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Global warming uncertainties and the value of information: An analysis using CETA*

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In this paper, we investigate the sensitivity of optimal carbon control strategies to parameters of the Carbon Emissions Trajectory Assessment (CETA) Model, and we use CETA in a simple decision tree framework to estimate the value of information about global warming uncertainties. We find that if an optimal control policy is used under uncertainty, the eventual resolution of uncertainty has high value relative to current research budgets, and resolving uncertainty about the costs of warming is nearly as important as resolving uncertainty about the extent of warming. In addition, we find that there is not a high premium on immediate resolution of uncertainty, if resolution would otherwise occur within, say, twenty years; this implies that time is available to plan and execute a carefully designed research program. On the other hand, we find that if the real world political process would result in a suboptimal control policy being chosen under uncertainty, and this choice could be prevented by early resolution of uncertainty, the benefit of early resolution may be as much as three orders of magnitude greater.

1. Introduction and summary

While there is great disagreement about what policies, if any, are appropriate responses to the threat of global warming, there is fairly general agreement on the need for research to improve our understanding of the warming problem. Nevertheless, there has been relatively little quantitative analysis of the value of information about global warming.[1]

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[1]Two exceptions are Manne and Richels (1991b) and Nordhaus (1991).

In this paper, we use the Carbon Emissions Trajectory Assessment (CETA) Model to investigate the value of information about global warming. CETA is an economic growth and energy use model that also incorporates representations of greenhouse gas accumulation, global mean temperature rise, and the adaptation/damage cost associated with this temperature rise.[2]

We begin our investigation of the value of information with a brief presentation of optimal policy for the central case parameter assumptions of the model. This is followed by results indicating the sensitivity of optimal policies to variations in key parameters. If optimal policy changes significantly as a result of variation in a particular parameter, the value of information about that parameter is likely to be high.

Continuing our investigation of the value of information, we use CETA in a simple decision tree framework to estimate the value of information about a few key model parameters. Based on the sensitivity results, the key parameters on which we focus in this paper are those relating to the extent of warming and the costs of warming.

A central issue concerns the choice of emissions control policy under uncertainty. In the standard decision analysis approach under uncertainty, the policy is set so as to maximize expected net benefits. However, the global warming problem is being considered in a highly political context involving governments of many countries with differing perspectives and interests. In this context, emissions control policies chosen in the absence of good information may be far from the optimal policy. Thus we present results assuming both that the policy under uncertainty is optimal, and that the policy is arbitrarily chosen in the political process.

If policy under uncertainty is chosen to maximize expected net benefits, our results suggest that the value of information can be up to hundreds of billions of dollars; numbers of this magnitude justify devoting serious attention to resolving uncertainties. While the value of information is greatest for information regarding the potential warming anticipated from a given increase in CO_2 concentration, the value of information regarding the future damage costs of warming and of adaptation to warming is nearly as great. Since research budgets are now directed primarily at resolving scientific uncertainties like that about the extent of potential warming, it would appear that budgets for research on impacts and adaptation are relatively under-funded.[3]

Although resolving uncertainty produces a large benefit relative to not resolving uncertainty, the benefit of resolving uncertainty quickly is surprisingly low. Specifically, we find that the benefit of resolving uncertainty now

[2]For a detailed description of CETA, see Peck and Teisberg (1992a).

[3]We say 'appear' because our analysis does not directly assess the *incremental* reduction of uncertainty obtainable for an *incremental* dollar spent on climate research vs. impacts research.

instead of 20 years from now is roughly 2% of the overall benefit of resolving uncertainty. This result is due to the fact that the optimal energy use policy in our model would be about the same over the next couple of decades, for any resolution of uncertainty about the key model parameters. However, by the middle of the next century, optimal energy use policies will become more sensitive to the key model parameters. Consequently, the benefits of accelerating uncertainty resolution by 20 years would be much higher later on.

If the emissions control policy under uncertainty is assumed to be arbitrarily chosen in a real world political process, there is obviously a wide variety of possible policies that might result. We consider two such policies: no emissions reductions and an emissions limit at the 1990 level. If these emissions control policies would be chosen under uncertainty, while optimal policies would be used once uncertainty is resolved, the value of resolving uncertainty now instead of twenty years from now is much greater – specifically, if the arbitrary policy under uncertainty were to be no emissions reduction, the benefit of resolving uncertainty is an order of magnitude greater; and if the arbitrary policy were to be an emissions limit at the 1990 level, the benefit is three orders of magnitude greater.

2. CETA model results and sensitivities

As a prelude to using the CETA model to estimate the value of information, this section briefly describes the model, discusses our Low, Central, and High case values for key model parameters, shows model results for our 'Central case' parameter value assumptions, and presents a brief summary of the sensitivity of the model's results to variations in key parameters.

2.a. The CETA model

The CETA model represents world-wide economic growth, energy consumption, energy technology choice, global warming, and global warming costs over a time horizon of more than 200 years.[4] Fig. 1 presents a schematic overview of the key relationships in the model. Energy technologies and the oil, gas, and coal resource bases are inputs to an energy submodel, which supplies energy inputs to a production submodel, and the

[4]See Peck and Teisberg (1992a) for a detailed description of CETA. The results in this paper are obtained using an updated version of CETA. In the new version, the utility function is population times the logarithm of consumption per capita, instead of simply the logarithm of consumption. The new utility function tends to increase marginal utility of consumption in the future relative to marginal utility of consumption now, because population grows over time. In addition, we now use a carbon cycle model adopted from Maier-Reimer and Hasselmann (1987), in which carbon emissions fall into five classes with differing atmospheric lifetimes of two years to infinity; before we had used a single class with a lifetime of 233 years.

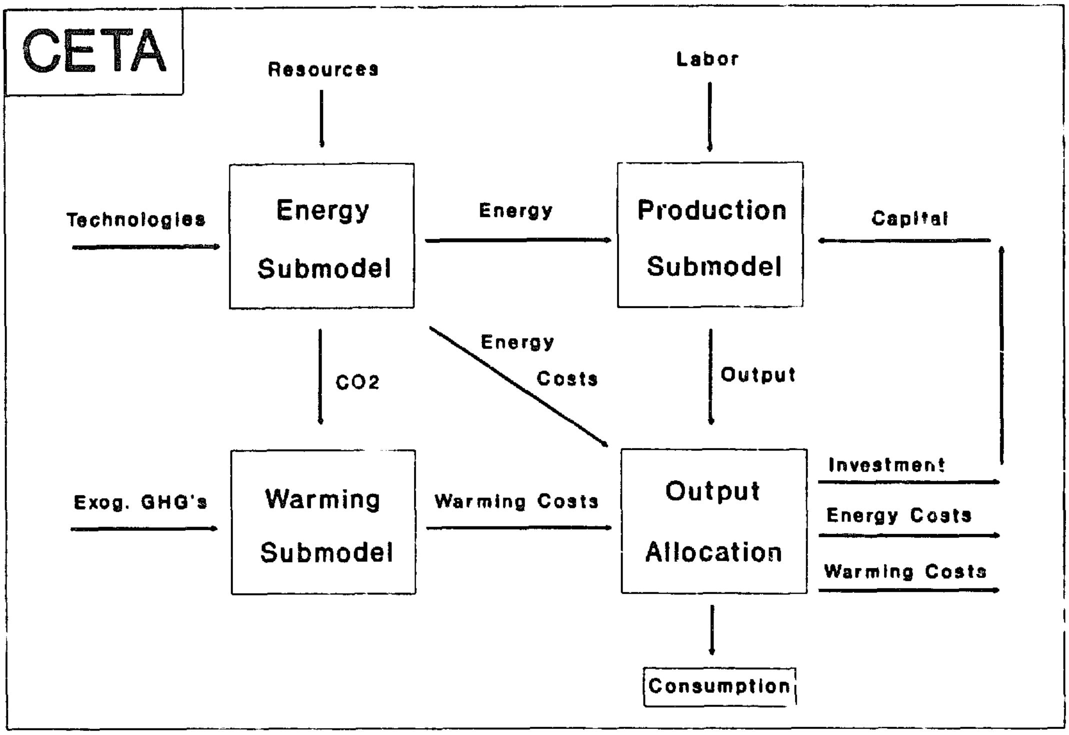

Fig. 1. CETA model overview.

