Flexible Design for Global Climate Change Policy

ESD.71 Engineering Systems Analysis for Design
Application Portfolio
December 2009

Nidhi R. Santen
Engineering Systems Division
Massachusetts Institute of Technology

Abstract

Current climate change policy decisions are based on relatively deterministic views of the future events and are dominated by considerations of “an” optimal carbon emissions path. This optimization approach encourages the false notion that carbon emissions policy in the distant future should (and can) be set today. However, many aspects of the future remain highly uncertain, creating the need for flexible climate policies—those than can incorporate learning and retain an ability to shift decisions in future periods. This flexibility is particularly important when considering the long time-horizons involved in climate change mitigation and that the potential for irreversibility of decisions is high.

The following project examines the opportunities that flexible global climate change policy can have on the overall net present welfare of the global macroeconomy. The system under study consists of an aggregated global economy, specified through a climate change lens, and includes the population’s preference for consumption versus investment, and possible damages to the physical environment from carbon emissions. The underlying evaluation model used for determining system values is the Dynamic Integrated model for Climate and the Economy (DICE-99) and the timeframe studied is 2015 through 2335.

The overall hypothesis under investigation suggests that implementation of a R&D-inducing carbon tax policy today provides a form of “insurance” against future carbon-emissions related climate damages (costs), and therefore represents a form of flexibility. Specifically, two variants of a carbon policy are studied in this project, considering different uncertainties and using two different methods of analysis. The first major exercise is an investigation to determine the value of flexibility between a policy that implements a carbon tax today with the opportunity to shift the tax level later and a business-as-usual no carbon tax case. The second exercise is an investigation to determine the value of a call option to implement a carbon tax policy when the system deems appropriate and examine how long we should wait to implement a carbon tax or not. Uncertainties considered in this project include the growth rate of total factor productivity, the growth rate of emissions intensity, and the sensitivity of the climate to carbon emissions.

Results from a decision tree analysis for the first exercise show that a flexible carbon-tax based policy path is the optimal strategy over two periods over all possible scenarios, and that the value of this flexibility is $0.019316 trillion. Results from a dynamic programming solution for the second exercise show again that the flexible strategy is preferred to the inflexible strategy at all risk levels, and that the value of the call option to implement a carbon-tax when deemed appropriate is $0.51 trillion. Overall, these results confirm the underlying hypothesis under investigation.

Table of Contents

I. Introduction

Overview

System Description

The system under study consists of an aggregated global economy, specified through a climate change- or carbon emissions-interested lens. It includes generalized capital, labor (in the form of population), and fossil fuel-consuming energy services. Through use of a social welfare function, the system also includes the population's preferences for consumption versus investment. Finally, it includes the physical environment (upper atmosphere, biosphere, and deep oceans), affected by carbon emissions. The study excludes regional-level considerations, and details on specific technologies and types of carbon reducing policies. The time frame for study is selected as 2015-2335 (in decadal increments), based on the planning scope of the main economic model used in the exercise and a realistic time-frame for making a first period decision in this study.[1]

Research Motivation

Current climate change policy decisions are based on relatively deterministic views of future events and are dominated by considerations of an optimal carbon emissions path (Figure 1.1). This optimization encourages the false notion that carbon emissions policy in the distant future should (and can) be set today. However, this way of thinking leads to the proliferation of inflexible systems incapable of adapting to future (inherently uncertain) events. Instead, designing a flexible emissions policy path that can respond to specific key future uncertainties allows the world to reduce the risks associated with less than favorable future outcomes and take advantage of favorable futures. Furthermore, in considering the future energy industry with respect to global CO_2 emissions and climate change, the potential for irreversibility of decisions is high; making good choices today critical.

---

[1] 1995 and 2005 are set as baselines (reference years) in the version of the DICE-99 (or DICE) model used in this study.

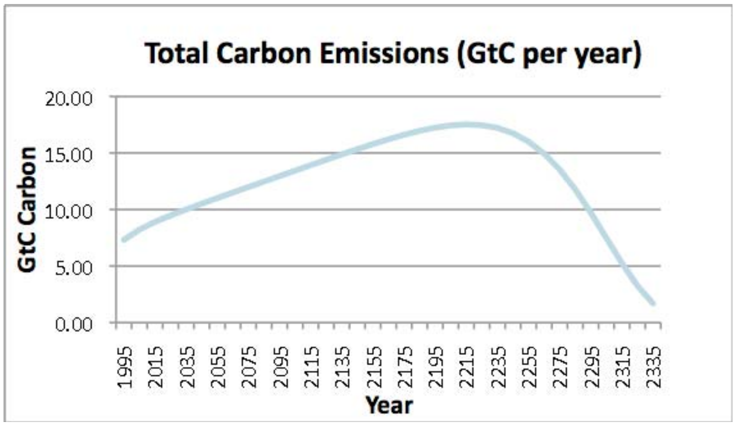

Figure 1.1. Ex. Optimal Emissions Path Under a Deterministic Future (From DICE-99)

Many aspects of the future remain highly uncertain (see below), creating a need for a flexible climate policy—one that can incorporate learning and leave a real ability to shift decisions in future periods. This is especially important (and useful) given the long time horizons involved in mitigating climate change and the reliance current estimates place on the role of technological change in the energy sector over time (and associated carbon emissions reduction) (Figure 1.2). Incorporating wise policy decisions is also important given the role of policy-induced technological change--economic theory holds that implementation of a carbon reduction policy will spur technological innovation in order to meet reduction goals.

The current exercise is carried out in the context of a larger research project aimed at improving ENTICE-BR, a global economic model with endogenous energy technical change, considering uncertainty in returns to energy R&D and climate response[2]. However, one of the first steps in improving such a model consists of exploring the effect of key uncertainties on the optimal design of the system, and developing a method for finding policy alternatives that build flexible systems (policies that incorporate these uncertainties and encourage the system to shift in the presence of various realized events, to incorporate learning). This exercise is devoted to developing this method.

Box 1. As an illustration of the type of irreversibility that exists in the system under study, consider the following example:

Avoiding future catastrophic climate events will probably require staying beneath a certain level of cumulative CO_2 *emissions over the next two to three-hundred years. The trajectory at which per year emissions proceeds, however, is not fixed due to the reality and influence of stock versus flow pollutants (stock* CO_2*, defined as the cumulative mass of* CO_2 *actually in the atmosphere is what drives climate change; flow* CO_2 *contributes to stock* CO_2*). Consequently, although one might consider it easy to shift policies later if* CO_2 *reduction techniques do not work today, in reality, several decisions may have been made during the meantime—erection of large conventional coal facilities with long life spans and huge sunk costs or low investment in R&D and resulting non-maturation of needed technologies—which may make those shifts impossible or at least highly impractical.*

---

[2] MIT Joint Program, Syracuse University, and Penn State collaboration: http://globalchange.mit.edu/research/projects/NSF-TechnicalChange.html.

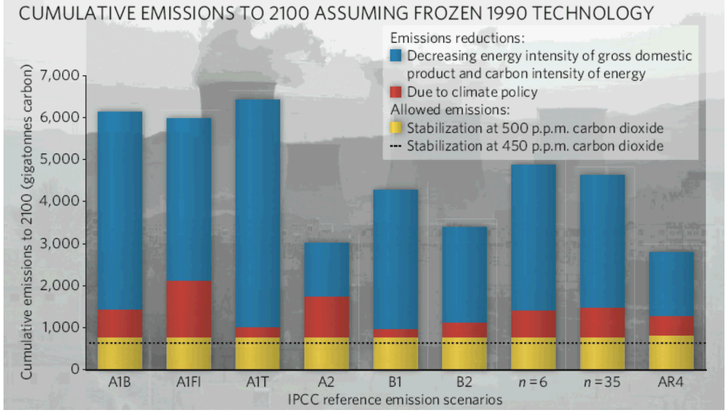

Figure 1.2. A highly contested matter, the IPCC reference emission scenarios include "built in" (blue) levels of spontaneous technological change and de-carbonization. This potentially deemphasizes the need for active carbon reduction policies and can bias policy analyses based on these scenarios.[3]

Principal Design Levers

The principle policy decisions (also known as design levers or decision variables) available to improve system performance are based on a fundamental tradeoff between consumption today and consumption at some point in the future. The framework adopted for this exercise assumes that making certain types of carbon emissions reducing decisions today (environmental policies that drive investments in R&D and technological change) will reduce the amount of consumption and productive investment today, but will return opportunity for higher consumption in the future due to the lowered climate damages incurred by society. The principle decision variable called upon in this study is thus a carbon emissions reduction policy (μ_t). In the evaluation model utilized for this study, μ_t is interpreted as a carbon tax.

System Benefits

Given the broad, aggregated nature of the system under study—the entire global economy—the list of individual benefits are potentially infinite. They are aggregated into a generalized measure of utility; the discounted sum of the utilities of welfare (hereafter referred to as NPV) will therefore be used to measure value. More generally however, the benefits of a well-functioning, low-carbon global economy are many and include mitigated impacts on agriculture, coastlines, and ecosystems; potentially

---

[3] Pielke, Jr., R. A., Tom Wigley, and Christopher Green. 2008. Dangerous assumptions. *Nature* 452(3): 531-532.

improved human health; overall sustainability and consideration for future generations; and reduced potential for catastrophic climate change.

Available Evaluation Models

The 1999 version of the Dynamic Integrated model of Climate and the Economy (DICE) developed by William Nordhaus at Yale University will be used for this exercise. (ENTICE-BR is based on DICE.) The model is a highly simplified, aggregated model of the global economy that approaches the problem of global warming from an economic viewpoint. It is an extension of the Ramsey growth model (based on a general form Cobb-Douglas production function), and includes investments in carbon-reduction. It is also an integrated model in that it includes economics, a full carbon-cycle, climate science, and climate impacts or damages. Its highly simplified nature represents both its strength and weakness. While analyzing detailed, regional or technology-specific questions is impossible with DICE, its small size makes the model perfect for understanding the links and drivers behind the economics of climate change and for testing policy design alternatives with respect to flexibility. Because of its size, DICE is also more easily modified, which was an important consideration for this exercise. It is the model that should be studied first, in order for the methodology developed to be extended to similar, but more complex models.

Key Contextual Factors–Uncertainties

There are several uncertainties that the decision-maker faces when considering optimal climate policy. Main contextual uncertainties (not all will be explored) in this case include:

- Population growth rate. In general, higher population levels yield higher carbon emissions, making reductions more challenging.
- Rate of innovation or technical change. As Figure 2 above shows, technical change is slated to majorly contribute to future carbon reductions. However, how fast innovation takes place is highly uncertain. This includes economy-wide technical change, reflected in increases in total factor productivity, and energy-specific technical change, reflected in decreases carbon emissions intensity (ratio of carbon emissions to economic output).
- Climate sensitivity, defined as the response of climate to carbon emissions. Our most sophisticated global climate assessment models continue to report results of temperature change due to emissions using uncertainty representing bounds, pointing to the challenge of accurately understanding and predicting climate responses to specified carbon levels.
- Political or regulatory changes of a non-climate nature. The option value of flexible climate policy will be determined via comparison with a “no policy” case. However, the appearance of additional non-climate related policies at any level are highly uncertain. They are important to the extent that they can change key economic drivers and can have potential unknown interactive effects with climate policy choices.

- Social or global cultural shifts. For example, panic and call for more rapid climate mitigation response or (alternatively), a revert back towards increased skepticism of human-induced climate change. Both of these can change considerations for optimal policies.

Research Question Statement

What is the optimal near-term climate policy design (carbon emissions tax) given uncertainties in productivity, emissions intensity, and climate sensitivity, and the flexibility to learn and revise the policy later?

This project seeks to answer this question from two perspectives, using two different methods of analysis.

II. Sources of Uncertainty

The three uncertainties explored in this study include the growth rate for total factor productivity (A_t), growth rate for emissions intensity (σ_t), and the feedback parameter in the climate model representing the sensitivity of the climate to carbon concentrations (λ_t). Below, these uncertainties are described, and their distributions are characterized.

Total Factor Productivity

Total factor productivity (A_t) represents the contribution to economic output not accounted for by inputs such as labor and capital. This can range from technology to workers' knowledge; total factor productivity can be thought of as the efficiency of the economy at transforming inputs into output and/or as level of technology in the economy. As one might imagine, the intangible and all-encompassing nature of total factor productivity influences its highly variable nature, and total factor productivity can digress from its forecasts for many reasons. For example, weather can be one aspect of total factor productivity, as its state has the ability to affect output (good weather promotes agricultural production), but does not directly affect either labor or capital. As another example, workplace training programs can increase worker knowledge, which can lead to higher levels of output with the same levels of labor and capital. Finally, technological growth in the form of more innovative use of existing machinery can lead to increased output with the same level of labor and capital. Projecting A_t has been met by significant challenge due to these unpredictable and diverse events.

