The Curious Role of "Learning" in Climate Policy: Should We Wait for More Data?

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Given the large uncertainties regarding potential damages from climate change and the significant but also uncertain costs of reducing greenhouse emissions, the debate over a policy response is often framed as a choice of acting now or waiting until the uncertainty is reduced. Implicit in the "wait to learn" argument is the notion that the ability to learn in the future necessarily implies that less restrictive policies should be chosen in the near term. I demonstrate in the general case that the ability to learn in the future can lead to either less restrictive or more restrictive policies today. I also show that the initial decision made under uncertainty will be affected by future learning only if the actions taken today change the marginal costs or marginal damages in the future. Results from an intermediate-scale integrated model of climate and economics indicate that the choice of current emissions restrictions is independent of whether or not uncertainty is resolved before future decisions, because, like most models, the cross-period interactions are minimal. With stronger interactions, the effect of learning on initial period decisions can be more important.

INTRODUCTION

International agreement on steps to mitigate greenhouse gases continues to be elusive. One characteristic of climate change that makes consensus difficult is the magnitude of uncertainty regarding both the costs and impacts. The amount of climate change that may occur and the effects resulting from such a change are potentially very large, including changes in precipitation patterns, sea

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level rise, frequency and severity of extreme climatic events, and even a shift in the ocean currents that warm Europe. But uncertainty about these effects remains very large. The costs of restricting greenhouse gas emissions are also uncertain, and are estimated by some to be quite large as well.

Once emitted into the atmosphere, these gases have long lifetimes, hundreds to thousands of years for some of them. As a "stock pollutant," their effects on the global environment are a function of their total concentrations in the atmosphere, which change slowly as a result of emissions over many decades. The uncertainties in climate change, the long-time scales involved, and the potentially irreversible effects - combined with the fact that control policies taken today can be reconsidered later - make the climate change issue one of deciding what to do now given that we may resolve some of the uncertainties in the future. Thus, discussions of climate policy are typically framed as a choice of acting now or waiting until we know more about the problem. Costly actions taken now might prove to be unnecessary if climate change turns out to be not as bad as we thought. On the other hand, we may regret not acting aggressively now if we learn that effects are more severe than expected. Researchers and interest groups alike have made both cases (e.g., Risbey et al. 1991a, 1991b; Schlesinger and Jiang 1991a, 1991b; Stevens, 1997; United Nations, 1992). In the policy debate the most common argument is that the expectation of future learning should lead to less action now (the so-called "wait to learn" argument).

In the economic literature, however, there is no consensus on the issue. One stream of thought focuses on the additional value of avoiding future damages when they are uncertain and irreversible, and concludes that the ability to learn should lead to lower emissions (e.g., Arrow and Fisher, 1974; Henry, 1974; Chichilnisky and Heal, 1993). Others reach the opposite conclusion: that the ability to learn should lead to higher emissions, because of irreversibility in the long-lived capital stock (e.g., Viscusi and Zeckhauser, 1976; Ulph and Ulph, 1997; Pindyck, 1999). The most general result is from Epstein (1980), who shows that learning in the presence of an irreversibility can lead to either more or less of the irreversible development activity, the direction depending on the shape of the marginal cost function (i.e., the derivative of the objective function). If the marginal cost is concave then learning leads to less of the activity, and if it is convex then learning leads to more of the activity. Unfortunately, requiring strict concavity or convexity is overly restrictive for representing climate change, as shown by Ulph and Ulph (1997). Further, Epstein's result does not address the conditions under which learning has no effect on activity level or what determines its magnitude.

A number of studies of uncertainty and decision-making in the climate issue use integrated economic-climate models. Several of these address uncertainty, but do not consider the influence of learning on the near-term decision, focusing instead on related but distinct questions. Examples include the optimal decision under uncertainty when the uncertainty will later be resolved (Hammitt et al. 1992), the comparison between choice under perfect certainty and choice under uncertainty that is later resolved (Manne and Richels, 1992; 1995), the advantages of adaptive policies (Scott et al. 1999; Lempert et al. 1996) and the value of information (Nordhaus, 1994; Nordhaus and Popp, 1997). Some studies do not treat uncertainty, but have been influential in thinking about the timing of abatement strategy (Wigley et al. 1996; Yohe and Toth, 2000).

Studies that have explicitly examined the effect of learning in empirical models of climate change (Nordhaus, 1994; Kolstad, 1996; Ulph and Ulph, 1997) have found that learning seems to have almost no effect on the period 1 strategy. Their explanations for the lack of an effect of learning rely on two characteristics of the models:

1) The irreversibility constraint does not bind: i.e., the damage losses are not severe enough to drive period 2 emissions to zero[1] (Kolstad, 1996; Ulph and Ulph, 1997) and,

2) The stock nature of greenhouse gases: the fact that the existing stock decays very slowly means that period 1 emissions have very little influence on the total stock of greenhouse gases in the atmosphere (Kolstad, 1996; Nordhaus, 1994).