CO_2 by-product to the warming submodel. In the production submodel, energy, labor, and capital inputs are used to produce output which is then allocated to consumption, investment, energy costs, and damage costs of warming. Because energy costs (and energy technology choices) are considered together with warming damage costs, the time paths of CO_2 emissions and carbon taxes in our model reflect an optimal balancing of the cost of emission reduction and the benefit of reduced global warming.

2.b. Low, Central, and High case assumptions for key parameters

To define our Central case and sensitivity cases, we identify a set of potentially important model parameters and define Low, Central, and High case values for each. We associate the label 'Low' with the parameter value that implies warming is less of a problem, and 'High' with the value that implies warming is more of a problem. While we frequently are able to rely on some authority in setting the Central case value, we typically can only offer our own rough estimates for the Low and High case values; we think of the latter as 5 and 95 percent points on subjective cumulative probability distributions. Table 1 lists the parameters we identify as potentially important, and gives the Low, Central, and High case values we have chosen for each.

The parameters in the table are grouped according to whether they effect

Table 1

CETA parameter values.

Parameter	Case Low	Central	High
1. *Cost of control related*			
AEEI (%/year)	0.5	0.25	0
Oil and gas resources (exajoules)	37110	24740	12370
Coal resources (exajoules)	75000	150000	225000
Non-electric backstop cost ($/GJ)	10	15	20
Electric backstop cost (mills/kWh)	37.5	50	62.5
2. *Benefit of control related*			
Warming per $2\times CO_2$ (°C)	1	3	5
Adaptation/damage function percent(% gross prod)	0.5	2	3.5
Adaptation/damage function power	1	2	3
Annual temp. adj. rate (%/yr)	1	2	10
Exogenous GHGs (see text)			
Carbon cycle (see text)			
3. *Cost and benefit related*			
Labor growth rate (% of EMF12)	75	100	125
Discount rate (%)	4	3	2

the cost of emission control, or the benefits of emission control, or both. Discussions of parameters in each of these categories follow.

2.b.1. Cost of control related parameters

Cost of control related parameters include those affecting future uncontrolled emissions and the costs of reducing those emissions. Future uncontrolled emissions depend on future gross production, energy use per unit of gross production, and the mix of energy sources used. Thus, many parameters in CETA play a role in determining future emissions. In the following paragraphs we identify those we believe to be most important.[5]

The Autonomous Energy Efficiency Improvement rate (AEEI) is the most important determinant of energy use per unit of gross production. Our Central case value is the one we use for the Stanford Energy Modeling Forum Global Climate Change study (EMF-12). The High case is twice this, and the Low case is zero.

The availability of various energy types, in particular the size of the Oil and Gas Resource Base and the size of the Coal Resource Base, are important parameters affecting (uncontrolled) carbon production per unit of energy used. Our Central case resource bases are those used in the EMF-12 study, and the Low and High cases are 50% and 150% of the Central case, respectively.

[5]The growth rate of the labor force is perhaps the most important determinant of future emissions. However, this parameter affects both the costs and benefits of emissions reductions and so appears in the third category of parameters.

Other cost of control related parameters include those affecting the cost of reducing future emissions. There are two main ways in which future emissions may be reduced. These are through energy conservation and through substitution of carbon-conserving energy for carbon-intensive energy. The more important mechanism in CETA is substitution, particularly of the Non-Electric Backstop technology (which is carbon-free) for synthetic fuels made from coal (which are very carbon intensive). Thus the Price of the Non-Electric Backstop technology is a key parameter affecting the cost of reducing future emissions. We take our Low, Central, and High cases to be \$10/GJ, \$15/GJ, and \$20/GJ, respectively; these compare to the EMF-12 base case assumption of \$16.67/GJ.

A second kind of substitution occurs in the electric sector, where the (carbon-free) Electric Backstop may be used in place of fossil based electric power generation. Although the Electric Backstop is quantitatively less important than the Non-Electric Backstop, it remains a significant parameter affecting the cost of reducing future emissions. For the Electric Backstop price, we use Low, Central, and High cases of 37.5, 50, and 62.5 mills per kilowatthour.

2.b.2. Benefit of control related parameters

This class includes parameters relating to the carbon cycle, the potential warming rate, exogenous greenhouse gas emissions, the lag between potential and actual temperature change, and the adaptation/damage cost function.

The carbon cycle is a complicated and poorly understood system by which CO_2 emissions produce elevated atmospheric CO_2 concentrations over decades or centuries following the emissions. In CETA, we represent the carbon cycle using the simple response function estimated by Maier-Reimer and Hasselmann (1987). This response function, which summarizes the behavior of a coupled ocean–atmosphere carbon cycle model, effectively divides new carbon emissions into five classes, each with a different atmospheric lifetime ranging from infinity to two years. Total atmospheric CO_2 over time is then the sum of atmospheric CO_2 across these five classes.

Our Central case uses the Maier-Reimer and Hasselman CO_2 class fractions (0.13, 0.20, 0.32, 0.25, 0.10), associated with lifetimes of infinity, 363, 74, 17, and 2 years, respectively. For our High case, we retain the same lifetimes, but change the fractions to: 0.18, 0.30, 0.32, 0.15, 0.05. For our Low case, we change the fractions to: 0.08, 0.10, 0.32, 0.35, 0.15.

Associated with a given concentration of CO_2 in the atmosphere is an equilibrium global mean surface temperature rise, or 'potential warming' from CO_2. Commonly, predictions of warming are presented in terms of the potential warming expected from a doubled atmospheric CO_2 concentration – e.g. a warming of 3°C may result from doubled CO_2 concentration. In CETA, a prediction of this nature is used to benchmark a logarithmic potential warming function of CO_2 concentration. Thus, we represent uncertainty about potential warming in terms of the potential warming function benchmark. We use 3°C as our Central case, 1°C as our Low case, and 5°C as our High case.[6]

In addition to CO_2, there are other greenhouse gases that contribute to global warming. Among the more important are methane (CH_4), nitrous oxide (N_2O), and chlorofluorocarbons (CFCs). Also, there is a certain amount of CO_2 emissions which is due to deforestation and is independent of the energy sector. In CETA, we treat the emissions of these greenhouse gases as exogenous.

Our Central case for exogenous gas emissions in CETA is roughly consistent with IPCC Scenario B.[7] To explore the implications of uncertainty about warming attributable to exogenous gases, we simply define Low and High emissions cases which are 50% and 150%, respectively, of the Central case.

Actual temperature will rise slowly to the equilibrium level implied by the concentration of CO_2 (and other greenhouse gases) in the atmosphere. In CETA, this is represented by a temperature rise in each time period that is proportional to the difference between the potential temperature in that time period and the actual temperature in the preceding time period. We refer to the proportionality factor as the annual temperature adjustment rate.

In our Central case, we assume the annual temperature adjustment rate is 2%.[8] For the Low and High cases we use 1% and 10%, respectively.

Great uncertainty surrounds the adaptation/damage cost function. In CETA, this function can be represented in a variety of ways. For example, it can depend on the level of temperature, or its rate of change, or both. Also, there is wide latitude to choose its functional form.

For purposes of exploring the implications of uncertainty, we use an adaptation/damage function that is defined on the level of temperature rise, rather than on its rate of change.[9] The damage function we use is of the form:

$$C_t = \alpha \cdot L_t \cdot T^{\lambda}{}_t, \tag{1}$$

where C_t = annual warming cost, time t,
α = a scaling constant,

[6]The range here is suggested by National Academy of Sciences (1991), based on the range of results obtained from climate models.

[7]See IPCC (1990, p.14).

[8]See Schlesinger and Jiang (1990).

[9]This choice is made for simplicity – a large number of model runs is required to analyze uncertainty, and these runs generally solve more easily for damage functions defined on the level of temperature rise. See Peck and Teisberg (1992b) for results from CETA using rate of temperature change damage functions.

L_t = labor input index, time t (1990 = 1.0),
T_t = temperature rise (above pre-industrial),
λ = power of the damage function.

Note that the damage function above shifts upward over time with growth in the labor force, L_t (which is expressed in efficiency units to reflect future productivity growth); this specification reflects the idea that willingness-to-pay to avoid warming effects will grow with population and income.

In the above function, the scaling parameter, α, is set so that damages are a certain percentage of gross production, at 3°C of temperature rise We refer to this damage percentage at 3°C as the Adaptation/Damage Percent, and use it as one parameter representing uncertainty about the damage cost of temperature rise. For our Central case, we assume that the Adaptation/Damage Percent is 2.[10] For our Low and High cases we use 0.5% and 3.5%, respectively.