DICE uses a typical exponential growth function to estimate future total factor productivity; still, the growth rate used in this function remains highly uncertain. A proxy measure for total factor productivity growth rate is GDP per capita growth rate, and will be used in this study. Uncertainty in A_t will be characterized using a probability distribution estimate for the growth rate of A_t based on the MIT Joint Program on the Science and Policy of Global Change's most recent Integrated Global System Model probabilistic climate forecasting work; this estimate was developed from historical observations of productivity.[4] The histogram and CDF for the growth rate of A_t in the MIT Joint Program report are provided below in Figures 2.1 and 2.2[5]. The average total factor productivity growth rate per decade is

---

[4] Webster, M., Paltsev, S., Parsons, J., Reilly, J., and H. Jacoby, (2008), "Uncertainty in Greenhouse Gas Emissions and Cost of Atmospheric Stabilization," MIT Joint Program on the Science and Policy of Global Change Report No. 165, November 2008.

[5] The initial growth rate was developed from an annual growth rate based on 1997-2000 data from the MIT Joint Program report. This does not correspond exactly with a 1995 base, but it comes close and is used as a proxy for this exercise.

16.61%, the maximum is 17.14%, and the minimum is 16.00%. The volatility, approximated by one standard deviation, is 0.20%. For integration into DICE, the distribution was normalized around a median of 1.0, and then applied to the value DICE used in its base model (a low 3.8%). This allowed use of the amount of uncertainty expected around the parameter without imposing actual values based on another study that may have incorporated different assumptions into its estimation.

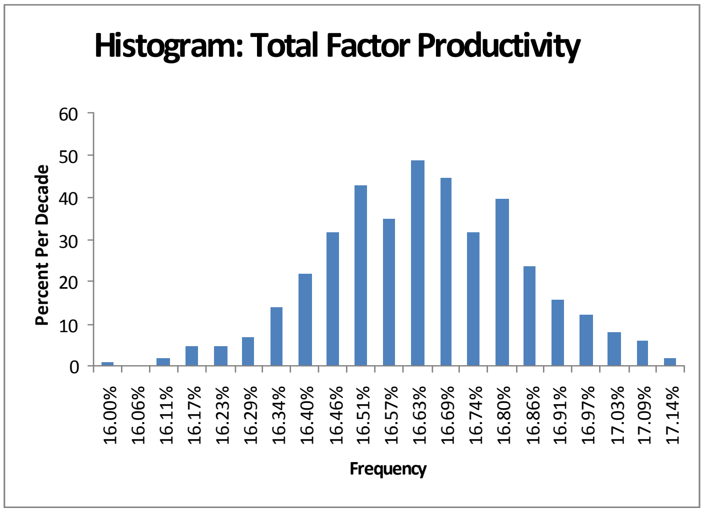

Figure 2.1. Total Factor Productivity Growth Rate Histogram (n=400)

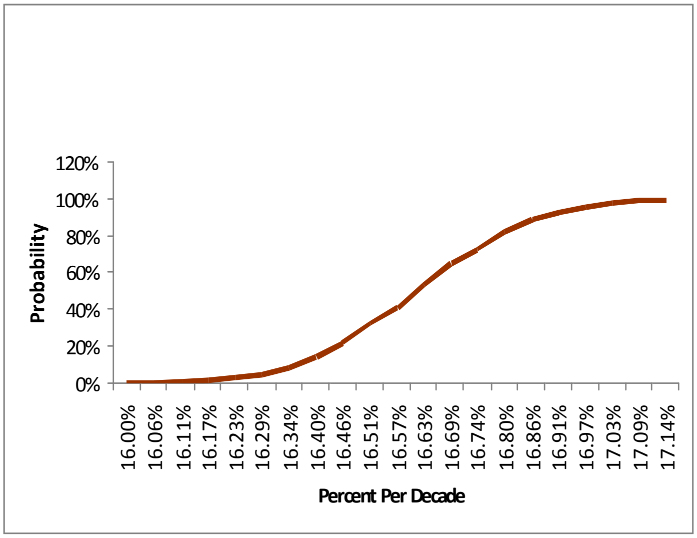

Figure 2.2. Total Factor Productivity Growth Rate Cumulative Distribution Function (n=400)

CO_2 Emissions Intensity

The CO_2 emissions intensity parameter (σ_t) represents the trend in CO_2-equivalent emissions per unit of output without a carbon-reducing policy in place. The growth rate for σ_t is negative and is interpreted as the rate of de-carbonization or emission-reducing technological change of the economy. Emissions intensity is highly variable and uncertain throughout time, and difficult to predict accurately. It depends upon several measures, including the specific mix of emission-releasing technologies present in the economy at any given time, the contribution of energy–related services to output, additional environmental and other regulations dictating operation of energy-related services, financial considerations such as participation in any emission credit markets, and even local-political sentiment regarding emission of CO_2. The list continues, but all of these events are uncertain themselves.

Uncertainty in σ_t will also be characterized using a probability distribution estimate for the growth rate of σ_t based on the MIT Joint Program's most recent IGSM probabilistic climate forecasting work, which is also estimated from historical observations.[4] The histogram and the CDF for the growth rate of σ_t from the MIT Joint Program report is provided below in Figure 2.4. The average total factor productivity growth rate per decade is -9.39%, the maximum is -20.00%, and the minimum is -0.086%. The volatility parameter, approximated by one standard deviation, is 3.37%. Integration of the distribution into DICE was performed in the same manner as with the previous uncertain parameter, A_t.

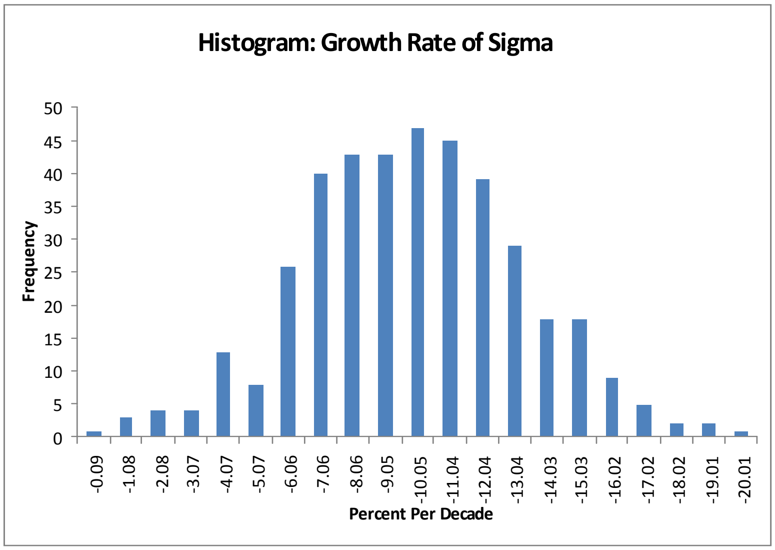

Figure 2.3. Emission Intensity Growth Rate Histogram (n=400)

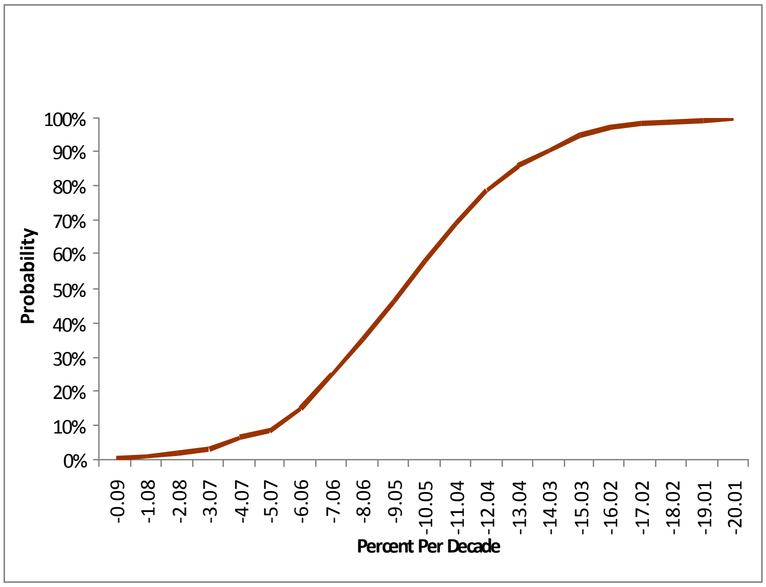

Figure 2.4. Emission Intensity Growth Rate Cumulative Distribution Function (n=400)

Climate Feedback (λ)

Finally, the feedback parameter in the climate model of DICE is also highly uncertain. The parameter appears in the climate model in DICE as a cloud-related parameter. In general, climate parameters are the result of calibrating climate models to empirical measurements, yet these models remain extremely elusive. Uncertainty in this parameter is a combined facet of the fact that we still have much to learn about how the climate system really works, as well as a likelihood that the parameter itself changes due to changes in the system.

The distribution used to characterize this uncertainty is also based on the MIT Joint Program's work. Their work shoes that the climate feedback parameter (λ) is equal to 4.1/climate sensitivity parameter, and that the climate sensitivity parameter (used in the IGSM) follows a log-normal distribution (μ=0.46020, σ=0.49617) plus 1.3357[6]. Sampling from this distribution, the histogram and the CDF shown in Figures 2.5 and 2.6 were constructed.

---

[6] Forest, C. E., Stone, P. H., and A. P. Sokolov, (2008), "Constraining climate model parameters from observed 20th century changes," Tellus, 60A, pps. 911-920.

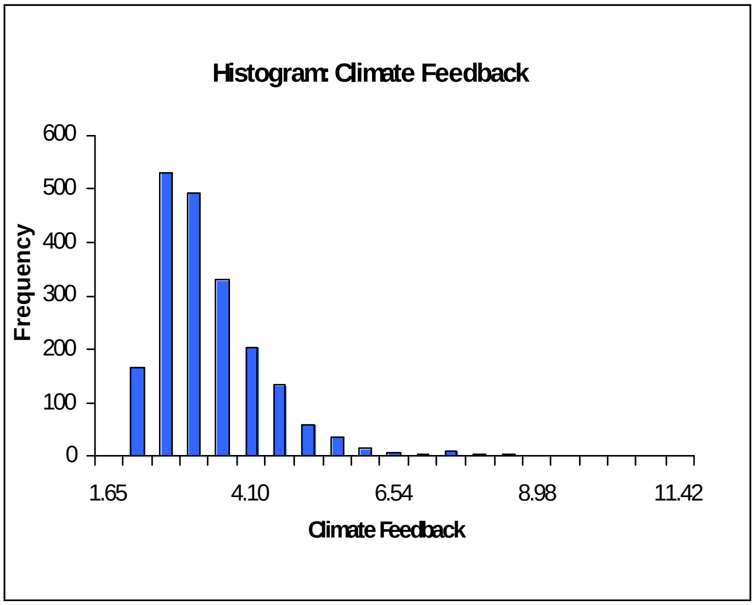

Figure 2.5. Climate Feedback Histogram (n=2000)

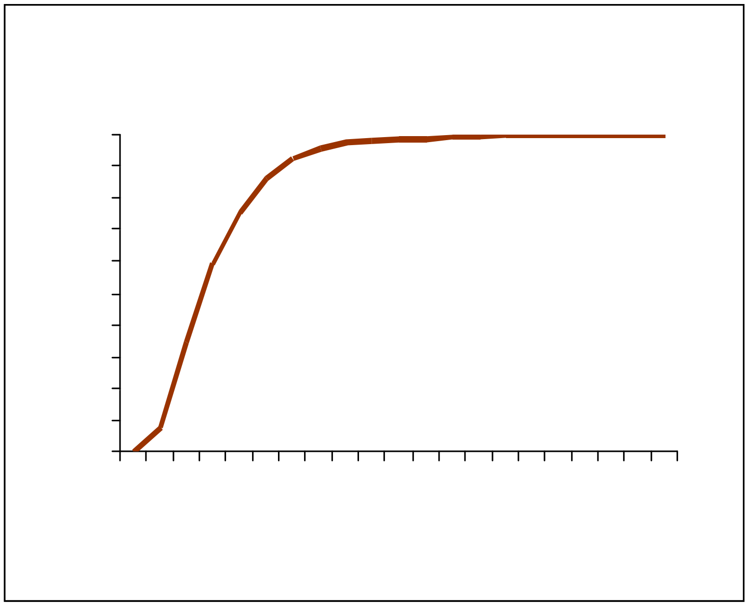

Figure 2.6. Climate Feedback Cumulative Distribution Function (n=2000)

III. System Designs

Description of Flexibility

Flexibility in the system outlined above is introduced by providing the option for policy-makers (designers of the global emissions reduction policy path) to "ramp up" or slow down future carbon taxes (or emissions control rate, μ_t) based on future outcomes of the key uncertainties outlined above. While this may seem a trivial option, embedded within original policy decisions are huge amounts of infrastructure that may be built, with very real irreversibilities (see Box 1 for a longer description). This flexibility is most easily seen when compared against a "no policy" scenario. This no policy scenario represents proceeding with "business-as-usual," where consumption proceeds unlimited in the current period and no to low investment in R&D and future carbon reduction technologies is made. In the event that productivity increases are minimal, emissions intensity greatly increases, and climate sensitivity is high, mitigation options will be few and climate damages severe. In the system under study, this in turn leads to very low net present value of welfare values.