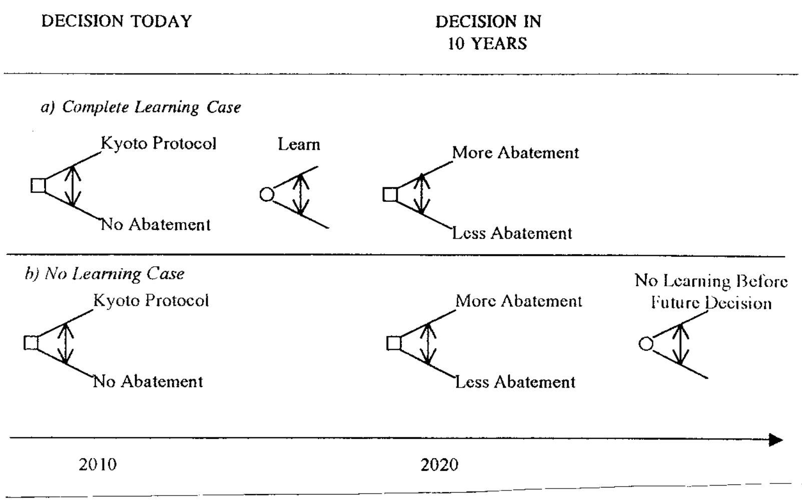
Further, results from empirical models are contradictory, with learning leading to more period 1 abatement in results from Nordhaus (1994) but less abatement in results from Ulph and Ulph (1997).

In this paper, I clarify the effect of learning by representing the process of sequential choice, with the possibility of learning, in a simplified way with a two-period decision.[2] The first period represents "now": actions over the next few years. The second period represents the opportunity to do something different "later," whether we have reduced uncertainty or not. Then the question is: how does the optimal first period strategy change if uncertainty is resolved before the second period decision is made? The influence of learning is examined by considering two extreme cases: (1) "No Learning," in which the uncertainty at the time of the period 2 decision is the same as for period 1; and (2) "Complete Learning," in which all uncertainty is resolved before the period 2 decision.

1. According to Kolstad and Ulph and Ulph, the irreversibility of the period 1 decision is only binding if, when the true state of nature is revealed in period 2 through learning, one would wish to undo the action in period 1. If damages are not severe enough to warrant a decision to "negatively emit" (take carbon out of the atmosphere), then the irreversibility of emissions in period 1 becomes irrelevant.

2. A two-period model of sequential decision gives insight into the general effect on the period 1 decision that would be obtained from a model with three, four, or more decision points.

Figure 1. Policy Choice as Two-period Decision with and without Learning



These two cases are illustrated in Figure 1. The upper part of the figure shows the Complete Learning case. After ten years uncertainty about climate impacts is eliminated, and the decision about increasing or relaxing emissions constraints is made with perfect knowledge. The lower panel shows the No Learning case where the decision today and the one in ten years are made under the same level of uncertainty. The effect of learning can be seen by comparing the best decision made today in these two cases.

The analysis below demonstrates the conditions for the existence of an effect of learning on strategy choice, and explains the factors that determine the direction of the learning effect. Section 2 develops general results using an analytical dynamic programming model of a two-period decision. Section 3 demonstrates the effect of learning with an integrated assessment model that represents much of the complexity in the economic and climate systems. Section 4 summarizes the main findings.

2. AN ANALYTICAL MODEL OF LEARNING

The choice of climate policy under uncertainty can be defined as a dynamic programming problem. Define

$t = 1,2$

$X_t \equiv$ the set of all possible emissions levels that can be chosen in period t

$x_t \equiv$ the level of emissions allowed in period t, chosen from the set X_t

$\theta \equiv$ severity of damage costs from climate change

$C_1(x_1, \theta) \equiv$ abatement costs and damage costs in period 1

$C_2(x_1, x_2, \theta) \equiv$ abatement costs and damage costs in period 2

and let $E_\theta\{\cdot\}$ denote the expectation w.r.t. the marginal distribution of θ.

In each period t, a level of allowed emissions x_t is chosen. Each period has a total cost function $C_t(\cdot)$ stated in terms of emissions level, which includes both abatement costs and damages from the accumulated stock of carbon. The uncertainty in the damages from climate change is represented by different states of the world θ that may obtain, and so the damage costs (and therefore the total costs) are also a function of θ.

Next, define two value functions, one representing the minimized costs over both periods, and the other the minimized costs in period 2 only:

$V_1(x_1, x_2, \theta) \equiv$ the sum of abatement costs and damage costs over both periods given emissions level x_1 at $t = 1$, emissions level x_2 at $t = 2$, $\tilde{\theta} = \theta$,

$V_2(x_1, x_2, \theta) \equiv$ the abatement and damage costs at $t = 2$ if the emissions level x_2 is chosen in light of $\tilde{\theta} = \theta$, given that the emissions level at $t = 1$ was x_1.

In the "learning" case, the uncertainty in the damage costs θ is completely resolved before the period 2 decision is made. In the "no learning" case, the uncertainty in θ will be the same in both periods. Comparison of the optimal period 1 strategy in these two cases will show the maximum possible effect of learning on strategy. For this study, we consider learning to be autonomous or exogenous, in which the true state is revealed with the passage of time. Other approaches to modeling learning include *active learning*, in which the evolution of the climate and economy are observed and beliefs are updated, and *purchased learning*, in which improved information is purchased with an explicit cost that is modeled (e.g., R&D). Exploration of those cases is a logical extension of this work. In this model, learning only resolves the uncertainty in damage costs, while abatement costs are treated as certain. Also, it is important to note that, in reality, learning can lead to an *increase* in uncertainty. Learning resolves uncertainty in this model as a representation of the assumptions embedded in the "wait-to-learn" arguments, rather than a representation of all possibilities.