We also identify the Adaptation/Damage Power parameter, λ, as important.[11] For our Central case, we choose a power of 2, and for our Low and High cases we choose powers of 1 and 3, respectively.

2.b.3. Cost and benefit related parameters

The Labor Force Growth Rate (in efficiency units) is a key parameter which drives future potential production as well as affecting damage costs; thus this parameter affects both the costs and benefits of emission reductions.

Our Central case labor growth rates use the EMF-12 assumptions to the year 2100. After 2100, we assume that growth slows from roughly 2% per year in 2100 to 0.25% per year starting in 2150. Our Low case is 75% of the Central case growth rates, and our High case is 125% of the Central case rates.

A second important parameter, the utility discount rate, also affects both the cost and benefit of emission reduction. The discount rate affects the cost of reduction in our model because current production decisions affect future production possibilities. This dependence is due to the existence of exhaustible resources in the model, and to assumptions that prevent excessively rapid changes up or down in technology use rates over time. The discount rate affects the benefit of emission reduction because of the long time delay between emission reduction and the effect of that reduction on temperature.

[10]This is based on the work of Nordhaus (1990a), who presents an estimate of damage for the US (one-quarter of one percent of GDP), and offers a guess that the inclusion of non-quantified costs and extension of the estimate to the world as a whole might increase it to one or two percent of world gross production.

[11]In earlier work, we identified the power of the damage function as a key parameter affecting the optimal CO_2 emissions reduction policy – see Peck and Teisberg (1992a).

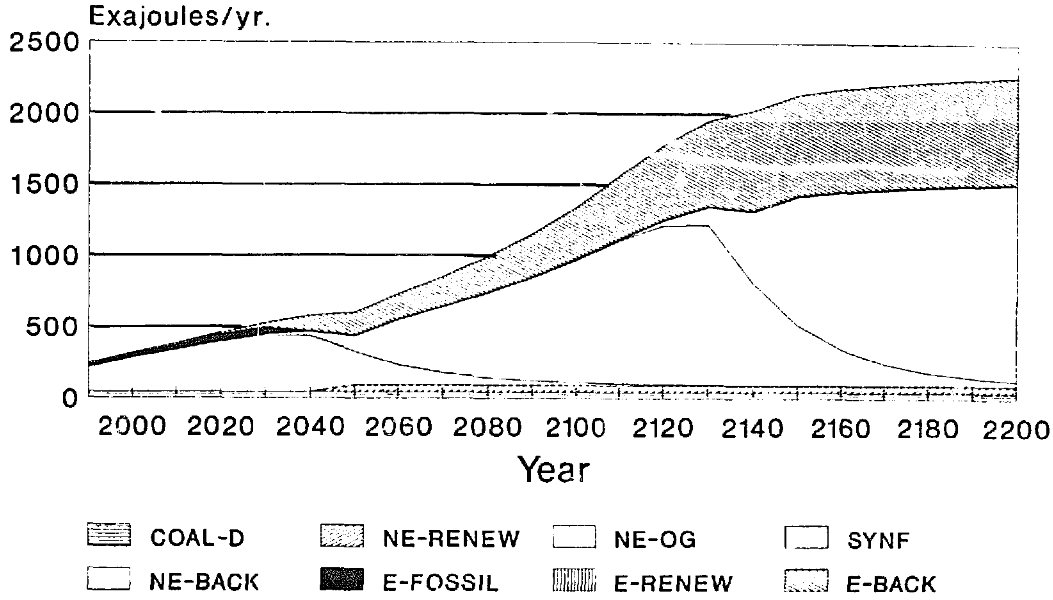

Fig. 2. Energy use, Central case.

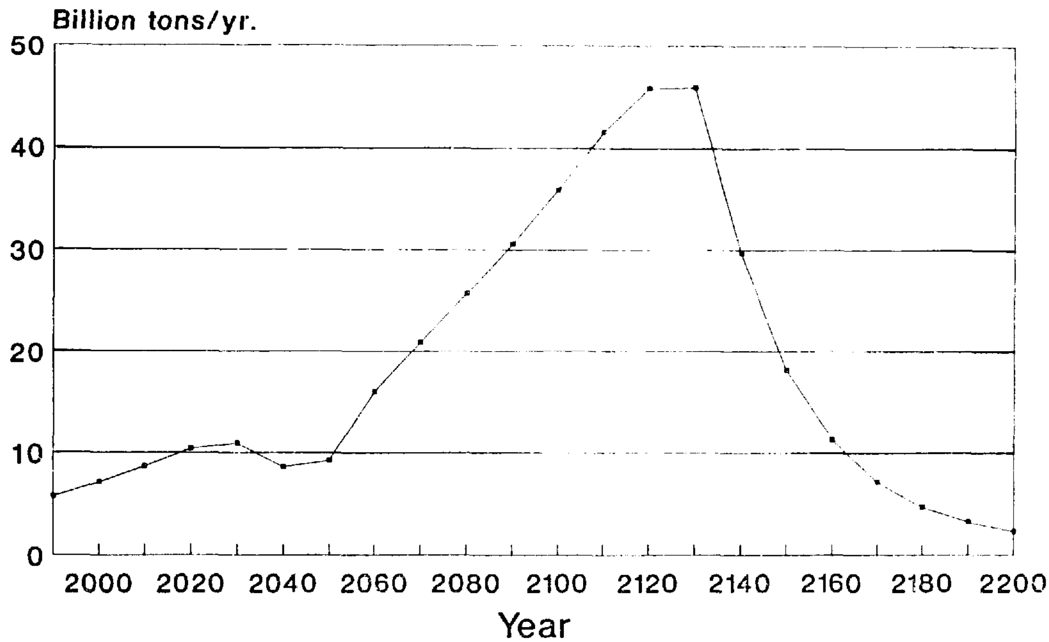

Fig. 3. Carbon emissions, Central case.

For our Low, Central, and High cases we use discount rates of 4%, 3%, and 2%, respectively.

2.c. Central case model results

Fig. 2 presents energy use patterns for our Central case parameter values. In the electric sector, the major energy use transition is the switch from fossil fuel technologies to the carbon-free backstop technology around 2030. In the non-electric sector, there are two major transitions: the switch from oil and gas to coal-derived synthetic fuels around 2050, and the switch from coal-derived synthetic fuels to the backstop around 2150.

Fig. 3 presents the carbon emissions path for the Central case. Carbon emissions rise gradually at first, then dip slightly around 2040 as the electric backstop comes on line. Beginning in 2060, emissions rise to a peak of about 45 billion tons per year before ultimately returning to pre-1990 levels by 2200. The surge in emissions beginning in 2060 is due to the transition from oil and gas to coal-derived synthetic fuels, and the subsequent drop in emissions is due to depletion of the coal resource base supporting the synthetic fuels industry.

Fig. 4 shows the path of atmospheric CO_2 concentration for the Central case. Concentration rises steadily until 2150, and then begins a gradual decline to the end of the time horizon shown. The initial rise in concentration occurs because new carbon emissions are being produced faster than the natural processes of the carbon cycle can remove carbon from the atmosphere. However, as the carbon emissions rate starts to fall beginning in 2140, the rate of carbon removal begins to exceed the rate of new emissions, causing the atmospheric concentration to begin a slow descent.

Fig. 5 shows the path of temperature for the Central case. Temperature rises steadily throughout the time horizon shown, reaching a level of about 6.5°C (over pre-industrial) by the year 2200. It is noteworthy that temperature rises steadily even though CO_2 concentration is declining by the latter part of this time period. Actual temperature responds with a long lag to concentration, and this accounts for the failure of temperature to turn down before the last year shown in the figure.

Fig. 6 presents the carbon tax path for the central case. The carbon tax begins at about \$10 per ton and rises monotonically to about \$160 per ton by 2200. The rise in the tax rate is attributable to rising temperature and the quadratic relationship between temperature and damage assumed as our Central case. However, the carbon tax does not rise high enough to make the carbon-free non-electric backstop technology competitive with synthetic fuels, and the backstop takes over only as a result of exhaustion of the coal resource base.[12]

2.d. Sensitivity results

To reduce the volume of information we need to report for the sensitivity cases, we present sensitivities in terms of the carbon emissions and carbon tax at two points in time. The first point in time is 2030, which is before the

[12]The tax would have to reach about \$208 per ton to make the backstop competitive.