Instead, if a carbon policy is implemented today (which trades off current consumption for investment in R&D and technologies for future mitigation), with an option to change course later should uncertain outcomes dictate, expected net present value of welfare can be maximized. Analogous to the canonical parking garage example of flexibility, the "cost of flexibility" in this exercise comes in the form of increased investments in R&D for carbon reducing technologies and reduced consumption today. See Box 2 for a more detailed analogy of this exercise to the parking garage example.

Box 2. Analogy to the Parking Garage.

Although the system under study in this exercise exhibits a higher degree of abstractness, an analogy to the canonical parking garage flexibility example can be made and provides a useful illustration.

Fixed (Optimal) Design Under Deterministic Future

Garage*: Set number of initial levels (floors) and a defined expansion path irrespective of changes in demand. This design is "optimal" according to a deterministic demand.*

Climate Policy: *Set carbon tax level ($) and defined future carbon tax levels irrespective of changes in productivity, emission intensity, and climate sensitivity. This carbon tax path is either an "optimal" one based upon deterministic paths of the three uncertainty variables or based upon a BAU scenario with no carbon tax.*

Payoff Value

Garage: *NPV total costs*

Climate Policy*: NPV welfare*

Potential "Cost" of Flexibility

Garage: *Stronger columns built into original structure design*

Climate Policy*: Reduction in present consumption in order to comply with carbon tax policy (equivalent to investing in R&D for new emission reduction technologies)*

Initial Flexible Design Decision

Garage: *# levels (or floors) for first year*

Climate Policy: *level of initial 2015 carbon tax.*

Flexibility Options

Garage: *Additional levels or stop construction based on demand changes. Grow if demand grows sufficiently; do not grow if demand does not grow.*

Climate Policy*: Change in course for carbon tax level based on productivity, emission intensity, and climate sensitivity changes. Increase tax if productivity decreases, emission intensity increases, or climate sensitivity increases (and vice versa).*

Design Alternatives

Two system designs are examined in the current exercise—one that implements policy in the form of a carbon tax (the flexible policy), and one that imposes no policy (the fixed policy). Table 3.1 summarizes the design alternatives.

The fixed policy essentially represents a business-as-usual scenario, whereby there is no carbon tax ($0 per ton per year) throughout the entire timeframe. Note: this scenario does have embedded within its assumptions a predetermined level of savings or investment (at 25.3% of GDP and declining) so the business as usual level of technological change still exists.

The flexible policy imposes a carbon tax (or emissions control rate, μ_t) that begins with either a high tax rate ($30 per ton of carbon) or a low tax rate ($10 per ton of carbon) in 2015, and retains the option to change the tax rate in a future period (2065) if necessary to $80 per ton (high) or $30 per ton (low). Therefore, four combinations of the flexible policy exist (High/High, High/Low, Low/High, and Low/Low). Appendix A contains a snapshot of the DICE-99 model that will be used in this analysis. The decision variable is highlighted in blue and uncertainty variables are highlighted in yellow. Due to the size of the model, only one snapshot is provided for illustration purposes.

Table 3.1. Summary of System Designs and Policy Decision Values

Design	Emissions Reduction (μ_t) ($ Tax)
Fixed "No" Policy ("Business-as-Usual")	No Control ($0 per ton) Both Decision Points
Flexible Policies (Carbon Taxes)	2015: High ($30) / 2065: High ($80) 2015: High ($30) / 2065: Low ($30) 2015: Low ($10) / 2065: High ($80) 2015: Low ($10) / 2065: Low ($30)

IV. Decision Analysis

Description of Decision Analysis

Stages. Using the Excel-based DICE-99 evaluation model and "bilink" tools in Tree-Age Pro 2009, a 2-stage decision analysis of the alternative policy designs was performed to determine the optimal carbon emissions policy choices to maximize expected net present value of welfare. All five design alternatives (one fixed; four flexible) were included in the tree.

Decisions. The entire 300+ year DICE time frame was condensed into two stages: the first 50 years (2015-2055) and the rest of the years (2065-2335). Therefore, carbon tax policy decisions were made in 2015 and for the flexible cases, again in 2065. Table 3.1 provides a summary of the possible values the decision variable (μ_t) took in the decision tree.

Uncertainties. For the purposes of the decision analysis, only two of the three uncertainties were incorporated—the growth rate of emission intensity (σ_t) and the climate feedback parameter (λ_t). Using the distributions presented in Section 2 above, and a three-point Pearson-Tukey approximation, probabilities and random variable values were extracted for both uncertainties from the 5%, 50%, and 95% fractiles. At the end of each stage, the emission intensity growth rate had three chance outcomes (a high, medium, and low level); at the end of the last stage only, the climate feedback parameter also had three chance outcomes (representing a high, medium, or low climate sensitivity). Incorporating the climate sensitivity only at the end of the second stage implies that society won't ever really know the true value of this parameter. While we may learn a little about climate sensitivity between now and then, given the enormous complexities of the global climate system, this assumption is not too far removed from reality so it was interesting to model in this fashion. Table 4.1 provides a summary of the uncertainty variable values and their associated probabilities and Figures 4.1a and 4.1b provides a graphical illustration of their future scenarios.

Table 4.1. Summary of Uncertainty Variable Values and Probabilities (Used for Both Stages)

Parameter	High	Medium	Low
Emission Intensity Growth Rate (σ_t)	$P(\sigma=-30.055) = 0.185$	$P(\sigma=--15.885) = 0.63$	$P(\sigma=-1.082) = 0.185$
Climate Feedback Parameter (λ_t)	$P(\lambda=4.682) = 0.185$	$P(\lambda=2.908) = 0.63$	$P(\lambda=1.134) = 0.185$

Payoffs: Payoff values represented the net present value of welfare, which considers the level of climate damages imposed on the economy due to accumulated carbon concentrations.

Finally, due to the size of the decision tree (208 terminal nodes), a full depiction of the decision tree has not been included. Figure 4.2 provides a snapshot of the rolled-back (solved) tree collapsed around the optimal strategies.

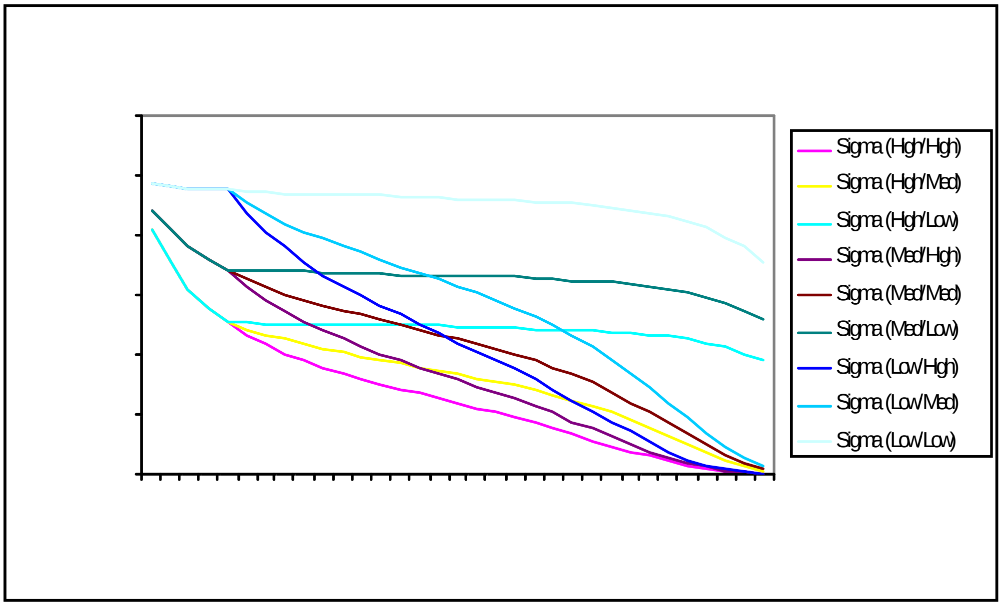

Figure 4.1a. Decision Analysis Emission Intensity Scenarios

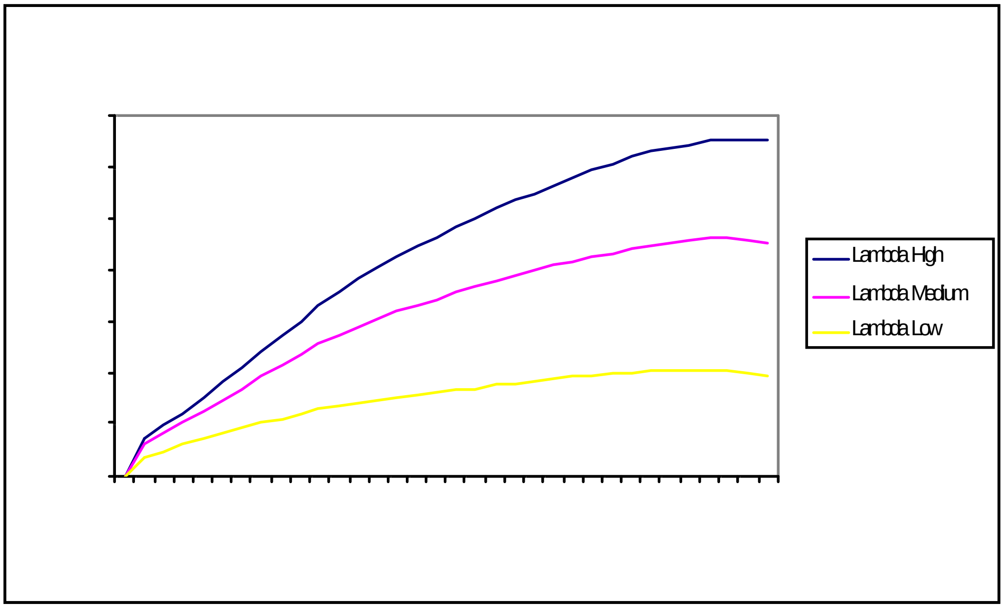

Figure 4.1b. Decision Analysis Temperature Scenarios (given λ)