A dynamic programming problem is always solved through backward induction, first finding the optimal choice for the last period, and working backwards. Thus, the first step for the problem posed here is to choose, at t = 2, the emissions level x_2^* that minimizes the sum of abatement and damage costs given that period 1 emissions level was x_1 and that the severity of climate change damages is θ. In the "learning" case, the optimal emissions level x_2^* is chosen with certainty about θ, and the value function for period 2 is

$$V_2^L(x_1, \theta) = \min_{x_2 \in X_2} [C_2(x_1, x_2, \theta)] \ . \tag{1a}$$

In the "no learning" case, the optimal emissions level x_2^* must be chosen under uncertainty in θ, and the value function for period 2 is

$$V_2^N(x_1) = \min_{x_2 \in X_2} [E_\theta\{C_2(x_1, x_2, \theta)\}] \ . \tag{1b}$$

Without learning, the best strategy is the one that minimizes the expected value of the costs.

Once the second period optimal strategy, x_2^*, is found, the next step is to substitute this expression into the value function V_1, and solve for the optimal period 1 strategy. We choose the optimal period 1 emissions level x_1^* that minimizes the expectation of the sum of costs over both periods:

$$V_1(x_1, \tilde{\theta}) = \min_{x_1 \in X_1} [E_\theta\{C_1(x_1, \tilde{\theta}) + V_2(x_1, \tilde{\theta})\}] \ . \tag{2}$$

Several characteristics of this abstract model are worth highlighting. First, the stock nature of the problem is represented by the dependency of C_2, the cost in the second period, on x_1, the decision made in the first period. In multi-period decisions about stock pollutants, capital stock, or other quantities that accumulate over time, the costs and/or benefits in any period are partly a function of decisions made in previous periods. Analogously, the current period's decisions will have cost/benefit impacts in future periods. This formulation is in contrast to flow-type problems in which the implications of each period's decision are felt in that period only, and costs have no relation to what has previously occurred (e.g., noise pollution).

The second point to note is the difference between the learning case and the no learning case. In the no learning case, there is only a single choice of x_2^* that must minimize the mean or expected costs across all possible states of the world, since we don't yet know which one is the true state. In the learning case many different optimal choices of x_2^* exist, each minimizing costs in the particular state of the world θ. Of course, even when there is learning by period 2, the period 1 decision must still be made based on the expected value over all possible states, as can be seen by equation (2).

The effect of learning can be evaluated as the difference between x_1^L, the solution to equation (2) when uncertainty is completely resolved (equation (1a)), and x_1^N, the solution to equation (2) when no learning occurs (equation (1b)). Rather than show a formal derivation, we consider alternative functional forms that will later be useful in examining the empirical model.

A. Cost Functions with and without Cross-Period Interaction

Begin by assuming that the period 2 cost function has no cross-products between the period 1 and period 2 strategies. In constructing the cost functions we make the simple assumptions that the first period costs, given a state of the world θ, are linear,

$$C_1(x_1, \theta) = a(\theta)x_1 + b(\theta) , \tag{3}$$

and that the second period costs are a simple quadratic function of both periods' decisions,

$$C_2(x_1, x_2, \theta) = c(\theta)x_2^2 + d(\theta)x_2 + e(\theta)x_1^2 + f(\theta)x_1 + g(\theta) . \tag{4}$$

The stock nature of the problem is represented by the terms $e(\theta)x_1^2$ and $f(\theta)x_1$ in the second period cost function. The decision made in the first period will influence costs in the second period.[3]

The first step is to solve the second period decision. There are two cases: one with learning and one without. It can be shown (Webster, 2000) that the optimal period 2 strategy for the case where uncertainty is resolved is:

$$x_2^{*L} = \frac{d(\theta)}{2c(\theta)} . \tag{5}$$

Because the period 2 emissions level will be chosen after we know the true state of the world as represented by the coefficients a - g, the optimal strategy is a function of those values. In contrast, the optimal period 2 strategy without learning will be a function of the expectation of these coefficients, since their true values will still be uncertain:

3. These terms do not capture any change in the marginal damages that may occur with a non-linear damage function. In this formulation the total period 2 damage is a function of period 1 strategy, but the marginal damage is not. The dependence of marginal damage on first period strategy is a different effect, and is treated in the next example.

$$x_2^{*N} = \frac{\bar{d}}{2\bar{c}} . \tag{6}$$

Having solved for the optimal period 2 strategy in each case, we substitute for x_2 in equation (4), and then solve for the optimal emissions level x_1^* that minimizes costs over both periods. It also can be shown (Webster, 2000) that the optimal period 1 emissions for both cases is

$$x_1^{*L} = x_1^{*N} = -\frac{\bar{a}+\bar{f}}{2\bar{e}} . \tag{7}$$

Although the period 1 decision does affect the *total* costs in period 2 (damages from the remaining stock), it does not interact in any way with the period 2 decision through an influence on *marginal* cost. The lack of dependency of period 2 decisions on period 1 actions is clear from equations (5) and (6), since x_1 does not appear in either solution. This result leads to a more general proposition. For any two-period sequential decision under uncertainty represented by equations (1) and (2).

$$\text{If } \frac{\partial^2 C_2}{\partial x_1 \partial x_2} = 0 \text{ then } x_1^L = x_1^N .$$

Proof of this proposition is given in Webster (2000). In sum, if today's decision has no effect on the marginal costs of tomorrow's decision, then whether we learn or not (which does influence tomorrow's decision) is irrelevant for today.