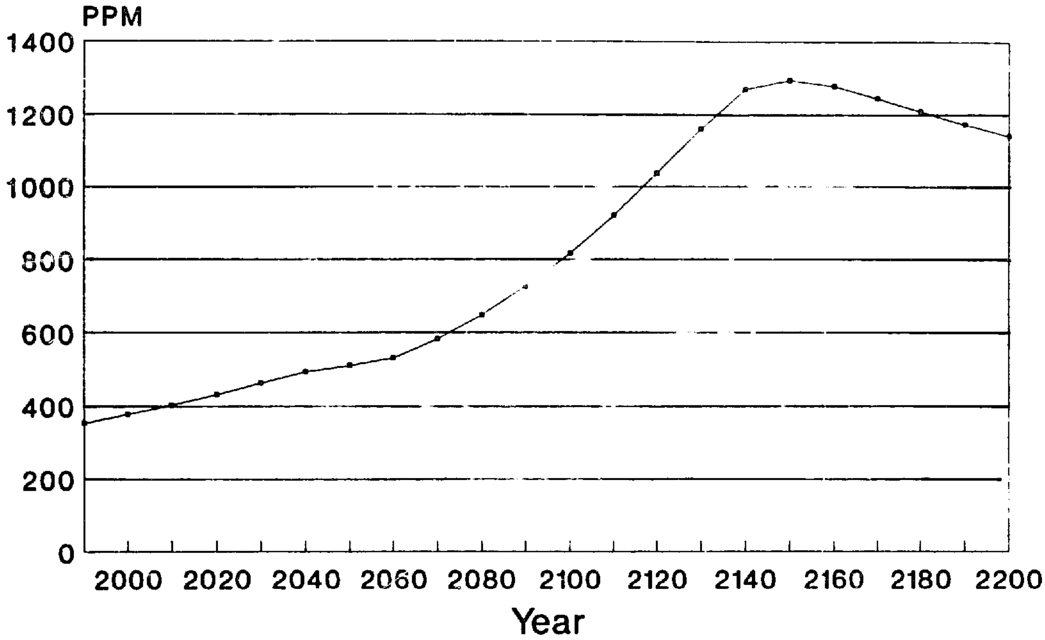

Fig. 4. CO_2 concentration, Central case.

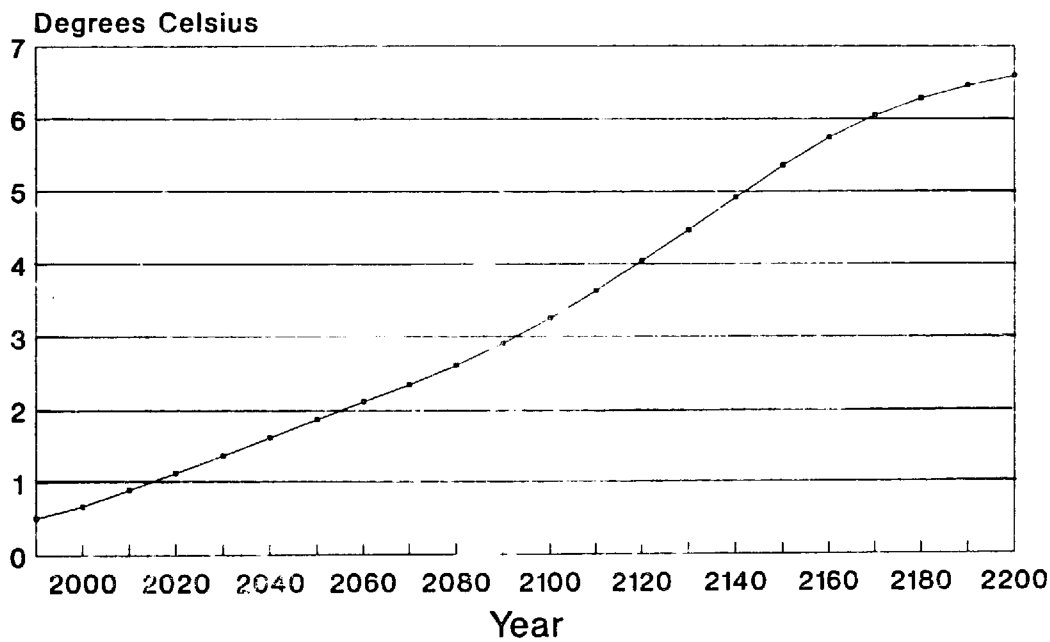

Fig. 5. Temperature rise, Central case.

major transition to synthetic fuels begins; and the second point is 2100, which is well into this transition. Tables 2 and 3 present these sensitivity results for the carbon emissions and the carbon tax, respectively.

Consider first the cost of control related parameters. Varying these parameters shifts the marginal cost of control function, while leaving the marginal benefit of control function undisturbed. Evidently, variations in these parameters induce only small shifts in the cost of control function in

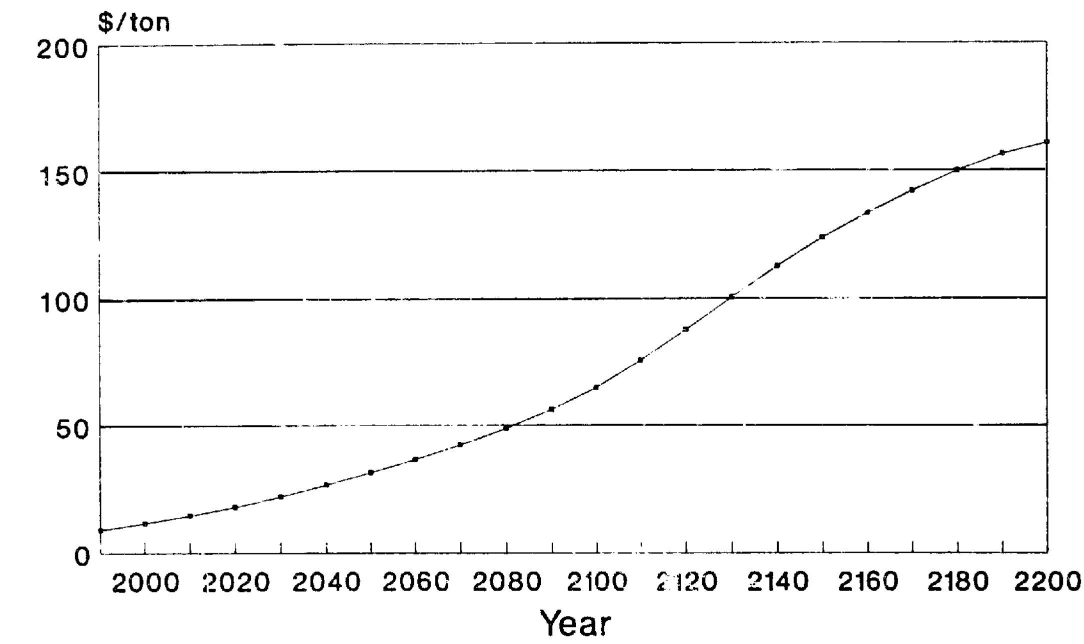

Fig. 6 Carbon tax, Central case.

Table 2

Sensitivity of optimal emission rates to parameter values.

Parameter	Optimal emissions rates 2030 Low	2030 High	2100 Low	2100 High
1. *Cost of control related*				
AEEI	10.0	11.8	29.3	42.4
Oil and gas resources	11.1	11.5	34.8	35.5
Coal resources	10.8	10.9	27.7	36.0
Non-electric backstop cost	10.9	10.9	2.5	34.3
Electric backstop cost	10.9	13.3	33.2	37.0
2. *Benefit of control related*				
Warming per $2 \times CO_2$	11.3	10.2	38.9	7.1
Adaptation/damage function percent	11.2	10.5	38.5	31.0
Adaptation/damage function power	11.1	10.7	38.3	21.0
Annual temp. adj. rate	11.1	10.3	37.7	25.7
Exogenous GHGs	11.0	10.8	35.9	34.9
Carbon cycle	10.9	10.8	35.8	34.9
3. *Cost and benefit related*				
Labor growth rate	8.5	13.9	20.9	54.2
Discount rate	10.4	11.2	35.5	28.0

2030, but larger shifts in 2100. Optimal carbon taxes, however, are relatively unaffected in either 2030 or 2100.

We can draw three conclusions from the above observations. First, the insensitivity of optimal emissions in 2030 implies that resolving uncertainty

Table 3

Sensitivity of optimal carbon taxes to parameter values.