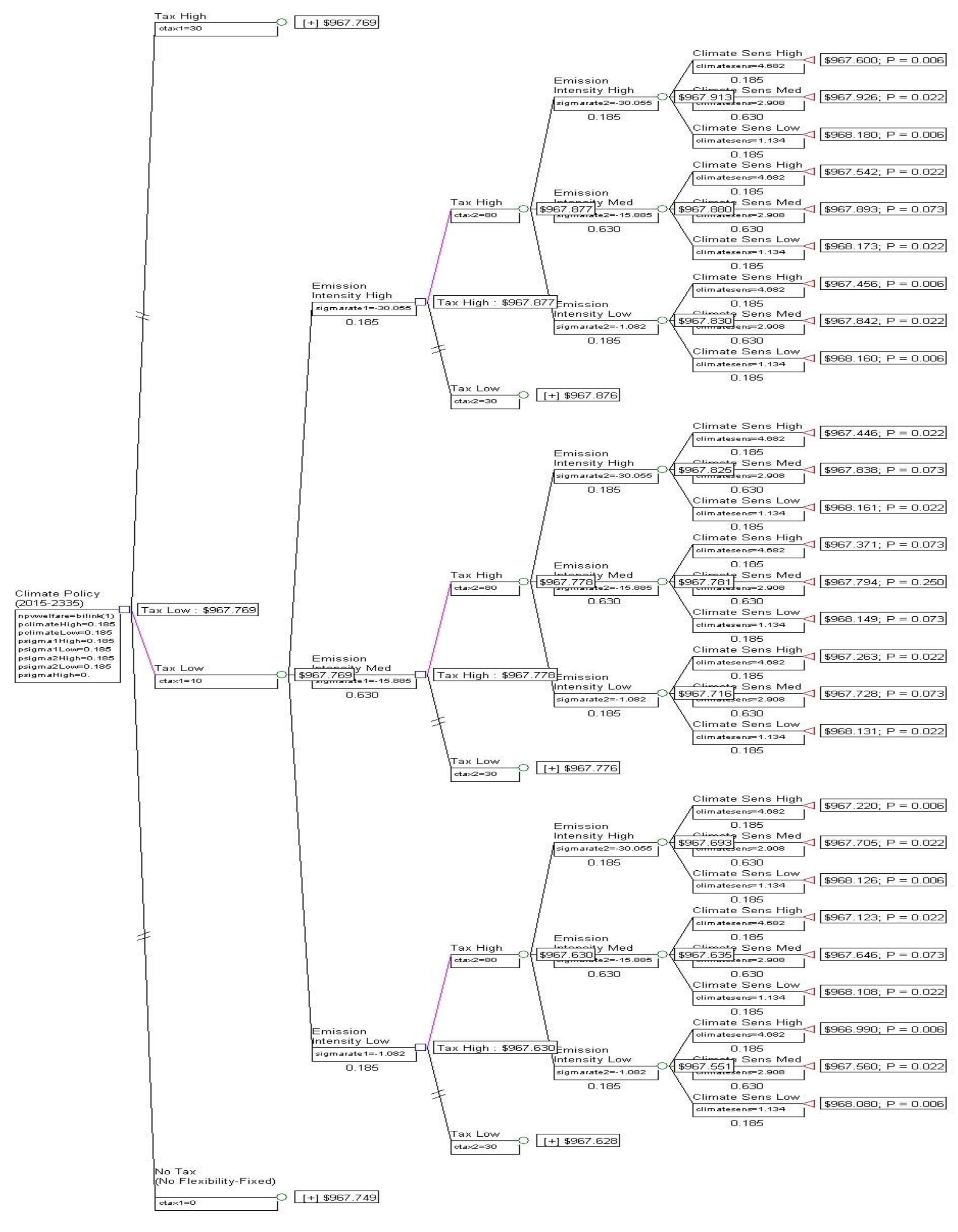

Figure 4.2. Climate Policy Strategy Decision Tree (Collapsed around Optimal Strategy)

Solution: Optimal Strategy

Based on the solution to the decision tree in Figure 4.2 above, the optimal carbon policy strategy over two periods given uncertainties in emission intensity and climate sensitivity is to initiate a low carbon tax ($10 per ton carbon) in 2015, and increase the carbon tax to a high carbon tax ($80 per ton) in 2065. The calculated expected value for NPV welfare of this optimal strategy (defined at the root node when the decision tree is solved) is $967.769 trillion. Note that due to rounding, it appears that in Figure 4.2, the policymaker is indifferent to the two flexible policy options (both show an expected value for NPV welfare of $967.769 trillion). However, the underlying values (non-rounded) are $967.768612 trillion for the low carbon tax flexible strategy case and $967.768501 for the high carbon tax flexible strategy case. Therefore, the decision to initiate a low carbon tax in 2015 first *is* the actual optimal strategy.

It is interest that irrespective of the future uncertainties (especially climate sensitivity), the decision for Period 2 (2065) is to tax high.

- Under high emission intensity and all climate sensitivity scenarios, the decision in Period 2 is to tax high ($80 per ton).
- Under medium emission intensity and all climate sensitivity scenarios, the decision in Period 2 is to tax high ($80 per ton).
- Under medium emission intensity and all climate sensitivity scenarios, the decision in Period 2 is to tax high ($80 per ton).

The value of flexibility, determined by the difference between the flexible policy strategies and the inflexible policy strategy is $0.019316 trillion and $0.019205 trillion for the optimal (low carbon tax) strategy and the high carbon tax strategy cases, respectively. The incremental flexibility gained between the optimal strategy and the other flexible strategy is $0.0111 trillion. The strategies are ranked and these values are summarized in Table 4.2.

Table 4.2. Value of Flexibility Table for Decision Tree Analysis

Rank	Strategy	Expected Value NPV ($ trillion)	Value of Flexibility ($ trillion)
1	Tax Low	$967.768612	$0.019316
2	Tax High	$967.768501	$0.019205
3	No Tax (No Flexibility-Fixed)	$967.749296	

An expected value of perfect information (EVPI) analysis was also performed in the decision tree analysis, to determine the maximum amount that the global society should be willing to pay to decrease our uncertainty about future emission intensity growth rates and future climate feedback (sensitivity). Table 4.3 below shows the expected value of the three uncertainties considered in this decision tree analysis, and shows how important uncertain climate sensitivity is when considering optimal policy strategies. In terms of the amount we should be willing to pay for perfect information about one of the uncertainties, climate sensitivity trumps the either of the emission intensity growth rates by almost an order of magnitude.

Table 4.3. Expected Value of Perfect Information Table for Uncertainties in Decision Tree Analysis

Uncertain Variable	EVPI ($ trillion)
Period 1 Emission Intensity Growth Rate (σ_1)	$0.000260
Period 2 Emission Intensity Growth Rate (σ_2)	$0.001608
Climate Feedback (Sensitivity) Parameter (λ_t)	$0.011614

Figure 4.3 below shows the VARG curves for the decision tree analysis. While the curves track each other closely, it is worth remembering that the NPV utility values considered are in trillions of dollars, and thus small shifts imply notable differences in overall utility.

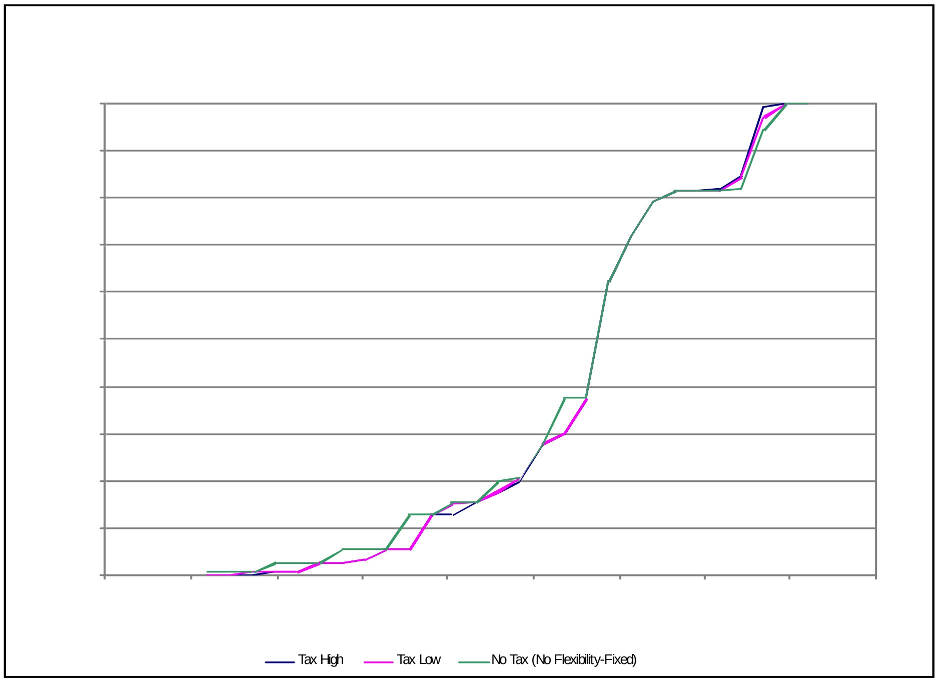

Figure 4.3. Decision Tree Analysis VARG Curve

Considering multiple criteria for preferred policy designs, the VARG shows that overall for low risks, a low tax in Period 1 is preferred to either a high tax or no tax. For higher probabilities, this choice shifts and a no tax policy is preferred over either of the tax policies. A multiple criteria table at various risk assumptions is shown in Table 4.4. In general, discussions about climate change gravitate towards risk-aversion because society wants to avoid dangerous irreversible environmental damages. Table 4.4 guides a risk-averse society to institute a tax (at least a high tax, but a low tax is even better) in Period 1 and a risk-seeking society to proceed with business-as-usual with no carbon tax. This guidance tracks logic and the underlying hypothesis of this study well—that carbon tax-induced investments in R&D today stimulate innovation and future technologies that can provide additional options for reducing GHG emissions later.

Table 4.4. Multiple Criteria Table for Decision Tree Analysis

Risk Assumption	Preferred Period 1 Design
P10	Tax Low
P15	Tax High
P50	No Tax (Inflexible Case)
P75	No Tax (Inflexible Case)
P90	No Tax (Inflexible Case)

Extension: Sensitivity and Threshold Analyses

In Period 2 (2065) the optimal strategy is to tax high ($80 per ton) irrespective of future uncertainties in the growth rate of emission intensity and climate sensitivity. Given this result, a sensitivity analysis was performed on the system to determine various thresholds when the decision in Period 2 *would* change. Although variables' probabilities and values used in the decision tree analysis were documented in the literature, sensitivity analyses were conducted on these numbers. The eight charts (1)-(8) in Figure 4.4 present the results of sensitivity and threshold analyses on the following variables:

Period 2 Sensitivities

- Climate Feedback (Sensitivity) Parameter (λ_t) Probabilities (for High and Low)
- Emission Intensity Growth Rate (σ_2) Probability (for High and Low)

Period 2 Thresholds

- Climate Feedback (Sensitivity) Parameter (λ_t) Value
- Emission Intensity Growth Rate (σ_2) Value
- Carbon Tax Decision (μ_2) Value

Period 1 Sensitivity

- Climate Feedback (Sensitivity) Parameter (λ_t) Probabilities (for High and Low)

Period 1 Threshold

- Climate Feedback (Sensitivity) Parameter (λ_t) Value

Climate Feedback Parameter (λ_t)

First, because the decisions in Period 2 did not change across different values or probabilities of the uncertain variables, these parameters were tested first. The original probabilities for the climate feedback parameter (provided in Table 4.1 above) were 0.185, 0.630, and 0.185 for the high, medium, and low values, respectively. The two-way sensitivity analysis chart in (1) shows the probability values that can be jointly held by the low climate feedback parameter and high climate feedback parameter values (x and y axes, respectively) such that a low carbon tax ($30 per ton) in Period 2 would be preferred over a high carbon tax. For example, for a low climate feedback parameter probability of 0.248 and a high feedback parameter probability of 0.083, the decision in Period 2 would be continue a low carbon tax. Chart (1) also shows the wide range of probabilities that the low climate feedback parameter can take for this decision to be optimal. The threshold chart in (2) shows the different values the climate feedback parameter would need to take in order to switch decisions in Period 2 with the original probabilities restored. The original values for the climate feedback parameter (provided in Table 4.1 above) were 1.134, 2.908, and 4.682 for the low, medium, and high scenarios, respectively. For values between 0.10 and 2.908, the optimal strategy is to continue a low carbon tax. It is the high value scenario that is driving the optimal strategy in this case.

An additional Period 1 point sensitivity analysis on climate sensitivity was conducted after the Period 2 point sensitivity analyses showed the optimal strategy's relatively greater sensitivity to climate sensitivity than the other variables. This analysis asked when the decision in Period 1 would change as a result of the climate sensitivity probabilities changing. Results in (7) and (8) show that the decision to initiate a low carbon tax in Period 1 was also affected by the probabilities used for the climate feedback parameter. In fact, for probabilities greater than 0.165 for the high climate feedback parameter, the decision in Period 1 would have switched to the high carbon tax ($30 per ton). A threshold analysis for this parameter shows that the Period 1 decision is driven by the medium climate sensitivity parameter: Between 0.10 and 1.27, the optimal strategy is the inflexible case, between 1.27 and 2.908, the optimal choice is to tax low, and between 2.91 and 10.00, the optimal choice is to tax high.

Overall, the optimal strategy is most sensitive to changes in the climate feedback parameter.

Emission Intensity Growth Rate

The two way sensitivity chart in (3) shows that for all probability values that can be jointly held by the low and high Period 2 emission intensity growth rate parameter (x and y axes, respectively) a high carbon tax ($80 per ton) in Period 2 would be preferred over a low carbon tax. Because the strategy is to choose a high tax across all possible probability values, the optimal strategy is not sensitive to the Period 2 emission intensity growth rate. Charts (4) and (5) confirm this, by showing that the high carbon tax decision in Period 2 always yields a higher expected NPV than a low carbon tax decision. Chart (4) is simply the sensitivity chart underlying the strategy chart in (5), and explicitly shows this phenomenon.