What happens when there is an interaction term? To illustrate this case, assume the same linear cost function for period 1 as in the previous example, but in the period 2 cost function add a quadratic term $d(\theta)x_1 x_2$. Following the same procedure as above, the cost-minimizing strategy in period 1 when learning will occur is:

$$x_1^{*L} = \frac{2\bar{a}}{E_\theta\left\{\frac{d^2(\theta)}{c(\theta)}\right\}} , \tag{8}$$

while the cost-minimizing period 1 emissions level in the no learning case is:

$$x_1^{*N} = \frac{2\bar{a}\,\bar{c}}{\bar{d}^2}\ . \tag{9}$$

The period 1 strategy now depends on learning. The solutions have a common component, $2\bar{a}$, scaled by the expectation of a non-linear function, d^2/c, in the case of learning, and by the non-linear function of expectations in the case of no learning.

What might the cross-period interaction[4] term $d(\theta)x_1 x_2$ represent? As noted earlier, it could represent non-linearity in the damage function. If a larger stock of CO_2 from higher period 1 emissions changes marginal damages in period 2, then this effect will show up in this cross-term. A threshold damage level as a step function would be an especially large interaction term, since at the threshold, the marginal damage is a delta function. It could also represent a dependency of the marginal cost of mitigation in period 2 on period 1 decisions (e.g., capital stock effects). In general, the non-linearity need not be in the simple form $d(\theta)x_1 x_2$; this is the simplest case for which the difference in solutions with and without learning (equations 8 and 9) are straightforward expressions. The point is that some dependence of the marginal abatement cost or marginal damage on the first period strategy is a *necessary* condition for that strategy to diverge under learning.

A special case of the solutions (8) and (9) will be useful in Section 3. Consider the discrete distribution case where there are two possible states:

$$\theta = \{low,\ high\}.$$

Denote the cost coefficients as

$$a(low) = a_L\ ; \quad a(high) = a_H\ .$$

We also define

$$P \equiv \Pr\{\theta = high\},$$

the probability of being in the *high* damage state of the world. Thus, the expectation with respect to θ can be written:

4. The "interaction" described here, the dependence of marginal costs in period 2 on the period 1 strategy, is independent of learning. This interaction is present even in the no learning case. Thus, it is a different phenomenon than "interactive learning" in the tradition of models of learning-by-doing (e.g., Miller and Lad, 1984).

$$\bar{a} = E_\theta\{a(\theta)\} = Pa_H + (1 - P)a_L .$$

For this simple case with only two discrete states, it can be shown that the optimal period 1 strategies become

$$x_1^N = 2\bar{a}\left(\frac{\bar{c}}{\bar{d}^2}\right), \tag{10}$$

$$x_1^L = 2\bar{a}\left(\frac{c_L c_H}{c_L d_H^2 P + c_H d_L^2 (1-P)}\right), \tag{11}$$

for the cases without and with learning, respectively. Note that only the bracketed term differs between equations (10) and (11). For this problem, the optimal period 1 decision is determined by the average or expected period 1 marginal cost $2\bar{a}$, scaled by a term representing the second period marginal costs. In Section 3 these expressions will be used to explore the divergence between solutions of an empirical climate assessment model.

B. The Direction of the Learning Effect

The previous examples show that a cross-period interaction is a necessary condition for learning to influence period 1 strategy. It is not, however, a sufficient condition. Also, it remains to be shown whether the effect is positive or negative. Even without deriving the expressions that demonstrate the determinants of the direction of the learning effect (see Webster, 2000), it is possible to provide some intuition on how learning might either increase or decrease the optimal emissions level in period 1.

In the simple model described above, learning always leads to a lower strategy level x_1^* because costs change monotonically with strategy level. There is a downside to doing too much, but no equivalent downside to doing too little.[5] Thus, the irreversibility and uncertainty leads to a lower level of the irreversible activity if learning and correction are possible later. If we consider the costs as damage losses and x_t as emissions, this is equivalent to the Arrow and Fisher (1974) result that learning leads to lower emissions in period 1. If we consider the costs as representing only abatement costs and x_t as emissions level, this is equivalent to the investment under uncertainty models of Pindyck (1991) in which learning will lead to higher emissions (i.e., less abatement with learning).

5. Or the opposite, depending on the signs of the coefficients.

Real-world problems such as a decision about climate policy involve both abatement and damage costs that change in opposite directions with the emissions level. A more general representation is to treat abatement costs (decreasing in emissions) and damage costs (increasing in emissions) separately. For a two-stage decision in which learning resolves uncertainty in damage costs, *the optimal emissions strategy chosen with learning may be higher or lower than without learning*. The irreversibility in both damages and control costs causes two effects from learning, pulling in opposing directions. Learning, thereby, can lead to higher or lower emissions depending on the relative magnitudes of the control costs and damage costs.

The dominant direction of the learning bias can be explained in terms of two elements of the decision: (1) the anticipation of the period 2 strategy, and (2) the regret over the period 1 choice given the outcome after learning. When a period 1 strategy is chosen under uncertainty, and then the uncertainty is resolved in period 2, some regret over the period 1 choice is inevitable.[6] Suppose in period 2 we learn that the damages from climate change are less severe than expected. Then we will choose a higher level of emissions in period 2 than we did under no learning. Because of the interaction, we will wish that we had anticipated this higher emissions level in period 2, and also chosen higher emissions in period 1. We will regret having spent more on abatement cost in period 1 than turned out to be necessary. Now, suppose instead we learn in period 2 that the damages are more severe than the expectation. In this case, we will lower emissions further in period 2 than we would have without learning. Because of the interaction, we will wish we had anticipated this lower emissions strategy by emitting less in period 1. We will regret not having taken enough precaution in the face of uncertain climate damage.