	Optimal carbon taxes			
	2030		2100	
Parameter	Low	High	Low	High
1. *Cost of control related*				
AEEI	21.8	22.8	66.2	65.4
Oil and gas resources	22.1	21.8	65.8	65.6
Coal resources	22.9	22.3	70.3	64.1
Non-electric backstop cost	21.8	22.3	76.8	66.4
Electric backstop cost	22.1	22.4	66.1	65.3
2. *Benefit of control related*				
Warming per $2 \times CO_2$	3.4	57.6	8.7	197.6
Adaptation/damage function percent	5.5	39.6	15.6	122.6
Adaptation/damage function power	12.0	32.5	17.8	162.3
Annual temp. adj. rate	10.7	51.9	30.4	162.5
Exogenous GHGs	19.1	24.8	58.1	71.3
Carbon cycle	19.2	25.2	59.3	71.0
3. *Cost and benefit related*				
Labor growth rate	17.4	28.3	40.3	106.8
Discount rate	12.6	44.9	37.9	136.4

about these parameters before 2030 is not likely to have high value – if roughly the same policy is optimal in this time frame regardless of parameter values, little is gained by resolving uncertainty about these values. Second, and conversely, the sensitivity of optimal emissions in 2100 implies that resolving uncertainty well before 2100 is likely to have relatively high value. Third, the insensitivity of optimal carbon taxes in both 2030 and 2100 implies that the marginal benefit of emission reduction function is relatively flat across the range of optimal emissions changes induced by variation in the cost of control parameters.

Next consider the benefit of control related parameters. As before, optimal emissions are insensitive to parameter variation in 2030, but not in 2100.[13] Here, however, optimal carbon taxes are sensitive to variation in the benefit of control parameters, both in 2030 and in 2100. The latter result is not surprising since benefit of control parameter variations directly change the marginal cost of emissions.

Briefly, we note that the above results have implications for the relative merits of tax vs. quantity instruments for controlling emissions under

[13]There are two reasons for the difference in sensitivity of optimal emissions between 2030 and 2100. In the early time frame, there is heavy reliance on relatively clean and inexpensive oil and gas and it makes sense to use these resources regardless of how uncertainties may be resolved. In the later time frame, oil and gas is exhausted, but the non-electric backstop technology is available on a large scale and this technology allows carbon emissions to be reduced at constant unit cost by displacing carbon intensive synthetic fuels.

uncertainty.[14] Specifically, the insensitivity of optimal carbon taxes to variations in cost of control parameters indicates that the marginal benefit of control function is fairly flat; and the insensitivity of optimal emissions in 2030 to variations in benefit of control parameters indicates that the marginal cost of control function is quite steep, at least in this early time frame. If the benefit of control function is flat relative to the cost of control function, a tax policy will generally be the preferable control instrument, when there is uncertainty about cost of control related parameters. On the other hand, when there is uncertainty about benefit of control related parameters (but the cost of control is known), tax and quantity instruments are equivalent, since either can be set so as to produce exactly the same quantity of emissions.

In exploring the value of resolving uncertainty, we focus on uncertainty in benefit of control related parameters. We do this because our model is well suited to determining optimal quantity policies (i.e. carbon limits) under uncertainty, but not well suited to determining optimal carbon taxes under uncertainty. By restricting our analysis to benefit of control parameter uncertainty, we know that the optimal quantity policies we find are equivalent to the corresponding optimal tax policies. Whereas, if we applied our analysis to cost of control parameter uncertainty, we could find 'optimal' carbon limits, even though these represent a policy which is inferior to some other policy employing carbon taxes.

There is an additional reason for restricting our attention to uncertainty about benefit of control related parameters. Our analysis assumes that an uncertain parameter is initially unknown, and then becomes known all at once at a specified later date. However, the cost of control parameters by nature become known in other ways that are not well represented by this analytical approach. Specifically, the AEEI and the labor growth rate both are perfectly known for past time periods, and uncertain for future periods, within the model time horizon; resource base estimates are progressively improved over time as a result of production and new exploration; and the two backstop costs may be uncertain until the first date the backstop technologies become available, but after this date these costs are perfectly known for the rest of the time horizon (unless one assumes that these costs continue to change over time according to some stochastic process – but such a specification would also be outside the bounds of what we can handle using CETA in a simple decision tree framework).[15]

[14]These observations are based on results in Weitzman (1974).

[15]Various forms of progressive resolution of uncertainty could be modeled using stochastic dynamic programming. However, such an approach would be impractical unless CETA were simplified to reduce the number of state variables now represented in the model. See Peck et al. (1989) for an application of stochastic dynamic programming to determine jointly optimal emission control and learning policies when damages depend on a discharge stock.

The results in table 2 also suggest the subset of benefit related parameters that are of most interest, and which we choose to focus on in the next sections. Looking at 2100, the parameter with the greatest effect on optimal emissions is the warming rate per CO_2 doubling, and the parameter with the second greatest effect is the damage function power. The damage function percent parameter also induces a significant change in optimal emissions. Thus we choose to focus in the next sections on the warming rate (a parameter related to climate) and on the two parameters that together define the damage function (parameters related to impacts and adaptation costs).

3. Estimating value of information if optimal policies are used

Decision analysis provides a general paradigm for calculating the economic value of information.[16] In this paradigm, information is valued as the difference between (1) the expected value obtained if the state of the world is known before a policy must be adopted, thereby allowing a potentially different policy to be applied in every possible state of the world, and (2) the expected value obtained if a single policy must be adopted (without knowledge of the state of the world) and then applied across all possible states of the world. The first expected value is generally higher than the second, since the policy in the first case may be tailored to the actual state of the world. Mathematically, the expected value of perfect information (EVPI) can be expressed as follows:

$$\mathrm{EVPI} = \sum_i \rho_i \cdot \left[\max_{P_i} V(P_i, S_i) \right] - \max_P \left[\sum_i \rho_i \cdot V(P, S_i) \right], \tag{2}$$

where S^i = state of world i,
ρ^i = probability of state i,
P = uniform policy across all states,
P^i = tailored policy for each state i,
V = value function of policy, state.

Using decision tree diagrams, the expected value of perfect information can be represented as the difference in the value of two decision trees. These trees are illustrated in fig. 7. In the upper tree, uncertainty about the state of the world is resolved first, and then a potentially different policy is chosen depending on the state of the world. In the second tree, the policy is chosen first, and then uncertainty about the state of the world is resolved. Manne and Richels (1991b) characterize this difference using the phrases 'Learn, then act' and 'Act, then learn.'

While the above approach to valuing information is conceptually simple, there are numerous challenges in applying it to the global warming problem.

[16] See, for example, Raiffa (1968).

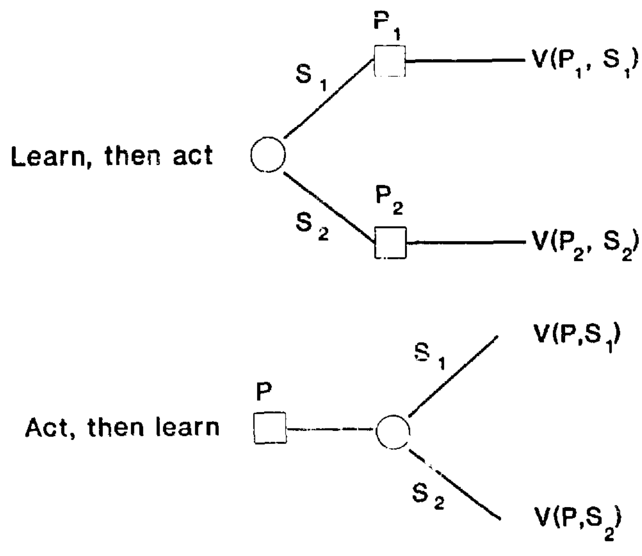

Fig. 7. Tree diagrams: Value of information.

First, there is a very large number of uncertainties involved in global warming. Second, available assessments of parameter uncertainties are typically limited to possible ranges at most, while information on distributional shapes and possible correlations among uncertain parameters is not available. Third, perfect information rarely becomes available all at once – instead, there is a continuing process of updating 'best estimates' over time as information is developed.[17] Finally, even without uncertainty, modeling of global warming is computationally demanding, since warming involves complex natural and human systems over a time scale measured in centuries.