Carbon Tax

Finally, the values for the carbon tax level in Period 2 were varied between 0 and 100 to determine whether the optimal strategy was sensitive to the values chosen for the low ($30 per ton) and high ($80 per ton) tax levels in Period 2. Interestingly, Chart (7) shows us that it does not matter what level carbon tax is chosen as the high carbon tax in Period 2—the decision is always to choose it over whatever the lower tax is set at because the higher tax always yields a higher expected NPV. Thus, the optimal strategy in Period 2 is not sensitive to the actual tax level.

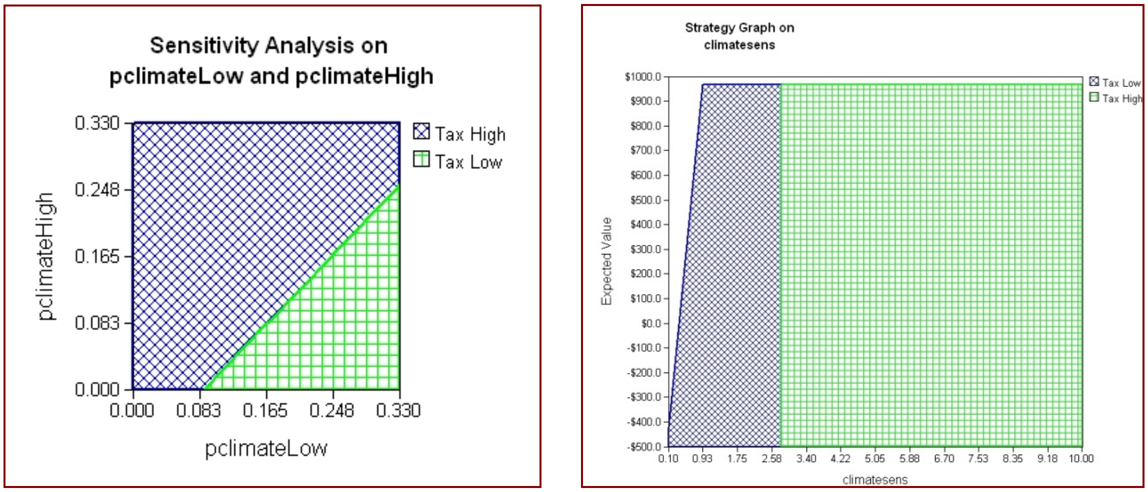

Figure 4.4. Sensitivity and Threshold Analysis Charts (1)—*Left* and (2)--*Right*

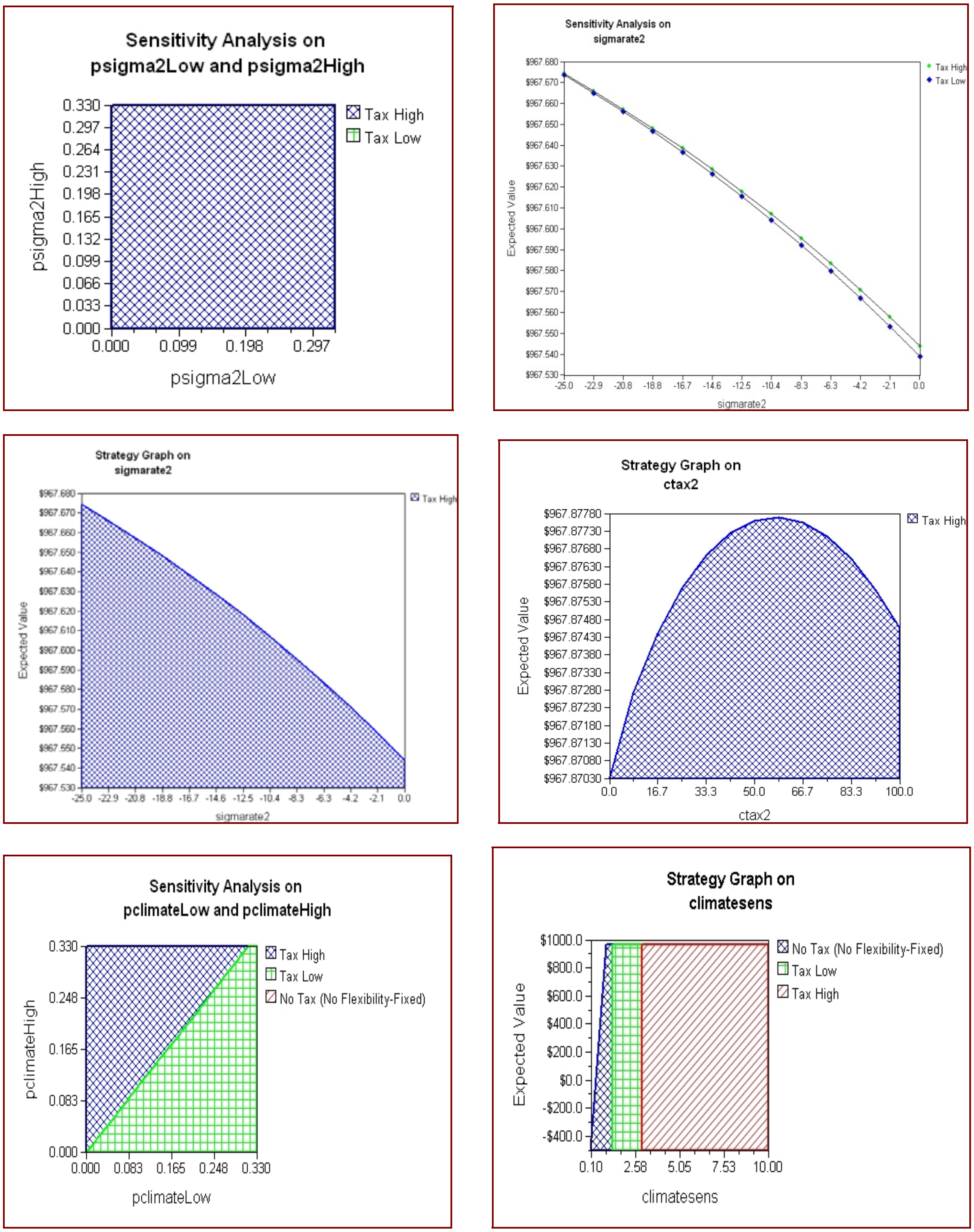

Figure 4.4. Sensitivity and Threshold Analysis Charts (3)-(8) in order from *Top Left, Top Right, Middle Left, Middle Right, Bottom Left and Bottom Right*

V. Lattice Uncertainty Analysis

Evaluation of a Major Uncertainty

Total factor productivity (TPF or A_t) growth rate, one of three uncertain variables in the current study is used in present lattice analysis. Total factor productivity represents the efficiency of the economy in transforming inputs into output; it is also often thought of as the level of technology in the economy. In terms of climate change and the need for climate policy, a higher A_t represents a higher level of technological progress, and thus presumably less need for carbon emissions control (Figure 5.3 shows MIT Joint Program determined potential evolutions for A_t given different growth rates). The idea here is that technology would have progressed enough by itself to help reduce future carbon emissions (irrespective of the amount of R&D investments that were allocated to increasing technology change).

This variable is chosen for the lattice analysis because of its relatively path independent nature; the system state in each stage is arrived at irrespective of whether the growth rate of A_t increases and then decreases or vice versa (for two periods, for example). Also, because this variable was left out of the decision analysis above, it is examined now. As indicated above, for integration into DICE, the distribution of the growth rate of A_t characterized through the previous MIT Joint Program empirical study was normalized around DICE's median growth rate of 3.8. The distribution used in the analysis is shown in Figures 5.1 and 5.2 below. The minimum value is 3.6598%, the maximum is 3.9211%, and the average value is 3.7996%. Due to the unique natures of this particular uncertain variable (it is *already* a growth *rate*), the long-time frame involved, and the sample data, although a volatility term was easily extractable, the required parameters u, d, and p were developed using a general procedure for calibrating a binomial distribution to data. The starting value in the lattice evaluation is 3.8%, the base value in DICE Period 1. Also, the time-frame for analysis was shortened by thirty years relative to the decision analysis above, and considers 2015-2314 in five 50-year time steps (six periods, excluding t=0 (before 2015)). Six stages were used to include the maximum number of decades from the original DICE model.

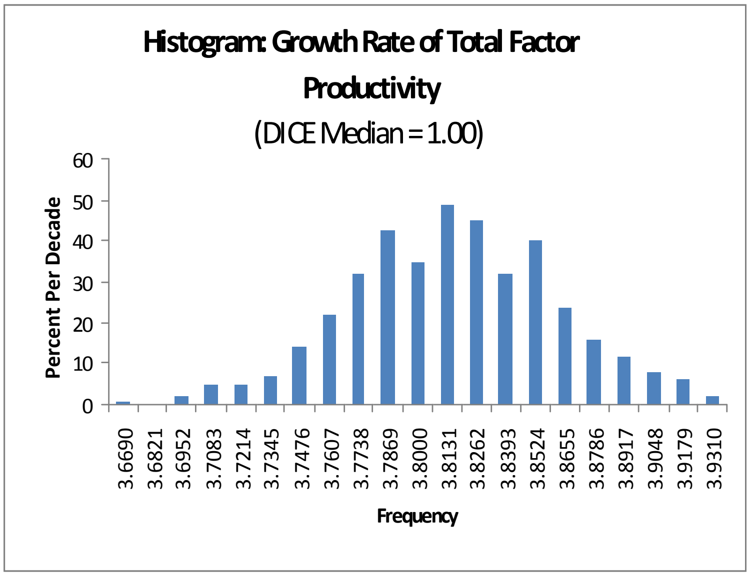

Figure 5.1. *Normalized* Total Factor Productivity Growth Rate Histogram (n=400)

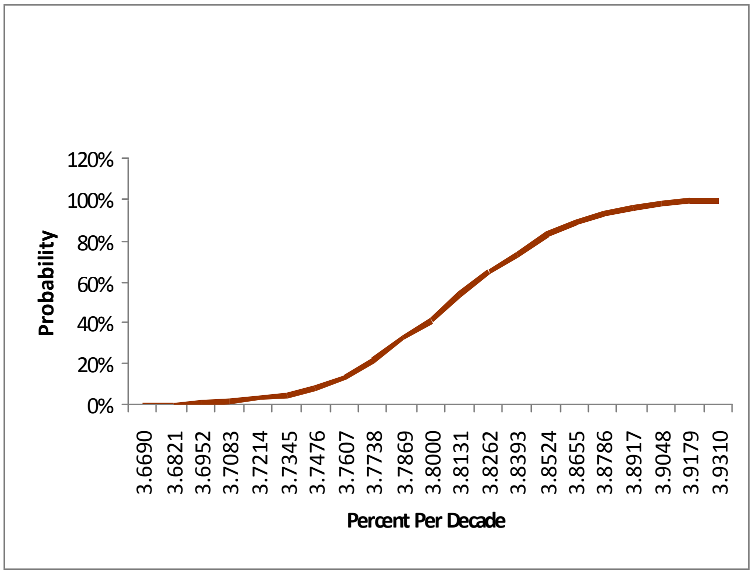

Figure 5.2. *Normalized* Total Factor Productivity Growth Rate Cumulative Distribution Function (n=400)

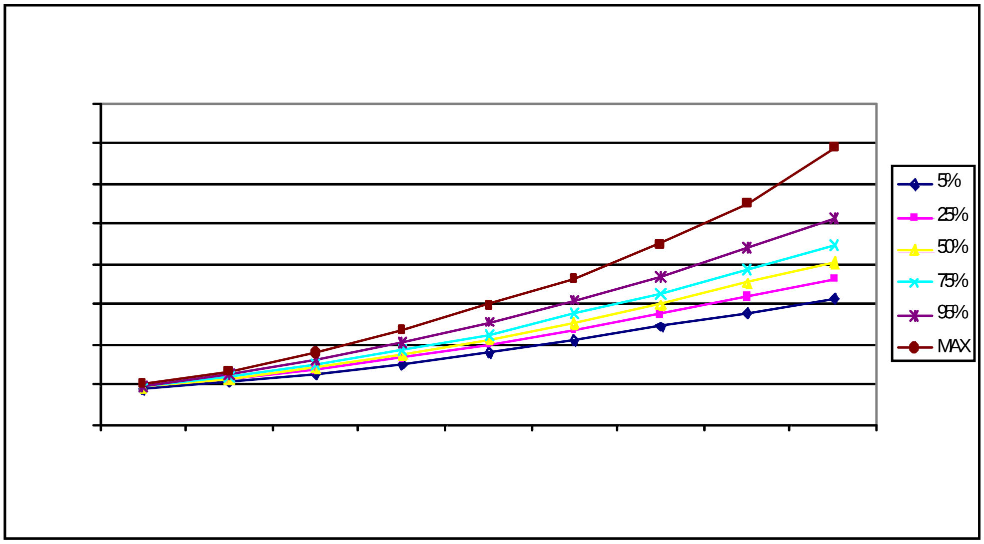

Figure 5.3. Fractiles of Evolution of Total Factor Productivity *Levels* in MIT Joint Program Work (n=400)

Using the average, maximum, minimum, and starting values for the growth rate of A_t above and Excel-2007's "Goal Seek" function, u, d, and p were extracted: u=1.016, d=0.9814, and p=0.5402. The growth rate values (of states) lattice and associated probabilities are shown in Tables 5.1 below. These lattices show the evolution of the uncertainty in the growth rate of $A_{t,}$ and were developed using a simple spreadsheet calculations. The A_t Growth Rate lattice begins with the initial growth rate 3.80 for A_t in Period 0, and is multiplied by its "up" factor in one case and by its "down" factor in another case in Period 1. This calculation repeats until the entire lattice is filled through Period 6, where there are seven different A_t growth rate values that the variable can take. The associated probability lattice uses a similarly simple approach, beginning in Period 0 with an initial probability of 1, and multiplying by p and (1-p) for the "up" and "down" paths, respectively, until the lattice is filled. The combination of these two lattices show the probabilities associated with each possible A_t growth rate value in each of the time periods. The associated PDF is shown in Figure 5.4.