The net effect of learning on strategy is determined by the relative magnitudes of these two regrets. When the decision is being made in period 1, we are still uncertain whether we will learn that damages are greater or less than the expectation. The probability distribution over damage costs reflects our belief in the relative likelihood of each state of the world that might be revealed in period 2. If, on balance, the dominant regret will be that we will have spent too much on abatement before learning that damage costs are lower, then learning will lead to a net increase in period 1 emissions. We call this the "sunk cost" situation. If, on the other hand, the dominant regret over all possible outcomes will be that we should have abated more, then learning will lead to a net decrease in emissions in period 1. We call this situation the "precautionary case." If the regret from abating emissions when damages are revealed to be low and the regret from abating too little when damages are revealed to be high

6. Except, of course, in the rare case that the revealed true state is exactly equal to the expectation under uncertainty.

balance each other, then learning may still not influence the period 1 decision, even in the presence of an interaction.

Thus, although the direction of learning effect is influenced by the convexity or concavity of the marginal costs (Epstein, 1980), it also is determined by the shape of the probability distribution over uncertain abatement costs and damage costs. When the expected damages from climate change are low (i.e., low expected net benefits) but there is a small probability of high damage cost (i.e., skewed towards high damages), learning will lead to lower period 1 emissions. The regret from learning that damages are high will dominate, since the low damages were already the expectation. Conversely, if expected damage costs are high, but there is a small probability of low damage costs (i.e., skewed towards low damages), then learning will lead to higher emissions in period 1. This dependence of the direction of the learning effect on the probability distribution can be illustrated with results from the integrated assessment model.

3. EFFECT OF LEARNING IN INTEGRATED ASSESSMENT MODELS

A. The MIT Integrated Global System Model

The analytical model above employed highly simplified cost functions. In this section the effect of learning is illustrated using a climate policy assessment model of intermediate complexity. 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 (Babiker, 2000) is a recursive-dynamic computable general equilibrium model, consisting (in the calculation applied here) of twelve geopolitical regions linked by international trade, ten production sectors in each region, and four consumption sectors. The climate component is a two-dimensional (zonal averaged) representation of the atmosphere and ocean (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 GCMs.

In order to choose one set of strategies as "optimal," we require a basis for comparing the costs of reducing emissions with the benefits of avoiding damages. We augment the EPPA mitigation cost model with the Nordhaus damage function (Nordhaus, 1994). This damage function has been widely used (e.g., Kolstad, 1996; Lempert et al. 1996; Peck and Teisberg, 1992; 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,

$$d(t) = \eta\, [\Delta T(t)]^{\pi} \qquad (12)$$

where $d(t)$ is the fraction of world product lost due to climate damages in year t, and $\Delta T(t)$ is the increase in global mean temperature from preindustrial levels.

Solving for an optimal sequential decision under uncertainty requires a large number of simulations of the empirical economic-climate model. Used directly, the IGSM requires too much computation time for this application, so we estimated a reduced-form version using the Deterministic Equivalent Modeling Method (Tatang et al. 1997; Webster and Sokolov, 2000). These simpler functional forms replicate the results of the original IGSM to within a 1% error of the mean (Webster, 2000). The reduced-form models are used in all calculations below.

To set up the sample calculation, the sequential decision problem for climate change is defined in Section 3B. The effect of learning in the IGSM is described in Section 3C, and then in Section 3D, results from the analytical model are used to explain the effect of learning in this model. Finally, in Section 3E, I use non-linearity in the damage function as an example of a strong interaction which can be added to the model to increase the effect of learning.

B. Sequential Decision Using the IGSM

As above, we frame a two-period sequential decision under uncertainty. The decision-maker represents the aggregate "Annex I," the industrialized nations that would constrain emissions under the Kyoto Protocol. The decision-maker seeks to minimize the net present value of total consumptions losses. These result both from constraints on carbon emissions and impacts of climate change. The stream of costs over time is discounted at a reference rate of 3%, which is subjected to sensitivity analysis. The possible strategies represent choice over levels of emissions abatement only; other possible complementary policies of research, adaptation, and geo-engineering are not considered here. Only Annex I nations constrain emissions in this model, while the less developed nations increase their emissions of greenhouse gases unrestricted over the 100-year time horizon.

The strategies are defined as maximum allowable growth rates in emissions. The first period strategy can be any rate between 0% per year (emissions stabilization) and 1.4% per year (unconstrained for all regions) over the years 2010-2019 (Table 1). The second period strategy is chosen from a low of –0.8% per year and a high of 1.2% per year (unconstrained), and constrains emissions for the years 2020-2100. The period 1 strategy also determines the absolute emissions level in 2010, as indicated in Table 2, which shows the reduction in relation to the Annex I Kyoto target (United Nations, 1997).