In the face of these difficulties, we adopt certain simplifications in this paper. First, based on results in the previous section, we limit our consideration to three key parameters affecting the benefits of emission reductions. These are the extent of warming per CO_2 doubling and the level and power parameters of the warming damage function. Second, for most of our analysis we treat each parameter in turn as the only uncertain parameter, and represent its probability distribution using three points, with probabilities 1/6, 2/3, 1/6 for the Low case, Central case, and High case, respectively.[18] However, we do conduct an experiment to explore the implications of joint uncertainty about more than one parameter. For this experiment, we simplify our problem even further by assuming that the two parameters are

[17]See Peck et al. (1989) for an analysis of optimal emission control with progressive updating of information.

[18]This is consistent with the approach suggested by Miller and Rice (1983) to best represent a normally distributed random variable, using a three point distribution. In the context of the Miller and Rice approach, the Low and High cases to which 1/6 probability is assigned correspond to roughly the 5% and 95% probability points on the underlying normal being approximated; the Central case assigned 2/3 probability corresponds to the mean of the normal distribution.

independently distributed and that these parameters can take on only a High or Low value, each with probability 1/2.[19] Finally, in all the cases we consider, we assume that information perfectly reveals parameter values.

The basic CETA model is specified as a constrained non-linear optimization problem with both the objective function and some constraints non-linear. To determine optimal policies under uncertainty, this basic problem is augmented to solve a set of parallel problems, each representing a different state of the world (e.g. the High, Central, and Low parameter value outcomes, for uncertainty about only one parameter). Each parallel problem has its own complete set of variables and constraints, indexed by the state of the world. In addition, the objective function is re-specified as a probability weighted sum of the present value utilities obtained in each state of the world. Finally, additional constraints are added to the problem to require that solution variables be the same across all states of the world, for as long as the state of the world is assumed to be unknown. After this time, these constraints are eliminated and the model solution variables are allowed to differ across states of the world. With this specification, the solution before resolution of uncertainty is a single policy which maximizes expected utility across possible states of the world.

4. Value of information results if optimal policies are used

4.a. One variable at a time uncertain

To illustrate the nature of the model solutions underlying our value of information estimates, we initially present some detailed results for uncertainty about the warming rate per CO_2 doubling. First, in fig. 8, we show the optimal paths of emissions if the warming rate is known now. Notice that optimal emission paths for alternative values of the warming rate begin to diverge immediately, although the divergence is quite small until the oil and gas resource base becomes depleted around 2050. After oil and gas is depleted, a choice must be made between using synthetic fuels derived from coal or the carbon-free non-electric backstop technology. If the warming rate is 1°C, synthetic fuels are chosen, and the coal resource base is exhausted over the subsequent 150 years. If the warming rate is 3°C rather than 1°C, synthetic fuels are still chosen, but the rate of depletion of the coal resource base is modestly slowed, resulting in emissions that are delayed, but otherwise similar to those for the 1°C warming case. If the warming rate is 5°C, the use of synthetic fuels is curtailed, particularly after 2080; as a result, optimal CO_2 emissions are significantly lower in this state of the world.

[19]Here too we use the Miller and Rice (1983) approach. We choose the two point marginal distributions to be roughly equivalent to the three point distributions described earlier. The two points are the Central case plus or minus one standard deviation, each with probability 1/2.

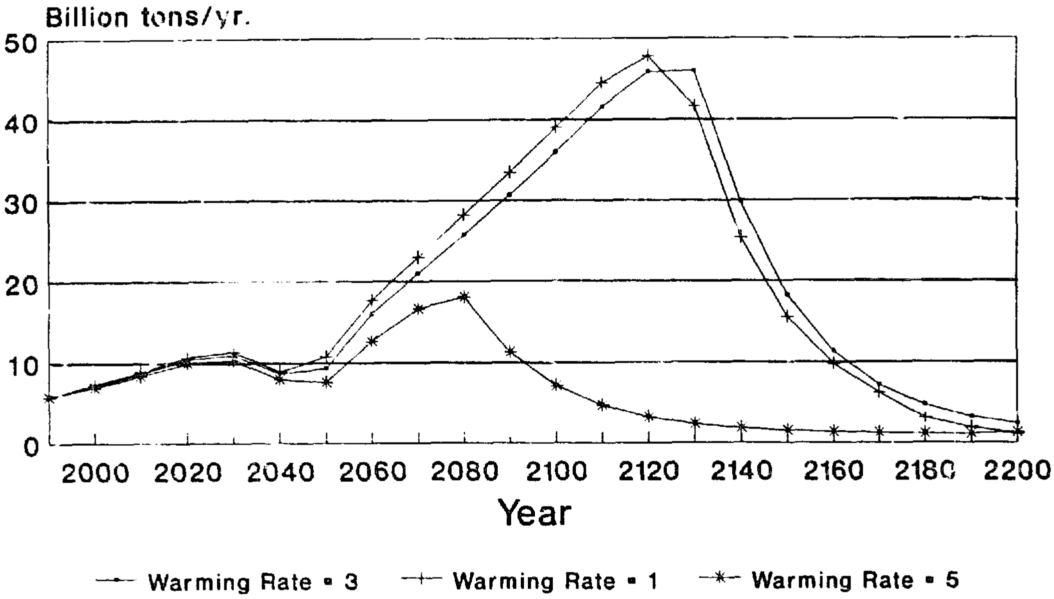

Fig. 8. Carbon emissions: Learn, then act.

If the true warming rate is assumed to be unknown for some period of time, the optimal carbon emissions paths will be the same initially, but later diverge once the warming rate becomes known. For example, suppose that the true warming rate becomes known after eighty years. In this case, the optimal emissions paths are as illustrated in fig. 9. Notice that the paths are identical over all states of the world until 2070, after which the optimal paths branch out to become roughly similar to the optimal paths in fig. 8.[20]

In the extreme, we might assume the warming rate remains unknown for the entire time horizon of the model. In this case, the optimal emissions paths will be the same across all states of the world for the entire time horizon. Fig. 10 illustrates this case.

The model solutions illustrated in figs. 8 through 10 may be used to calculate a variety of different values of information. First, by subtracting the objective function value for the solution in fig. 9 from the objective function value for the solution in fig. 8, we would get the value of knowing the warming rate now rather than having it be revealed in eighty years. This value is $56 billion.[21] Alternatively, by subtracting the objective function value for the solution in fig. 10 from the objective function value for the solution in fig. 9, we would obtain the value of knowing the warming rate in eighty years rather than never knowing it. This present value of information

[20]These paths are not identical to those in fig. 8 starting in 2080, because the optimal path under uncertainty prior to 2080 has affected important variables (e.g. the CO_2 concentration, the coal resource base, etc.).

[21]Actually, the difference in objective function values is denominated in expected "utils. Thus the difference in objective function values is converted to a dollar value using the dollar value of utility generated by the model solutions.