Table 5.1. A_t Growth Rate Value and Probabilities 6-Stage Lattice(s)

	t = 0	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
Period:	**0**	**1**	**2**	**3**	**4**	**5**	**6**
A_t Growth Rate:	3.80	3.86	3.92	3.99	4.05	4.11	4.18
		3.73	3.79	3.85	3.91	3.97	4.04
			3.66	3.72	3.78	3.84	3.90
				3.59	3.65	3.71	3.77
					3.53	3.58	3.64
						3.46	3.51
							3.40
Probabilities:	1.00	0.54	0.29	0.158	0.085	0.046	0.025
		0.46	0.50	0.403	0.290	0.196	0.127
			0.21	0.343	0.370	0.333	0.270
				0.097	0.210	0.284	0.306
					0.045	0.121	0.196
						0.021	0.067
							0.009
Cumulative Probability:	1.00	1.00	1.00	1.00	1.00	1.00	1.00

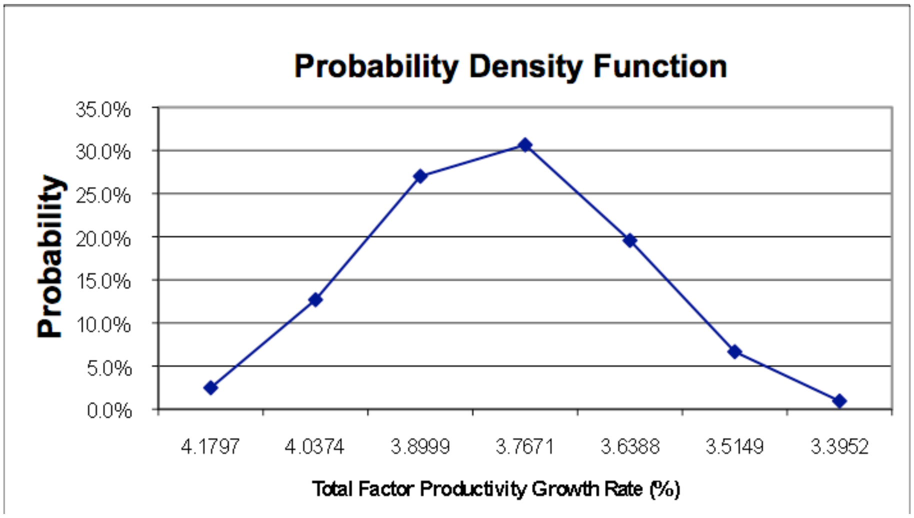

Figure 5.4. A_t Growth Rate PDF using Lattice Evaluation for Uncertainty (t=6)

VI. Decision Analysis Using Lattice Uncertainty Evaluation

Description of Decision Analysis

Given the lattice of probabilities and states for the growth rate of A_t in Table 5.1 above, a decision analysis using the DICE model was conducted to examine which stage (if any) is most appropriate to *implement* a carbon tax. This analysis examines the following one option/question: "How long should we wait to implement a carbon tax and induce additional R&D investments for technological change given the respective level of environmental damages?" The option is modeled as a call option, as the option is exercised within the system.

In the present analysis, the inflexible case remains a fixed-BAU scenario with no carbon tax ($0 per ton). For the flexible case, the system has the call option to institute a medium-level carbon tax of $45 per ton at any stage after t=0 should the level of environmental damages warrant the need for it. Box 3 provides a summary of the decision analysis, and once again compares it with the canonical parking garage case.

The decision whether to exercise the call option and implement the carbon tax is determined using a dynamic programming backtracking analysis. The dynamic programming approach determines if and when to implement a $45 per ton carbon tax by comparing--for a given period--the expected utility discounted from the future period plus the present value of utility in the current period between a system where the tax *is* implemented and a system where it is *not* implemented. The dynamic programming analysis starts in the last period (Period 6) and solves each time step independently, moving backwards through time such that the strategy chosen in the first period represents the best decision a policymaker can make in light of all possible future paths.

Utility flow, discounted utility flow, expected NPV utility flow, and dynamic programming decision lattices for the inflexible care are presented in Tables 5.2, 5.3, 5.4, and 5.5, respectively. Utility flow, dynamic programming decision analysis lattices, and the final decision lattice for the flexible case are presented in Table 5.6 and 5.7, respectively. Each of the dynamic

Box 3. Analogy to the Parking Garage (Continued).

Given the level of abstractness of the system under study, a continuation of the analogy to the canonical parking garage flexibility example can be made and provides a useful illustration of the Part VI decision anlaysis.

Uncertainty Considered

Garage: *Demand for parking spaces.*

Climate Policy: *Growth rate of total factor productivity (A_t) of the economy.*

Fixed Design

Garage: *Set number of initial levels (floors) and a defined expansion path irrespective of changes in demand.*

Climate Policy: *BAU scenario with no carbon tax.*

Flexible Design

Garage: *Additional levels or stop construction based on demand changes; do not grow if demand does not increase.* ***Climate Policy:*** *Implement a carbon tax only if future outcomes (based largely on the growth rate of A_t) warrant the opportunity or need to reduce future emissions-related damage.*

Call Option

Garage: *Build an additional level.*

Climate Policy: *Begin implementing the ($45 per ton) carbon-tax.*

Value Metric

Garage: *Expected NPV cash flow.*

Climate Policy: *Expected NPV per capita utility flow.*

programming steps noted above will be highlighted in the lattices that follow. Discussion is provided afterwards.

Notes: (1) Consistent with institutional difficulty in repealing certain types of policies, this analysis assumes that once the tax is implemented it cannot be repealed. (2) Other uncertain variables modeled in the decision analysis above (emissions intensity growth rate and climate sensitivity) are held constant, at the base DICE levels. (3) Due to the complex period-dependent nature of the DICE model, utility flows in each period are unable to be examined independent of previous periods; the growth rate of A_t for all periods prior to the period under investigation for the decision analysis are held at the base value for the growth rate of A_t in DICE (which is approximately the expected value for the growth rate of A_t in the previous periods). (4) The utility flow in Period 0 represents the cumulative utility in DICE in Period 0 (this represents the sum of utility flows in 1995 and 2005, appropriately discounted). (5) All utility flows and utility values are in trillion dollars.

Inflexible (No Carbon Tax) Case

The dynamic programming decision analysis required setting up and solving for utility flows (Table 5.2) in each period associated with each of the A_t growth rate states determined in the uncertainty evolution analysis above. These utilities were calculated using DICE. The Period 6 undiscounted utility flows appear in the last column in the dynamic programming decision analysis Table 5.5. The rest of the period specific undiscounted utility flows (Periods 0-5) were added to the expected discounted future period utility flows in each case (row) in each time period as the solution “rolled back.” As this analysis represents the inflexible (no carbon tax) case, Table 5.3 and 5.4 combined provides a check for the dynamic programming solution. As there is no alternative decision to be made in each time period of this case, the sum of discounted expected net present values of utility over the time periods should be equal to the dynamic programming solution—and it does: $2328.27.

Table 5.2. Inflexible Case (No Carbon Tax) Utility Flows

Period	t = 0	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
Utility Flow:	1285.57	807.62	700.66	690.94	718.48	716.91	803.62
		806.97	699.90	690.07	717.60	757.54	802.73
			699.14	689.27	716.78	756.72	801.84
				688.47	715.97	755.90	801.02
					715.21	755.07	800.19
						754.32	799.37
							798.68

Table 5.3. Inflexible Case (No Carbon Tax) Discounted Utility Flows

Period	t = 0	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
PV Utility Flow:	1285.57	477.88	245.32	143.15	88.08	52.00	34.49
		477.50	245.05	142.97	87.97	54.95	34.45
			244.79	142.80	87.87	54.89	34.42
				142.63	87.77	54.83	34.38
					87.68	54.77	34.35
						54.72	34.31
							34.28

Table 5.4. Inflexible Case (No Carbon Tax) Expected Utility Flows and Present Value of Expected Utility Flows

Period	t = 0	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
E [Utility Flow]		807.32	699.96	689.78	716.92	754.57	801.23
PV(E[Utility Flow])	1285.57	477.71	245.08	142.91	87.89	54.73	34.39
ENPV over 6 years	2328.27						

Table 5.5. Inflexible Case (No Carbon Tax) Dynamic Programming Decision Analysis

Period	t = 0	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
ENPV (Utility Flow)	2328.27	1762.75	1614.39	1543.10	1434.83	1192.18	803.62
NO FLEXIBILITY		1761.47	1613.92	1545.50	1446.40	1232.29	802.73
NO CARBON TAX			1612.13	1543.75	1444.80	1230.96	801.84
				1542.03	1443.21	1229.65	801.02
					1441.71	1228.34	800.19
						1227.13	799.37
							798.68

Flexible ($45 per ton Carbon Tax) Case

Answering the question posed above "How long should we wait to implement a carbon tax and induce additional R&D investments for technological change given the respective level of environmental damages?" next required setting up the undiscounted utility flows and dynamic programming solution for a case where a $45 per ton carbon tax is implemented in each period following the initial period. This case was set up so that a comparison could be made of utility in each period between systems with a carbon tax implemented (in all future years) and a system without one (inflexible case above). Utility flows from DICE are shown in Table 5.6, and the dynamic programming decision analysis lattice for the case with a permanent $45 per ton carbon tax is shown in the first lattice in Table 5.7.

Table 5.6. Fixed Case (with $45 per ton Carbon Tax) Utility Flows

Period	t = 0	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
Utility Flow:	1285.57	807.55	700.89	691.48	719.21	759.24	804.42
		806.91	700.13	690.62	718.33	758.35	803.53
			699.37	689.82	717.51	757.52	802.64
				689.02	716.69	756.70	801.81
					715.94	755.88	800.99
						755.13	800.17
							799.47

The second lattice in Table 5.7 shows the dynamic programming solution path for a system with the flexibility to wait to implement a $45 per ton carbon tax until a given period. The decision rule used to determine whether the carbon tax implementation call option should be used is whether the expected net present value of utility flows in a given period plus the value of being in the current state is greater under the flexible $45 per ton carbon tax case than the inflexible no carbon tax case. The case which has the higher expected net present value of utility flows in a given year is the case where per capita consumption less environmental damages incurred by emissions-related climate change is maximized. Overall, this rule helps determine whether implementing the carbon tax in a given period is worth the additional costs to utility incurred by society. The final decisions are shown in the final lattice in Table 5.7; it was developed by comparing utility flow values in each period in the dynamic programming solutions to the systems with and without the option to wait to implement the $45 per ton carbon tax.