Table 1. Strategy Choices in Each Period: Maximum Allowable Emissions Growth

Decision Period	Strategy Variable	Years	Most Stringent Constraint	Least Stringent Constraint (no limits on emissions growth)
1	*Policy2010*	2010-2019	0%/Year	1.4%/Year
2	*Policy2020*	2020-2100	-0.8%/Year	1.2%/Year

Table 2. Emission Targets for 2010 as a Function of Strategy Level

Policy2010 (x_1)	2010 Emissions Constraint	Emissions Growth Rate 2010-2019
0	100% of Kyoto	0%
0.2	85% of Kyoto	0.2%
0.4	70% of Kyoto	0.4%
0.6	55% of Kyoto	0.6%
0.8	40% of Kyoto	0.8%
1.0	25% of Kyoto	1.0%
1.2	10% of Kyoto	1.2%
1.4	Reference (no controls)	1.4%

Based on previous work (Webster, 2000; Webster and Sokolov, 2000), we consider three uncertain parameters that have the greatest impact on damage costs:

- *Climate Sensitivity*: this parameter determines the change in global mean temperature at equilibrium that results from a doubling of CO_2 (Sokolov and Stone, 1998).

- *Rate of Ocean Uptake*: 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 (Sokolov and Stone, 1998).

- *Damage Valuation*: to reflect the large uncertainty in the valuation of climate change impacts, the damage coefficient η from equation (12) is uncertain (Nordhaus, 1994).

The probability distributions for the three uncertain parameters are discrete two-point approximations based on continuous distributions, and are subjected to extensive sensitivity testing. The reference continuous distributions are obtained from expert elicitation. The distributions for climate sensitivity and for ocean uptake are given in Webster and Sokolov (2000), based in part on Morgan and Keith (1995). The distribution for the damage valuation is taken from Roughgarden and Schneider (1999), based on the assessment by Nordhaus (1994b). Because the distributions are based on expert elicitation, they are subject to all the biases of subjective judgment about probability (Morgan and Henrion, 1990). Also, for almost all parameters, there is wide disagreement between experts. It is crucial therefore to subject all results from decision models to sensitivity testing of the assumed distributions. We approximate the continuous distributions with the discrete distributions shown in Table 3. Sensitivity testing is then performed by varying the probability of the high damage state (Branch 2).

Table 3. Distributions for Uncertain Quantities

	Branch 1 (P = 0.8)	Branch 2 (P = 0.2)
Climate Sensitivity (°C)	2.5	4.5
Oceanic Uptake (cm^2/s)	2.5	0.5
Damage Cost Coefficient (%)	0.02	0.16

As in the analytical model of Section 2, learning is modeled as the revelation of the true state of damage costs in period 2. More sophisticated models of learning such as including explicit costs of reducing uncertainty or Bayesian updating of probability distributions from observations are left for future studies. Also, as above, learning does not resolve the uncertainty in abatement costs.

C. The Influence of Learning in the IGSM

Using the IGSM and the two-period sequential framing of emissions control choice, the effect of learning can be empirically demonstrated. When using the default probability distributions given in Table 3, the optimal strategy in period 1 is the same in both the learning and no learning cases, which is to leave emissions unconstrained. Emissions are constrained in both cases in period 2, and the optimal strategy depends on what is learned. The main focus of this paper, however, is what happens to period 1 emissions. To ensure that the equality of period 1 strategies is not dependent on the specific probability distributions used, we compare the optimal period 1 strategies for different assumptions of the probability of high damage cost. Sensitivity analysis not reported here indicates that, of the three uncertain parameters treated, the minimized total expected losses are most sensitive to the damage valuation parameter. If the probability of high damage cost ($\eta = 0.16$) is varied from 0 to 1.0, while the probabilities of high climate sensitivity and slow ocean uptake are kept at the reference values of 0.2, the same strategy (no controls) is optimal with and without learning.

Table 4. Optimal Period 1 Strategy With and Without Learning (% of Kyoto Reductions)

Probability of High Damage	No Learning Optimal Cap	Learning Optimal Cap
0.0 - 0.75	0%	0%
0.75 - 0.94	10%	10%
0.94 - 0.96	10%	25%
0.96 - 1.0	25%	25%

In order to find a divergence between the optimal strategy with learning and the optimal strategy without learning, the probabilities of all three uncertain parameters must simultaneously be adjusted far from the reference values. For example, Table 4 shows the comparison of optimal strategies with and without learning when the probability of high climate sensitivity (4.5°C) is assumed to be 0.85, and the probability of slow ocean uptake (0.2 cm^2/s) is also assumed to be 0.85. With these values and the probability of high damage valuation anywhere between 0 and 0.75, it is still optimal to leave emissions unconstrained in both cases. If the probability of high damage is increased further to between 0.75 and 0.94, it is optimal to constrain emissions just a little (10% of the Kyoto caps). The only difference between the strategies occurs when the probability of high damage cost is between 0.94 and 0.96: in this region, it is optimal to constrain emissions more if learning will occur (25% of Kyoto reductions with learning as compared to 10% without).[7] Finally, for probabilities between 0.96 and 1.0, the optimal strategies are again the same, 25% of the Kyoto reductions.

As the probabilities of all three uncertain parameters are varied simultaneously, other sets of assumptions will yield differences between strategy with and without learning, but only for a small fraction of possible assumptions. In addition, such regions of divergence in strategies only exist for assumptions about the uncertain parameter distributions that are inconsistent with expert judgment.

7. Welfare, not shown here, behaves as expected: discounted welfare is always higher in the learning case than the no learning case, and in both cases welfare decreases as the probability of high climate damage increases.