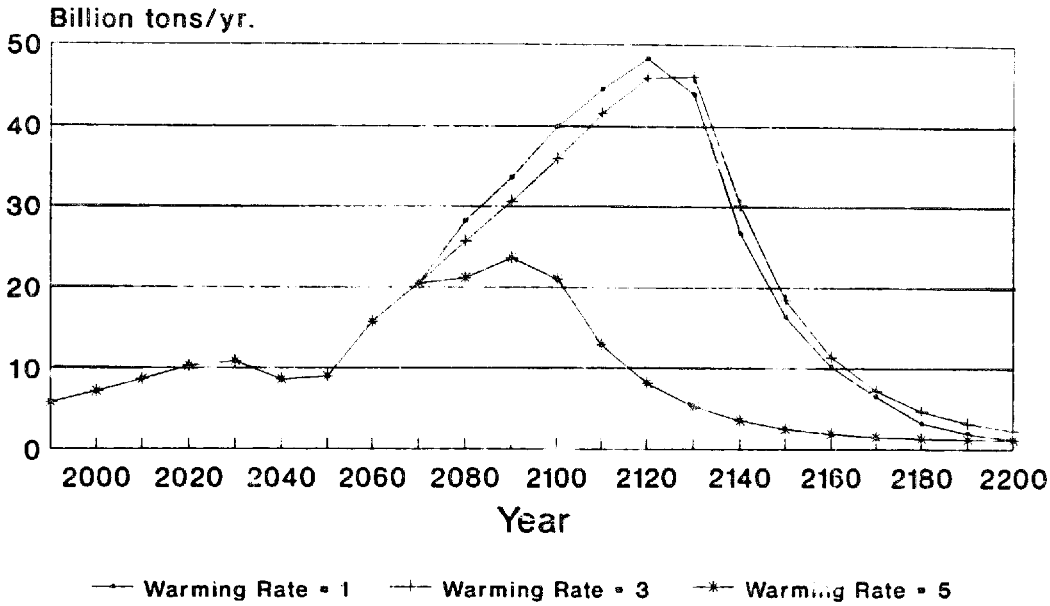

Fig. 9. Carbon emissions: Act, then learn

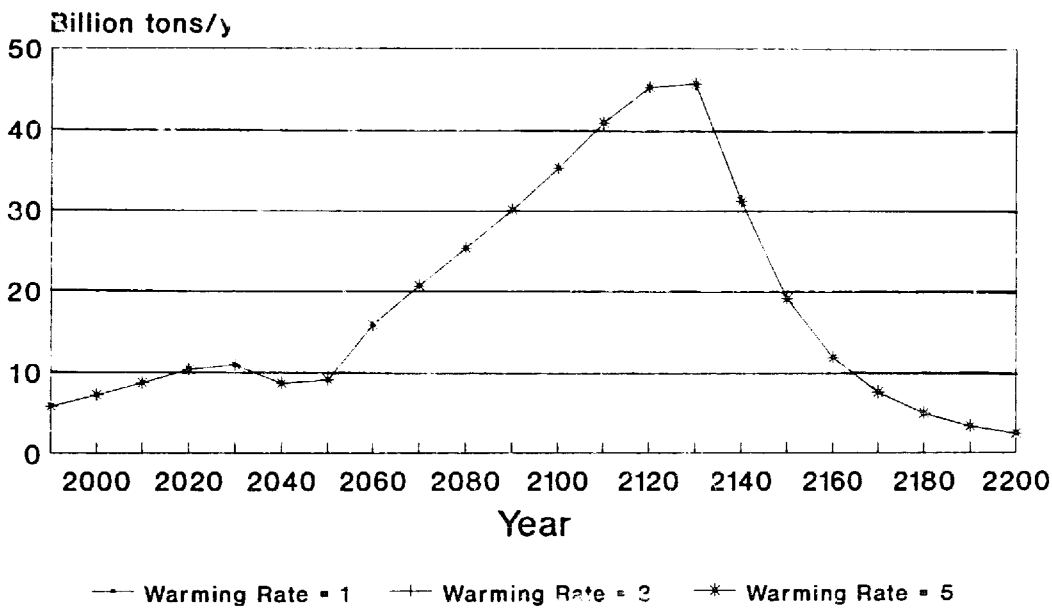

Fig. 10. Carbon emissions: Never learn.

is $92 billion. Lastly, by subtracting the objective function value for the solution in fig 10 from that for the solution in fig. 8, we would get the value of knowing the warming rate now rather than never. This value is $148 billion.

The solutions illustrated by figs. 8 through 10 are actually three members of a whole family of solutions produced by assuming that perfect information is revealed at various dates between 1990 and the time horizon of the model. Obviously, there is a large number of reasonable values of information that

Table 4

Information now vs. never: Optimal policy under uncertainty.

Parameter	Value of information (billion \$)
Warming rate per $2 \times CO_2$	148
Adaptation damage function percent	27
Adaptation damage function power	98
Total	273

Table 5

Information now vs. twenty years later: Optimal policy under uncertainty.

Parameter	Value of information (billion \$)
Warming rate per $2 \times CO_2$	6
Adaptation damage function percent	0.2
Adaptation damage function power	0
Total	6.2

could be calculated from the solutions in this family. From this large number of values, we select a subset of values that are of particular interest. First is the value of information now vs. never; this is 'the value of information' in a gross sense. Second is the value of information now vs. in twenty years, which is a measure of the value of resolving uncertainty sooner rather than later. We also generalize this second measure by calculating the value of accelerating uncertainty resolution by twenty years, as a function of the date to which the acceleration occurs.

Table 4 shows the gross value of information now vs. never for the three parameters we consider in this paper. Notice that the value of information is greatest for the warming rate parameter. However, the adaptation/damage function parameters have a total value of information which is nearly as high. Thus resolving uncertainty about the impacts of warming appears to be about as important as resolving uncertainty about the extent of warming.

Yet, 95% of the US global warming research budget is presently devoted to resolving physical uncertainties such as that surrounding the potential warming rate, and only 5% is devoted to resolving uncertainties about warming impacts, mitigation strategies, and adaptation costs.[22] This relative imbalance may not be justified.[23]

[22]See National Academy of Sciences (1991, p.70.)

[23]A definitive conclusion in this regard would have to be based on an assessment of the incremental resolution of uncertainty per incremental dollar spent on alternative lines of research. Since our analysis does not address this issue, our results are only suggestive of a misallocation of research money.

Table 4 also shows a 'Total,' which needs to be interpreted cautiously. We believe that it significantly understates the actual total value of information about the warming problem. This is the case, most obviously, because there is a large number of other uncertain parameters whose values of information are not included in the total reported in table 4. In addition, results we report in the next section suggest that when two or more parameters are simultaneously treated as uncertain, the value of resolving uncertainty about all of them is greater than the sum of the values of resolving uncertainty about each of them treated in turn as the only uncertainty.

Table 5 shows the value of perfect information now, assuming that the same information would otherwise become available in twenty years. While the total of $6.2 billion dollars is not a trivial sum, it is not particularly large in relation to an annual US global warming research budget of $1 billion, and it is small relative to the gross values of information reported in table 4. The results in table 5 thus suggest that there is not a high premium attached to immediate resolution of global warming uncertainties.

We believe that the low premium on immediate resolution of global warming uncertainties is due to the short run insensitivity of optimal decisions to alternative parameter values. In general, when optimal policies are roughly the same regardless of how uncertainties are resolved, there is little economic benefit derived from resolving uncertainties. In the global warming problem, policies in the short run (20 or even 40 years) are not sensitive to parameter values. We believe that this insensitivity in the near term is the result of reliance during this period on inexpensive and relatively clean oil and gas – it makes sense to use this resource regardless of whether uncertain global warming parameters take on high or low values.

Although optimal emissions policies are relatively insensitive to parameter values in the short run, this is not true indefinitely. By the year 2100, for example, optimal policies are significantly different for different parameter values. Thus we should anticipate that the premium on early resolution of uncertainty would tend to increase over time, if uncertainty remains unresolved. To confirm this hypothesis, we consider another measure of the value of information: the value of accelerating uncertainty resolution by twenty years, as a function of the date to which the acceleration occurs.

Fig. 11 shows the value of resolving uncertainty twenty years earlier, as a function of the date at which this acceleration might occur. While not monotonically increasing, the lines in the figure are clearly upward trending. In a sense, the upward trends in the figure are understated, since the numbers graphed are the present values as of 1990 of these accelerations. If these values were re-expressed as contemporaneous present values, the upward trend would be more pronounced.

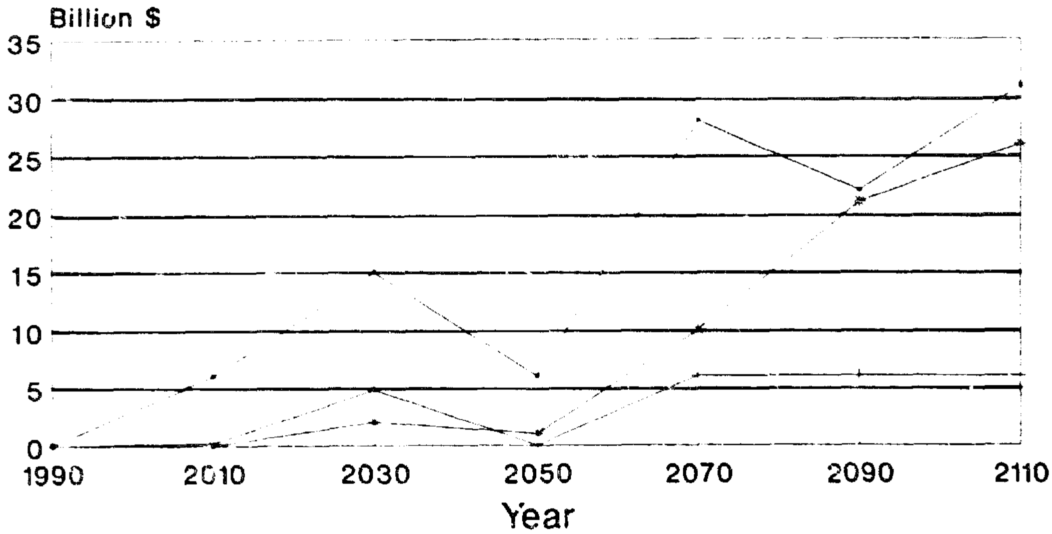

Fig. 11. Value of learning warming rate 20 years sooner vs. time.