Table 5.7. Fixed Case ($45 per ton carbon tax) and Flexible Case (with Call Option for $45 per ton carbon tax) Dynamic Programming Decision Analysis Lattices

Period	t = 0	t = 1	t = 2	t = 3	t = 4	t = 5	t = 6
ENPV (Utility Flow)	2328.74	1763.75	1616.81	1548.76	1449.58	1234.98	804.42
CARBON TAX ($45)		1762.04	1614.99	1546.92	1447.88	1233.57	803.53
			1613.21	1545.17	1446.28	1232.23	802.64
				1543.46	1444.69	1230.92	801.81
					1443.19	1229.62	800.99
						1228.41	800.17
							799.47
ENPV (Utility Flow)	2328.78	1763.82	1616.59	1548.22	1448.85	1192.65	803.62
WITH FLEXIBILITY TO IMPLEMENT TAX		1762.10	1614.76	1546.37	1447.16	1232.76	802.73
			1612.98	1544.63	1445.56	1231.43	801.84
				1542.91	1443.97	1230.12	801.02
					1442.47	1228.81	800.19
						1227.60	799.37
							798.68
Exercise CALL OPTION?	NO	**YES**	**YES**	**YES**	**YES**	**YES**	
		YES	**YES**	**YES**	**YES**	**YES**	
			YES	**YES**	**YES**	**YES**	
				YES	**YES**	**YES**	

					YES	YES	
						YES	

Solution: Optimal Strategy

Dynamic programming solutions show that the **value of the call option to implement a $45 per ton carbon tax in this case is $0.51 trillion** in terms of expected net present value of utility flows per capita. However, the decision lattice in Table 5.7 above also shows that when an option to implement a $45 per ton carbon tax is available, it should be called upon beginning in Stage 1, in 2015. This result indicates that the DICE model yields environmental damages due to future carbon emissions, given the expected contributions of technological change in the economy (A_t), which are too great to justify waiting to implement a carbon tax.

Final expected net present values of utility flows are $2328.27 trillion for the inflexible (no carbon tax) case, $2328.74 trillion for the case with a fixed $45 per ton carbon tax in each period, and $2328.78 trillion for the case with the flexibility to wait to implement a $45 per ton carbon tax.

The VARG curve below shows this result. The flexible case value at risk and gain curve is shifted to the right for each probability, indicating the higher NPV of utility flows for this case. It is noteworthy that while the call option does retain value, given that the option to tax is implemented in Stage 1 across all A_t scenarios, that the comparison above is really between the flexible case and the inflexible case.

As noted in the Decision Analysis Section, the most relevant alternate measure of value for the system under study is net present value of consumption per capita. However, while the values are different numerically, utility flows are simply based on a *direct* log-transformation of consumption flows. Therefore, when comparing across cases, the preferred system design would be the same. As such, a multiple criteria analysis for the case under study in this project considers preferred system designs based on risk assumptions. As Figure 5.5 and Table 5.8 below shows, at each level of risk (e.g., P10, P25, P50, P75, P95, and all risk levels in between), the flexible case is preferred over the inflexible case.

Table 5.8. Multiple Criteria Table for Decision Analysis Using Lattice Uncertainty Evaluation

Risk Assumption	Preferred Period 1 Design
P10	Flexible Case
P25	Flexible Case
P50	Flexible Case
P75	Flexible Case
P95	Flexible Case

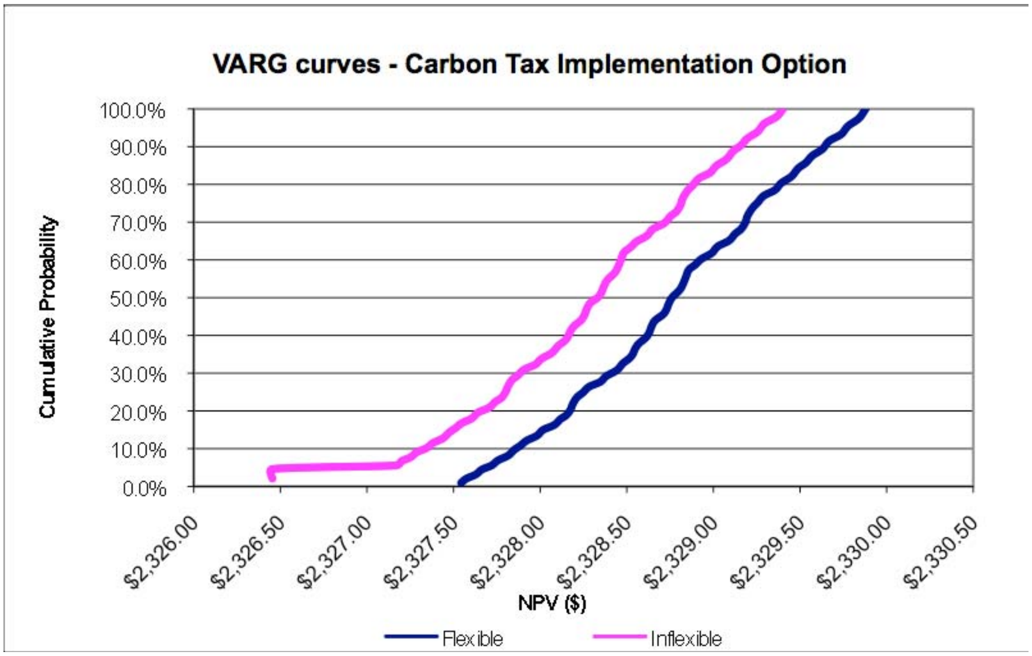

Figure 5.5. Lattice Decision Analysis VARG Curve

VII. Reflections

Conclusion: Discussion on Flexible Design

This project examined the opportunities that flexible global climate change policies might have on the overall net present welfare of the global macroeconomy. The system studied consisted of an aggregated global economy, specified through a climate change lens, and included the population's preference for consumption versus investment, as well as possible damages to the physical environment from carbon emissions. The underlying evaluation model used for determining system values is the Dynamic Integrated model for Climate and the Economy (DICE-99) and the timeframe studied was 2015 through 2335.

Broadly, the hypothesis under investigation suggests that implementation of a R&D-inducing carbon tax policy today provides a form of "insurance" against future carbon-emissions related climate damages (costs), and therefore represents a form of flexibility (See Box 1 and 2 for more details). Specifically, two variants of a carbon policy were studied, considering different uncertainties and using two different methods of analysis.

First, four flexible policy cases with a carbon-tax were tested against an inflexible policy case with no carbon tax (representing "business-as-usual") using a two-stage decision tree analysis approach. The four flexible policies were a high/high, high/low, low/high, and low/low carbon tax path, with an opportunity to change course between Period1/Period2 if it would yield higher NPV welfare. Two uncertainties were considered in this study—emissions intensity (σ_t) growth rate and a climate feedback parameter (λ) representing sensitivity of the climate to carbon emissions. Results of this analysis confirmed the overall hypothesis under study. A flexible carbon-tax based policy path of low/high was deemed the optimal strategy over two periods over all possible scenarios given the uncertainties considered. **The value of flexibility was $0.019316 trillion for the optimal strategy.** Sensitivity analysis on the uncertainties considered showed that the optimal strategy was most sensitivity to the climate feedback parameter (λ).

Second, a single flexible policy case with a call option to implement a medium-level carbon tax if and when the system could take advantage of it was tested against an inflexible no carbon-tax policy case. The overall hypothesis under investigation remained the same, but the specific question asked in this analysis was "How long should we wait to implement a carbon tax?" A lattice analysis approach was used to examine the evolution of the total factor productivity (A_t) growth rate uncertainty, and a dynamic programming-based decision analysis was performed using the lattice. This exercise consisted of a six-stage decision analysis considering one uncertainty. The dynamic programming solution to this exercise showed once again that the flexible strategy was preferred to the inflexible strategy at all risk levels, and that **the value of the call option to implement a carbon-tax when deemed appropriate was $0.51 trillion.**

Given the multiple decision point opportunities (33 periods), and multiple possible uncertainties to consider, the most appropriate method of analysis to use in exploring long-term flexible climate change policy with an evaluation model such as DICE, lies somewhere in between the decision tree analysis approach taken in the first exercise and the dynamic programming lattice approach taken in the second exercise. The underlying structure of the problem fits a traditional decision tree set up in that shifts in policy are possible from period to period, policy decisions at any one point in time can be selected from a wide range of choices (not limited to "high or low" or "yes or no"), and multiple uncertainties can take on several discrete values and probabilities. However, with such an approach, the well-known "curse-of-dimensionality" concern quickly reveals itself and the problem becomes computationally intractable. Dynamic programming provides a computationally efficient way of searching the solution space, and can thus provide a more appropriate method of analysis to such complex problems. The next step is thus to branch out of the Excel-based binomial lattice-based dynamic programming approach used in this exercise and build a more complex computer programming code to consider these complexities. Additionally, the binomial lattice-approach restricted the exercise to a path-independent uncertainty; whereas many of the uncertainties considered in macroeconomic climate policy models are path dependent, a more general dynamic programming approach can provide useful insights.

Extension: Policy Strategy-Induced Carbon Emissions and Temperature Paths

Overall system performance in this project was based on total net present value of welfare in the economy, guided by policy decisions about whether to implement a carbon tax. In between these two points—the point of policy decision and the final system payoff—lay the resulting paths of carbon emissions and carbon emission-induced temperature changes. In the system under study, these emissions and temperature changes have the potential to increase future costs and thus lower total net present value of welfare. Given the current examination of policies to mitigate overall damages from climate change, the carbon emissions and temperature change trajectories resulting from the various strategies considered in this project are noteworthy. Figures 7.1 and 7.2 show the emissions trajectories and the temperature change trajectories (above the preindustrial level) induced by the inflexible policy case, the optimal decision analysis case (low, then high carbon tax), and the optimal strategy in the lattice-based dynamic programming analysis case (implement a medium tax in every year after the initial period). In each case, the flexible policy (red and green) paths are lower than the inflexible policy (blue) path—implying that at least some of the total net present welfare value is derived from avoided future climate damages from implementing the carbon-tax over the inflexible case. Also, the decision analysis path appears at some points lower than the lattice analysis path, suggesting that the opportunity to shift policies between tax levels provides greater opportunity than simply waiting to implement a one level tax. Note: these showing these full trajectories are meaningful here only because the optimal strategies in both the decision analysis and the lattice analysis do not change across different values and probabilities of the uncertain parameters.

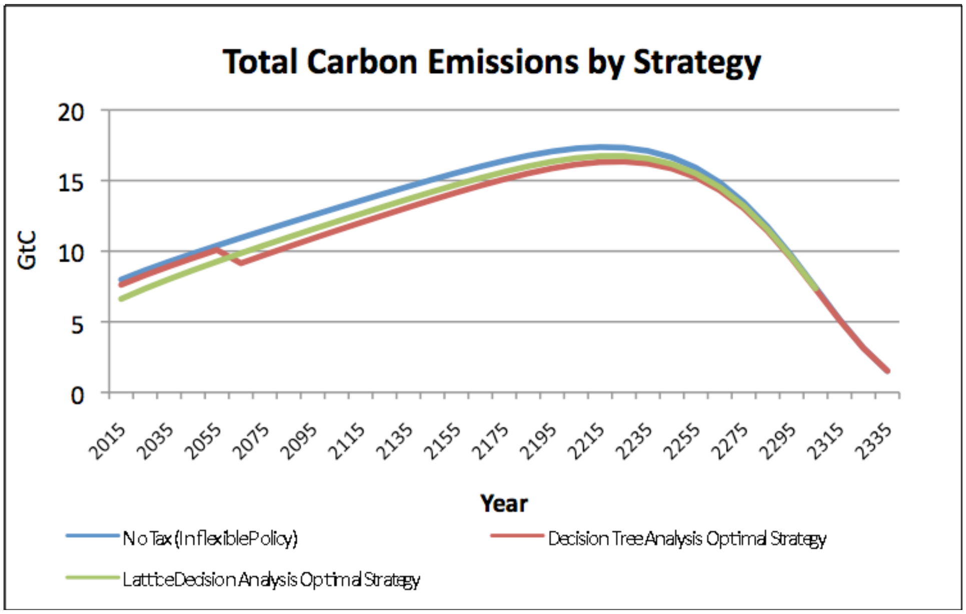

Figure 7.1. Total Carbon Emissions Paths Resulting From Different Policy Strategies

