

**Probabilistic Policy Experiments: The Use of
Energy-Economic-Environmental Models in the
Climate Change Policy Process**

by

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Abstract

This paper uses the Edmonds-Reilly model to explore an alternative approach for using energy-economic-environmental models when analyzing future CO₂ emissions. This approach—conducting probabilistic policy experiments—can be used to investigate the effectiveness of various policy options in the context of uncertainty. The analysis builds on work by Nordhaus and Yohe (1983) and Edmonds et al. (1986). A key feature of using a probabilistic approach is that it offers both analysts and policymakers an opportunity to move away from arguing about which scenario is the “right,” best guess scenario, and towards a discussion of which strategies are effective across an wide range of possible futures. This paper both develops a methodology for conducting probabilistic policy experiments and presents the results of 5 preliminary experiments using this approach.

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Probabilistic Policy Experiments: The Use of Energy-Economic-Environmental Models in the Climate Change Policy Process

Robert M. Margolis

Introduction

During the past 20 years expectations about future CO₂ emissions have changed dramatically. Early studies typically used time trend analysis to generate a single “best guess” or “business as usual” scenario, and predicted future CO₂ emission growth rates around 4.5% per year (Edmonds et al. 1986, 83). By the early 1980’s the consensus had shifted downward significantly: In 1982 Clark reviewed a number of studies and found a consensus CO₂ emission growth rate of 2% per year (Clark 1982, 4). Even more recently the IPCC business as usual scenario had an average CO₂ emission growth rate of 1.4% per year (IPCC 1991, 26). This downward shift in CO₂ emissions projections is closely linked to a downward shift in energy forecasts.

In addition, over the past 20 years, there have been a number of innovations in energy modeling/forecasting. Today the dominant mode of analysis has become “scenario analysis.” Analysts have developed a number of approaches to scenario analysis. For example, one approach focuses on the effects of potential policy intervention on a “base case” or “business as usual” scenario. This approach was used by Edmonds and Reilly (1983), Rose et al. (1983), Chandler (1988), the CBO (1991), and the IPCC (1990).

Another approach focuses on the uncertainty in future energy use and CO₂ emissions. Different forms of this approach were used by Edmonds et al. (1984, 1986), Nordhaus and Yohe (1983) and the IPCC (1992). While these

studies addressed uncertainty in future CO₂ emissions, they did not explore the effects of policies in the context of uncertainty.

This paper uses the Edmonds-Reilly model to demonstrate an alternative approach for using energy-economic-environmental models when analyzing future CO₂ emissions. This approach—conducting probabilistic policy experiments—can be used to explore the effects of policies in the context of uncertainty. It builds on work by Nordhaus and Yohe (1983) and Edmonds et al. (1986).

The body of this paper is divided into three sections. It begins with a review of the Nordhaus and Yohe (1983) and Edmonds et al. (1986) studies. This review is intended to give the reader a general understanding of the probabilistic approach to analysis. Second, the methodology for conducting probabilistic policy experiments is described. This section discusses both how input distributions for uncertain parameters were chosen and how scenarios were generated. And third, the results of five preliminary probabilistic policy experiments are presented and discussed.

Nordhaus and Yohe (1983) Probabilistic Scenario Analysis

The first formal probabilistic scenario analysis of future CO₂ emissions was performed by Nordhaus and Yohe in 1983. They developed a simple model of CO₂ emissions from energy use. The model included two types of energy: fossil (i.e., carbon emitting) and non-fossil (i.e., non-carbon emitting). They used their model to (1) estimate the inherent uncertainty surrounding future CO₂ emissions and atmospheric concentrations, and (2) determine which parameters were most important in producing the uncertainty.