In addition to varying the probability distributions, other assumptions of the decision model can be altered in an attempt to get a stronger effect on strategy by learning. Other cases that have been tested include

- Lengthening the first period from ten to forty years (i.e., first period decision determines emissions from 2010-2050),
- Assuming very slow ocean uptake with certainty (to increase the "irreversibility" of emissions),
- Varying discount rates between 0% and 10%,

and several other tests (Webster, 2000). In all of these cases, the optimal first period decision with learning and the optimal decision without learning are almost always the same. The ranges of uncertain parameters that result in a divergence are small, and usually occur under parameter distributions that are inconsistent with expert opinion. Similar results are obtained by modeling uncertainty in abatement costs and allowing learning to resolve this uncertainty (Webster, 2000).

D. Magnitude of the Learning Effect in the IGSM

The analytical model in Section 2 leads to a suspicion that the reason for this lack of influence of learning is that the inter-period interactions in this model are insignificant. And indeed, despite the complexity captured by the economic and climate models in the IGSM, few of the possible interactions over time of emissions control levels are represented in this model. The magnitude of the cross-period interactions can be estimated by examining the reduced-form models that are fit to the full IGSM. We estimate the control costs and the damage costs in each period as a function of the strategy level chosen in each of the two periods. To facilitate comparison with the analytical results from Section 2, we use the same quadratic functional form as the cost functions there, including a single linear cross-term.

Two estimated cost-functions were fit: one for low climate damage costs and one for high damage costs. The reduced-form estimates of total costs in period 2 as a function of the strategies are given in equations (13) and (14) for the high damage and low damage assumptions, respectively.[8]

8. Again, recall that the policies x_1 and x_2 are maximum allowable emissions growth rates. Thus, the total (abatement + damage) cost at first decreases with increasing x_i (as stringency is relaxed) until the effect of climate damage becomes large enough at high emission rates to increase the total cost.

$$TC_2(x_1, x_2, H) = 27108 - 2482x_1 + 153x_1^2 - 2648x_2 + 226x_2^2 + 177x_1x_2 \qquad (13)$$

$$TC_2(x_1, x_2, L) = 18712 - 2601x_1 + 145x_1^2 - 2962x_2 + 196x_2^2 + 161x_1x_2 \qquad (14)$$

From equations (15) and (16), we know that the optimal period 1 strategies with and without learning are each equal to a common term scaled by a term that varies depending on whether learning will occur. Using the coefficients from equations (13) and (14), and assuming that the probability of high damage costs $P = 0.5$ to maximize the uncertainty, the optimal period 1 strategies are proportional to:

$$x_1^L \propto \frac{c_L c_H}{c_L d_H^2 + c_H d_L^2 (1 - P)} = 0.00738 \qquad (15)$$

$$x_1^N \propto \frac{E\{c\}}{E\{d\}^2} = 0.00739 \qquad (16)$$

Because the ratio differs only slightly from 1.0, learning will have little influence on period 1 strategy.

What interactions in the IGSM are represented by these coefficients? One contributor is the vintaging of capital in the economic model component. In the EPPA model, a portion of the preexisting capital stock in any period is not malleable: the proportions of input factors are frozen at the current technology levels. As a result, low abatement in the first period results in investment in new carbon-emitting capital, some of which cannot be shifted if abatement is undertaken in the second period (Jacoby and Sue Wing, 1999). A less stringent policy in period 1 (higher emissions) will cause a higher marginal cost of emissions reductions in the second period. Another interaction in EPPA is the depletion of fossil fuel resources, but the interaction effect on period 2 strategy appears to be very weak.

An interaction is also present in the climate and ocean model components. The rate of ocean uptake of carbon will gradually slow over time due to rising surface temperatures, which will cause higher period 2 carbon concentrations in the atmosphere. The slowing of ocean uptake at higher temperatures[9] becomes an interaction; higher emissions in the first period cause an increase in surface warming, which will further lower the rate of ocean uptake of CO_2 and leave higher concentrations in the atmosphere[10] (Holian, 1998). Because of the change in ocean circulation, higher period 1 emissions increase the marginal damage cost of period 2 emissions. All of the cross-period interactions in the IGSM are relatively small effects, and therefore learning does not have an appreciable influence on period 1 strategy.

Other interactions might exist in the real world that are not represented in the IGSM. One example is a non-linear damage relationship. The Nordhaus damage function used in this study and elsewhere, while non-linear in temperature change, is very nearly linear over the range of CO_2 concentrations resulting from a reasonable range of near-term policy choices (Pizer, 1999). Much concern about climate change is motivated by the possibility of its effect on the rate of overturning in the North Atlantic Ocean. A shift in the rate of deep-water formation, in addition to its serious climatic implications, would also alter the marginal damages of future emissions, and would constitute an inter-period interaction. Another possible effect of period 1 policy on future marginal abatement costs is via the rate of technological improvement. If the rate of improvement in energy efficiency and in the development of low-carbon alternative technologies can be stimulated through the presence of a price on carbon from policy, as some argue it would be (e.g., Grubb, 1997), this dependence constitutes an inter-period interaction.

While each of these phenomena are argued to be important characteristics of the climate change issue, they are not represented either in the MIT IGSM or in most other climate assessment models. The main reasons for omitting them is that they are less well understood than other aspects of the system and difficult to represent in the models, and their likelihood and magnitude are highly uncertain. In the absence of these larger potential inter-period interactions, studies structured as sequential decisions will never find an influence of learning on today's decision. Thus the conclusion to draw from model studies is not that the likelihood of learning is irrelevant to the choice of near-term control, but that the models currently used for analysis are inadequate for addressing this question.

