is entirely determined by the period 1 decision. If H_{strength} is set to 0.2, this means that a period 1 strategy of 0% or no reductions will reduce the probability of stringent reductions in period 2 to 0.8, while a period 1 strategy of 10% (maximum reductions) would leave the probability of stringent reductions at 1.0. I explore the effect of this modification to the standard two-period model (Case A in Table 29.1).

29.3.3 Results with path dependency

In general, strengthening the hysteresis effect causes greater reductions in period 1 to be optimal, whether uncertainty is resolved between periods or not (Figure 29.5). If the period 1 strategy choice will alter the likelihood that dramatic reductions can be undertaken if necessary, this makes additional reductions desirable in the near term. A stronger hysteresis effect is needed to change the optimal decision when learning will occur, because in this model resolution of uncertainty already results in more stringent period 1 abatement than the no-learning case.

We can further illustrate the effect of hysteresis on the first period decision by varying the probability of the high damage valuation uncertainty (Figures 29.6 and 29.7). Increasing hysteresis leads to more stringent near-term abatement. The omission of any path dependency in a sequential model is likely to bias the optimal near-term abatement to be too little.

29.4 Discussion

The objective of this analysis is to draw attention to the implications for policy prescriptions and insights of methodological choices. We take a complex decision problem – climate policy; we observe some salient characteristics of that problem – uncertainty, ability to learn, ability to adapt and revise decisions over time; we choose a method suited to those characteristics – decision analysis. But another key feature of the new decision context of national governments, namely path dependency, is not typical of the individual decision-maker situations for which this tool was developed, and so is not normally accounted for in the way the decision models are constructed. But path dependency can lead to qualitatively different results and insights for near-term policy.

The formulation of path dependency presented here has been kept extremely simple to allow sensitivity analysis and to keep the focus on the basic concept. In fact, we do not know whether decisionmakers in future decades will be constrained or not in the range of emissions reductions that they can pursue, or how the likelihood of this constraint depends on today's policy choices. To get more robust insights from optimal sequential decision models, research into the magnitude of path dependency effects from institutional development and commitments is desirable. A related question where there is active research but more is needed is how technical change is influenced by regulation-driven price incentives.

In the interest of efficient policy, we often compare the costs of an action against its benefits. However, this static cost–benefit approach does not capture the whole picture, or even the most important part. On that basis alone, the optimal level of greenhouse gas mitigation in the near term is quite low. The true value of near-term mitigation policy is that of starting down the right path to maximize options for future policy adjustments. Recognizing this additional value justifies a greater level of abatement in the near term. This goal of creating and maximizing future options should be a primary focus in choosing the stringency and institutional design of climate policies.

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