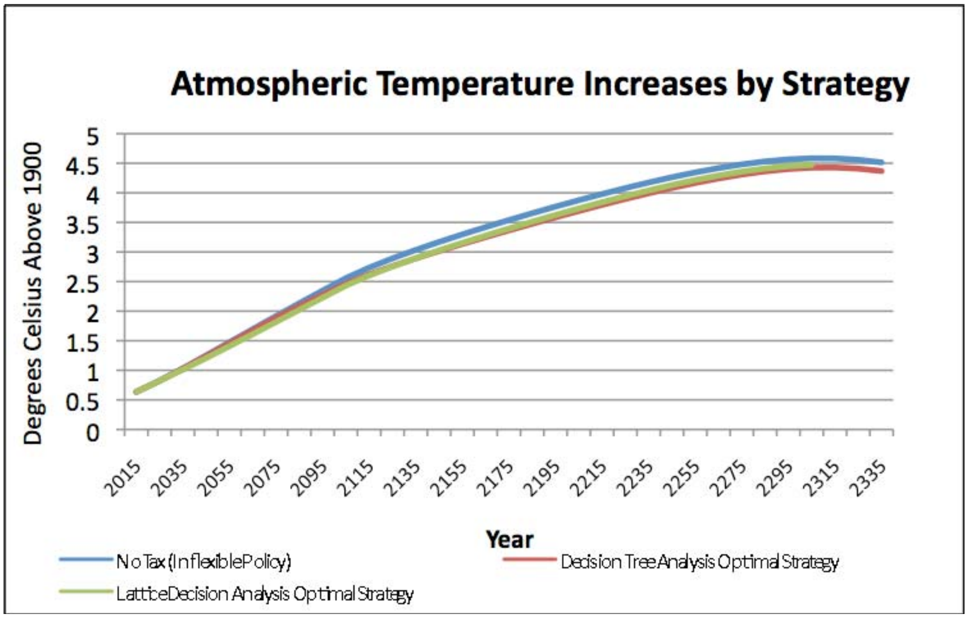

Figure 7.2 Global Temperature Increase Resulting From Different Policy Strategies

Lessons Learned: Application Portfolio and Course Reflections

I found the application portfolio exercises of profound value in ESD.71. The interim assignments tracked lectures and recitations in the course well, and provided me with an opportunity to apply the concepts to a system and topic relevant to my domain. Although I struggled in the beginning to clearly define the flexibility in the system I chose to study, I overcame this quickly and I appreciated the opportunity to apply the course concepts to a system that is quite likely at the “bounds” of the level of abstractness usually chosen for the application portfolio. On some occasions, the design concepts we learned did not fit neatly into my problem, and this challenged me to think deeply about them, applying their insights to my problem in a meaningful way. As one example, the parameters used in my lattice evolution of uncertainty were derived using a general binomial calibration methods rather that the method highlighted in lecture. My goal in ESD.71 was to develop an intuition about flexibility in designing engineering systems and to learn the mechanics of incorporating flexibility into and solving basic uncertainty and decision analyses. Moreover, my intent is to apply these concepts to energy planning and climate policy decisions under uncertainty. This application portfolio allowed me to achieve both of these goals. Specifically, the dynamic programming lattice analysis provided an excellent way to explore the steps involved in a dynamic programming backtracking analysis, which will prove useful as I embark on my development of more complex dynamic programs. I am also quite pleased that I am completing the course with a solid understanding of how to build and solve a decision tree from beginning to end—using many of TreeAge Pro’s features.

I found the course overall similarly useful. First, the Engineering Economy module during the first weeks of the class was invaluable to me. My comfort-level with Excel prior to the course was what I considered to be high, but the simulation procedures I learned during the module were new and incredibly helpful. I appreciated the instructing staff’s encouragement to take the course. A suggestion that I have for the course is to add a series of (short, 1-2 problem) assignments throughout the course to reinforce mechanics on the topics learned after the Midterm Quiz. This would include setting up and solving decision trees, lattice evaluations, and dynamic programming. While these concepts were learned through the application portfolios, I think it would be helpful to have everyone working on the same short problems outside of class, turning them in, and reviewing their mechanics during recitation. By the time these concepts were being introduced and discussed in lecture, the application portfolios had become the focus of students’ attention. As a final note, I will never forget the garage case and will always rely on it to some degree in initial considerations about flexibility in design. Thank you for that. As a final suggestion, I might have welcomed more time spent discussing nuances of the copper mine case and the nature of call and put options such that a second “canonical” case would be stuck in my head!

Appendix A. The DICE-99 Model (2-stage model shown for a 2015 and 2065 decision; 1995 and 2005 are reference years)

	1995	2005	2015	2025	2035	2045	2055	2065	2075
PARAMETERS AND EXOGENOUS VARIABLES									
OUTPUT AND CAPITAL ACCUMULATION									
damage coefficient on temperature	-0.004500								
damage coefficient on temperature squared	0.003500								
Abatement cost function coefficient	0.03000	0.03247	0.03500	0.03759	0.04023	0.04290	0.04560	0.04833	0.05107
Initial cost function coefficient	0.030								
Initial rate of growth of abatement cost coefficient (percent per decade)	-8.000								
Rate of decline in growth rate of abatement cost coefficient (percent per year)	0.500								
Growth rate of abatement cost coefficient (percent per decade)		-7.610	-7.239	-6.886	-6.550	-6.230	-5.927	-5.638	-5.363
Exponent of abatement cost function	2.150								
capital share	0.30								
rate of depreciation (percent per year)	10.00								
Initial capital stock ($ trillion)	47.000								
EMISSIONS									
Rate of decline in land-use change emissions (% per decade)	10.00								
Carbon emissions from land-use change (GtC per year)	1.13	1.02	0.91	0.82	0.74	0.67	0.60	0.54	0.49
Initial carbon emissions from land use change (GtC per year)	1.13								
Sigma (industrial CO2 emissions/output -- MtC/$1000)	0.274	0.243	0.242	0.240	0.239	0.238	0.237	0.236	0.236
Initial sigma	0.274								
Initial growth rate of sigma (percent per decade)	-15.885								

Rate of decrease in the growth rate of sigma (percent per year)	2.359								
Acceleration parameter of growth rate of sigma	-0.001								
Growth rate of sigma (percent per decade)	-15.885	-12.655	**-0.698**	**-0.576**	**-0.483**	**-0.411**	**-0.357**	**-0.315**	**-0.282**
World emissions limit (GtC per year)	6.80	6.69	6.58	6.49	6.41	6.34	6.27	6.21	6.16
Convergence parameter for optimal carbon tax	0.00								
POPULATION									
Population (millions)	5632.700	6484.29	7258.31	7944.36	8540.30	9049.68	9479.48	9838.39	10135.62
Initial population (millions)	5632.700								
Init population growth rate (per decade)	15.700								
Rate of decline in population growth rate (percent per decade)	22.200								
Cumulative population growth rate	0.00	0.14	0.25	0.34	0.42	0.47	0.52	0.56	0.59
PRODUCTIVITY									
Total factor productivity	0.01685	0.018	0.018	0.019	0.020	0.020	0.021	0.022	0.023
Initial level of total factor productivity	0.017								
Init productivity growth rate (percent per decade)	3.800								
Rate of decline in productivity growth rate (percent per decade)	0.000								
Productivity growth rate (percent per decade)	0.000	3.800	3.800	3.800	3.800	3.800	3.800	3.800	3.800
CONCENTRATIONS									
Initial atmospheric concentration of CO2 (GtC)	735.00								
Initial concentration of CO2 in biosphere/shallow oceans (GtC)	781.00								
Initial concentration of CO2 in deep oceans (GtC)	19230.00								
Carbon cycle transition coefficients (percent per decade)									
atmosphere to atmosphere	66.616								
biosphere/shallow oceans to atmosphere	27.607								

atmosphere to biosphere/shallow oceans	33.384								
biosphere/shallow oceans to biosphere/shallow oceans	60.897								
deep oceans to biosphere/shallow oceans	0.422								
biosphere/shallow oceans to deep oceans	11.496								
deep oceans to deep oceans	99.578								
Concentrations limit (GtC)	1192.8								
TEMPERATURE									
Exogenous forcing (Watts per square meter)	-0.1965	-0.06185	0.0728	0.20745	0.3421	0.47675	0.6114	0.74605	0.8807
Initial atmospheric temperature (deg. C above preindustrial)	0.43								
Initial temperature of deep oceans (deg. C above preindustrial)	0.06								
Speed of adjustment parameter for atmospheric temperature	0.23								
Equilibrium temperature increase for CO2 doubling	**1.13400**								
Coefficient of heat loss from atmosphere to oceans	0.44								
Coefficient of heat gain by deep oceans	0.02								
Temperature limit (deg C above preindustrial)	2.50								
WELFARE									
Social rate of time preference (percent per year)	3.00	2.92	2.85	2.78	2.71	2.64	2.57	2.51	2.44
Initial social rate of time preference (percent per year)	3.000								
Rate of decline of social rate of time preference (percent per year)	0.257								
Social time preference factor	1.00	0.74	0.56	0.42	0.32	0.25	0.19	0.15	0.11
Multiplicative scaling coefficient in utility function	333.51								
Additive scaling coefficient in utility function	1493.77								

ENDOGENOUS VARIABLES									
OUTPUT									
Output gross of climate damage and abatement costs ($ trill per year)	22.58	29.63	36.20	42.51	48.72	54.90	61.08	67.30	73.56
Abatement cost (percentage of gross output)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Output gross of climate damage ($ trill per year)	22.58	29.63	36.20	42.51	48.72	54.90	61.08	67.30	73.56
Climate damage (percentage of net output)	-0.129	-0.098	-0.119	-0.136	-0.144	-0.142	-0.129	-0.104	-0.067
Output net of climate damage and abatement costs($ trill per year)	22.61	29.66	36.25	42.57	48.79	54.98	61.16	67.37	73.61
CAPITAL ACCUMULATION									
Investment ($ trill per year)	5.72	7.13	8.40	9.67	10.95	12.24	13.55	14.89	16.27
Capital ($ trill)	47.00	73.59	96.92	117.81	137.80	157.50	177.27	197.34	217.72
EMISSIONS									
Industrial carbon dioxide emissions (GtC per year)	6.187	7.207	8.744	10.208	11.644	13.067	14.486	15.911	17.343
Total carbon dioxide emissions (GtC per year)	7.32	8.22	9.66	11.03	12.38	13.73	15.09	16.45	17.83
Control rate (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CARBON CYCLE									
Atmospheric carbon dioxide concentration (GTC.)	735.00	778.39	822.20	873.30	929.73	990.84	1056.35	1126.07	1199.86
Biosphere/upper ocean CO2 concentration (GtC)	781.00	802.13	829.52	860.87	897.08	938.04	983.48	1033.14	1086.78
Deep ocean carbon dioxide concentration (GtC)	19230.00	19238.63	19249.66	19263.79	19281.46	19303.22	19329.60	19361.09	19398.15
TEMPERATURE									
Atmospheric temperature (degrees Celsius above 1900)	0.430	0.277	0.372	0.484	0.605	0.730	0.857	0.985	1.113
Total increase in radiative forcing since preindustrial (Watts per square meter)	1.04	1.51	1.97	2.46	2.97	3.48	3.99	4.51	5.02
Lower ocean temperature (degrees Celsius above preindustrial)	0.06	0.07	0.07	0.08	0.09	0.10	0.11	0.12	0.14

WELFARE									
Consumption ($trill per year)	16.89	22.54	27.84	32.89	37.84	42.74	47.60	52.48	57.35
Consumption per capita ($thous per year)	3.00	3.48	3.84	4.14	4.43	4.72	5.02	5.33	5.66
Period-specific utility term	-32724.12	-27318.80	-22523.34	-18358.20	-14820.79	-11882.46	-9483.51	-7549.03	-6003.57
Welfare (in units of first period consumption)	**968.113668**								
Discount factor	1.00	0.64	0.44	0.31	0.22	0.16	0.11	0.08	0.06
Present value of consumption ($trill)	**971.20**								
CONTROL VARIABLES									
CARBON TAX ($ PER METRIC TON)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SAVINGS RATE (PERCENT PER YEAR)	25.30	24.02	23.18	22.72	22.43	22.26	22.16	22.10	22.10
KEY SHADOW PRICES									
CAPITAL									
Interest rate (percent per year)	4.53	3.93	3.66	3.50	3.39	3.30	3.22	3.15	3.08
Discount rate (percent per year)	4.54	3.93	3.64	3.48	3.36	3.26	3.17	3.09	3.02
Difference (as percentage of interest rate)	-0.07	-0.01	0.46	0.78	1.03	1.25	1.42	1.65	1.88
EMISSIONS									
Environmental shadow price of carbon ($ per metric ton)	6.10	9.73	13.85	18.38	23.31	28.61	34.24	40.15	46.27
Difference between carbon tax and ESP (% of ESP)	100	100	100	100	100	100	100	100	100
Iteration step	0.02	0.02	0.03	0.05	0.06	0.07	0.09	0.10	0.12
Unconstrained carbon tax	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00