9. The solubility of CO_2 in the surface ocean layer is governed by Henry's Law, which allows the conversion between concentration and partial pressure: $[CO_2]^{sea} = a_{sol} \cdot pCO_2^{sea}$. Henry's coefficient a_{sol} has a strong dependence on temperature.

10. The feedback mechanisms described here are distinct from an abrupt collapse or even slowdown of the thermohaline circulation. The mechanism described here is a gradual change in the rate of absorption of carbon by the surface ocean, but not in the vertical mixing between surface and deep ocean water.

E. Example of an Inter-Period Interaction: Non-Linear Damage Function

In the discussion above, we mentioned several sources of interactions not represented in the IGSM and other assessment models that could be significant for climate change. Here we present the case of a non-linear damage relationship as one example of the effect of learning in the presence of an interaction. The Nordhaus damage function used is linear in CO_2 concentrations, but in fact the precise characteristics of damages from climate change, particularly on natural systems, are poorly known.

To illustrate the effect of non-linearity, we modify the damage function in equation (12). Rather than having a single value for the coefficient η and the exponent π, these values change above a threshold level of CO_2 concentrations. Below 650 ppm, we use the same values as in previous examples. But above 650 ppm, the coefficient in the high damage case is double the high value below 650, and the exponent increases to 3. Thus the effect is that above the threshold, damages increase more rapidly. Note that the damages above the threshold are still far from catastrophic, but that this function now has a "kink" where the slope changes. This non-linearity creates a cross-period interaction, because the marginal damages in period 2 depend on the period 1 emissions and the resulting distance from the threshold.

Table 5. Optimal Period 1 Abatement with a Non-Linear Damage Function (% of Kyoto Reductions)

Probability of High Damage	No Learning Optimal Cap	Learning Optimal Cap
0.0 - 0.15	0%	0%
0.15 - 0.45	0%	25%
0.45 - 0.85	25%	25%
0.85 - 1.0	25%	40%

Table 5 shows the optimal period 1 strategy with and without learning when the damage function is non-linear. Notice that in both cases as the probability of high damage increases so does the optimal level of abatement in period 1. In contrast with the no interaction case shown in Table 4, there are significant regions for which the stringency of period 1 abatement is influenced by learning. With a probability of high damage between 0.15 and 0.45, 25% of Kyoto reductions are optimal with learning as compared to no reductions without. In these regions, it is optimal to abate more in period 1 if we will learn later. The more stringent policy in period 1, while having imposing immediate abatement cost, has a double benefit: in addition to the reduction in carbon emissions that may cause damage later, there is an additional gain by decreasing the probability of future catastrophe. If it turns out (after learning) that it is a low damage world, emissions caps can be lifted and the wasted effort will be minimal. Without learning, we will never know, and so a higher probability of damage is required before an increase in stringency is justified. As the probability of a high climate damage changes, there is variation in whether the additional gain outweighs the additional abatement cost in only the learning case. There are probability ranges where it does (0.15-0.45; 0.85-1.0) and ranges where it does not. Other cases can be constructed with interactions that will lead in the other direction; i.e., more stringent abatement is optimal if we will not learn later (see, e.g., Webster, 2000b).

4. IMPLICATIONS FOR POLICY

Whether there is an effect of learning on the first period decision depends on the existence of an interaction effect between periods. Using a climate model of intermediate complexity, it is seen that, for most parameter distributions, the optimal emissions control today is independent of whether or not learning will occur. This result can be traced to the fact that the cross-period interactions in this model and many others in use are small. When an inter-period interaction is added, the strategy today will depend on whether we will learn, and may lead to more or less stringent abatement depending on the relative shapes of the probability distributions of control costs and damages.

In climate policy discussions an argument continues over the advisability of waiting for better understanding of climate change before undertaking costly emissions abatement. In fact, the ability to learn more and reduce uncertainty in the future is *not* necessarily a valid argument for delaying abatement. The ability to learn may lead to either higher, lower, or the same level of emissions today, depending on several factors including the probability distributions of the costs and benefits of emissions reductions.

So, what is the "act now or wait to learn" debate really about? To some degree, it does not emerge from differing beliefs over whether we will learn or not. The policy prescriptions are influenced by differing beliefs about the expected costs of abatement and the expected climate damages. Those who believe that climate damages will be small and emissions abatement costly will argue for a delay in abatement. Those who believe that climate damages are more likely to be severe and emissions abatement cheap will argue for beginning emissions abatement activities immediately. Many prescriptions result from the differences in perception of costs and benefits and not from considerations of the effects of uncertainty reduction in future decades.

These results have important implications for research in climate modeling. The omission of possible inter-period interactions from integrated assessment models changes the qualitative insights regarding what we should do today. The inclusion of possible interactions, and explicit treatment of their uncertainty, should be a priority for integrated assessment modeling. Of particular importance are the 3D ocean circulation and potential thermohaline collapse, induced innovation effects of policy, and threshold effects in ecosystems damage. Of course, whether these interaction effects exist, and if so the magnitudes of the effects, are not well known. In fact, as we have shown here, it is the uncertainty in these phenomena, and not the other uncertain parameters traditionally treated, that might cause the prospect of learning to bias strategy choice under uncertainty.

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