4.b. Value of information if two parameters are uncertain

In this section we present results of an experiment intended to explore the implications of joint uncertainty about two or more parameters. Our results suggest that the value of resolving uncertainty about two or more parameters treated as jointly uncertain is likely to be greater than the sum of the values of resolving uncertainty about each parameter treated in turn as the only uncertainty.

Because of the computational difficulty involved in solving the CETA model over a large number of states of the world, we further simplify the problem we consider in this section.[24] First, we shorten the time horizon over which the model is solved to 2170 from 2250. Second, because of the shortened time horizon, we consider a relatively near term value of information question - specifically, what is the value of having perfect information now instead of forty years from now? Third, we substitute two point distributions for the three point distributions we used in the preceding section.

In shifting from three point distributions to two point distributions we again use the Miller and Rice (1983) approach. Under this approach, the two points to be used to approximate a Normal distribution are the mean plus or minus one standard deviation; each of these points is then assigned

[24]Analyzing one uncertain parameter with three possible values involves the simultaneous solution of three parallel CETA specifications. Two parameter uncertainty with three possible values for each uncertain parameter would involve simultaneous solution of nine parallel CETA specifications. Not only did the run-time become excessive in this case, but we also encountered numerical problems in converging to an optimal solution.

Table 6

Information now vs. in forty years: One parameter uncertain.

Parameter	Value of information (billion $)
Warming rate per $2 \times CO_2$	24
Adaptation damage function percent	9
Total	33

Table 7

Information now vs. in forty years: Two parameters uncertain.

Parameter	Value of information (billion $)
Warming rate per $2 \times CO_2$	33
Adaptation damage function percent	22
Both parameters together	47

probability one-half. Since we earlier identified the Low and High case parameter values with the mean plus or minus 1.732 standard deviations, it is a simple matter to calculate the implied standard deviation for each parameter, and from this to determine the parameter values associated with the Low and High points in the two point distribution.

Since we are using a near term value of information (perfect information now vs. forty years from now), we choose to consider uncertainty about the two parameters that have the highest value of information in the short term. As fig. 11 indicates, these are the warming rate and the adaptation/damage function percentage.

To create a reference point for comparison, we first calculate the value of information assuming single parameter uncertainty as was done in the preceding section; however, we here use the shortened time horizon and the two point distributions. Table 6 below shows our results; these are in fact quite similar to those we would have obtained (for learning now vs. forty years from now) using the longer horizon and the three point distributions of the preceding section.[25]

Table 7 shows the comparable results for value of information when two parameters are treated as simultaneously uncertain. While the general magnitude and pattern of results are similar, there are some noteworthy differences. First, the value of information about either parameter is higher if the other parameter is treated as uncertain (table 7) than if the other parameter is treated as known and equal to its Central case value (table 6).

[25] With the three point distributions and the longer time horizon, the values of information now vs. forty years from now are 21 and 5 billion for the warming rate and damage function percentage, respectively.

Second, the value of resolving uncertainty about both parameters simultaneously (\$47 billion) is well in excess of the sum (\$33 billion) of the values of resolving information for each of the two parameters treated as the only uncertain parameters. This result suggests that the sum of the values of information for two or more parameters each treated as the only uncertain parameter understates the value of resolving uncertainty about all those parameters at once.

5. Value of information results if suboptimal policies are used

In the previous section, we presented results assuming that emissions control policy under uncertainty would be based on a balancing of the expected costs and benefits of emissions reduction. In this section, we assume that policy under uncertainty will be arbitrarily determined by a real world political process involving the governments of many countries with differing perspectives and interests.

While it is difficult to forecast what kind of emissions reduction policy might emerge from the political process, the policy that emerges is unlikely to be the optimal one.[26] We consider two possible suboptimal policies that might emerge: one is a policy of no emissions reduction before uncertainty is resolved, and the other is a policy of limiting emissions to the 1990 level until uncertainty is resolved. In either case, we assume that when uncertainty is resolved, the policy will revert to the optimal one for whatever state of the world is revealed.[27]

As in section 4, we consider each parameter in turn, assuming the values of the other parameters are known and equal to their Central case values. As we discuss below, the bulk of the value of information we calculate in this section is attributable to the shift from a sub-optimal to an optimal policy, which we assume accompanies the resolution of uncertainty. Consequently, the sum of the values of information for each parameter is in this case likely to overstate the value of resolving all uncertainties together. We believe it may be most reasonable to interpret these numbers as follows: the largest value of information estimate for any single parameter may approximate the

[26]It is not plausible to believe that the policy process might first reach consensus on probabilities of alternative states of the world, and then agree on an emissions control policy that is optimal given this uncertainty. Rather, when there is uncertainty about the nature of a problem and there are multiple bargaining parties, there is a strong tendency for policy to gravitate toward readily understood 'focal points,' such as limiting emissions to their 1990 level; such focal point policies would be optimal only by chance.

[27]There is an argument, of course, that a suboptimal policy may also be chosen after uncertainty is resolved. However, this is less likely if uncertainty is resolved quickly, since in this case there is less time for vested interests to develop as a result of previous policy. If an optimal policy is more likely with quick resolution of uncertainty than with slow resolution, the benefit of resolving uncertainty quickly is even higher than our numbers suggest.

Table 8

Value of information (billion $): Information now vs. twenty years later.

Parameter	Policy under uncertainty No control	1990 Limit	Optimal
Warming rate per $2 \times CO_2$	90	2828	6
Adaptation damage function percent	22	2911	0.2
Adaptation damage function power	65	2897	0

value of resolving all uncertainties together, and thereby moving to the optimal policy for the state of the world that is revealed.

Table 8 presents estimates of the value of information now vs. twenty years later assuming no emissions control or a 1990 emissions limit in the interim before uncertainty is resolved. For comparison, the table also shows the comparable values of information from table 5; the latter, of course, are based on the assumption that an optimal policy is used under uncertainty.

Not surprisingly the new numbers in table 8 are much larger than the comparable numbers from table 5. One can interpret the new values of information in table 8 as being the sum of (1) the conventional value of information, and (2) the additional value from adopting a best policy under uncertainty instead of using one of the two sub-optimal policies. The previous value of information numbers from table 5 correspond to term (1) in the sum above, while the new numbers in table 8 correspond to the sum of (1) and (2). Evidently the value from adopting a best policy under uncertainty vs. no emissions control is high; and the value from adopting a best policy under uncertainty vs. the 1990 limit is huge.

Among our earlier results is the rather comforting one that information in twenty years is almost as good as information now, implying that we can proceed in a relatively unhurried fashion to design and implement a careful research program. However, the results in table 8 present a very different picture – if the emissions control policy under uncertainty will be some arbitrary policy like those considered here, it is critical to resolve uncertainty quickly.

6. Conclusion

The global warming problem is a complicated one, and placing a value on resolution of global warming uncertainties is a difficult task. In this paper, we have presented a first effort at such an analysis. Obviously, there are important caveats that should be attached to our analysis.

First, the CETA model cannot perfectly represent the future for the next 200 years, even if the key parameters of the model are completely known.

Both the climate model and the economic growth model in CETA are very simple representations of extremely complex systems over a very long period of time; these simple representations necessarily omit many real world factors that bear on the warming problem.

Second, our representation of uncertainty and learning is both limited and simplified. We limit the number of parameters that we treat as uncertain at a given time, we limit the number of possible values that each may take, and we assume that these parameter values are either completely unknown or perfectly known. In addition, the possible values that parameters may take are in most cases just our own estimates of 5 and 95% probability points for these parameters.

However, we have conducted a self-consistent exercise to identify important driving variables and to estimate the value of information for a selected subset of these variables. Caveats notwithstanding, we believe that our results support the following tentative conclusions:

(1) If an optimal policy is used under uncertainty, the value of information is large enough to justify current research efforts, and perhaps to justify increased emphasis on research into the impacts of warming and cost of adaptation to warming.

(2) If an optimal policy is used under uncertainty, ample time is available to plan and execute a well-designed research program to resolve uncertainties.

(3) However, if the political process will choose suboptimal policies and this choice could be prevented by early resolution of uncertainty, the urgency of resolving uncertainty is dramatically increased.

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