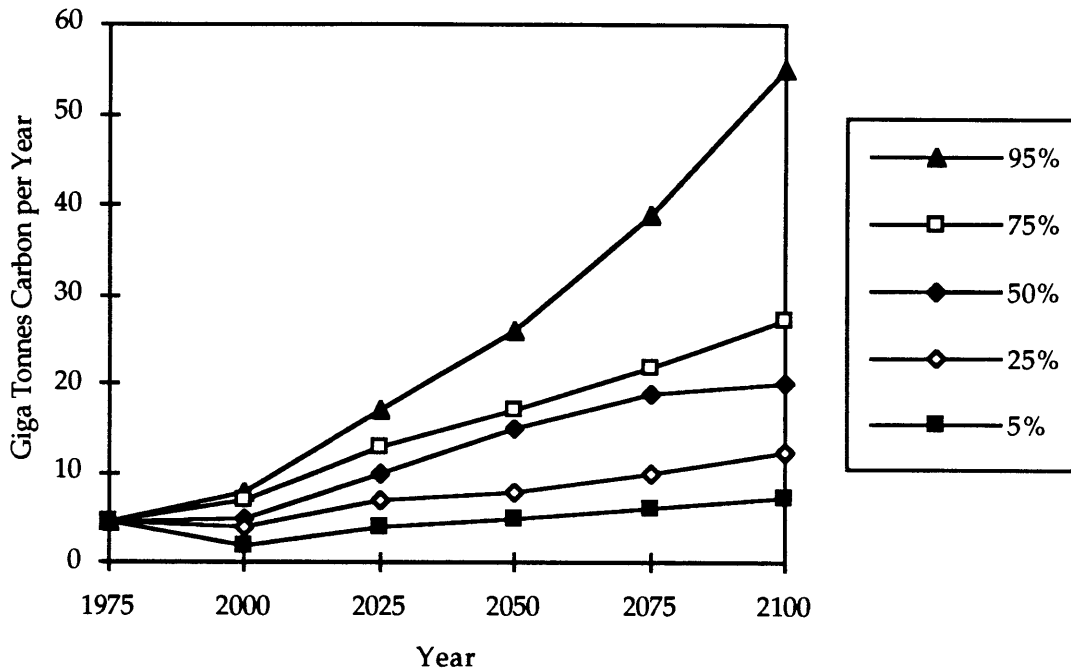
Nordhaus and Yohe developed a set of probabilistic scenarios by assigning probability distributions to ten key input parameters.¹ As Nordhaus and Yohe point out, their approach does not try to resolve current uncertainties but only to represent them as accurately as possible and to integrate them into the modeling process in a consistent fashion (Nordhaus and Yohe 1983, 88). The distinct advantage of a probabilistic approach over a more qualitative one, like the approach included in the 1992 IPCC supplement report, is that it gives policymakers a sense of the relative likelihood of different outcomes.

Percentiles for carbon emissions from the Nordhaus and Yohe analysis are shown in figure 1. Figure 1 indicates that, based on Nordhaus and Yohe's analysis, in the absence of policy intervention for the year 2050 there is a 5% chance that carbon emissions will be below 5 GtC/yr, a 25% chance that carbon emissions will be below 8 GtC/yr, a 50% chance that carbon emissions will be below 15 GtC/yr, a 75% chance that carbon emissions will be below 17 GtC/yr, and a 95% chance that carbon emissions will be below 26 GtC/yr.

Nordhaus and Yohe also ranked parameters by their relative contribution to uncertainty. They found that the parameter representing the ease of substitution between fossil and non-fossil fuels was the most important parameter influencing the uncertainty in carbon emissions. The second most important parameter was the general productivity growth rate (a parameter which affects both energy and labor productivity). It is interesting that Nordhaus and Yohe found uncertainty about the population growth rate to rank relatively low on their list of importance.

¹For sampling purposes Nordhaus and Yohe discretized the distribution for each of the 10 uncertain variables into high, medium and low values. They did this in such a way as to make the variance of the discretized values equal to the variance of the continuous variable. They sampled 1000 of the possible 59,049 ($=3^{10}$) outcomes (Nordhaus and Yohe 1983, 90).

Figure 1: Carbon Emissions Percentiles From Nordhaus and Yohe Probabilistic Scenario Analysis



Source: Nordhaus and Yohe 1983, 94.

Finally, Nordhaus and Yohe explored the effects of policies aimed at reducing carbon emissions from the energy sector by applying various levels of carbon taxes on fossil fuels. However, in their policy scenarios they set all ten uncertain parameters at their most likely values. Thus they did not explore the effects of carbon taxes in the context of uncertainty.

Edmonds et al. (1986) Uncertainty Analysis

Edmonds et al. conducted a similar uncertainty analysis in 1986. Like the Nordhaus and Yohe study, Edmonds et al. focused on representing uncertainty about various model parameters as accurately as possible. However they used a different model—the Edmonds-Reilly model—which

has much more detail in its description of energy producing and consuming sectors than the model developed by Nordhaus and Yohe.

Edmonds et al. conducted a Monte-Carlo analysis using the Edmonds-Reilly model. First they defined uncertainty ranges for 79 input variables governing: population; economic growth; energy conservation; the resource base for fossil fuels, uranium, and biomass; technology descriptions for electric power generation, synfuel conversion, and solar power; environmental costs; and the effects of energy prices on overall economic activity. Then they used Monte-Carlo sampling to generate 400 scenarios. For each scenario they tracked 95 output variables. Finally, they determined the relative contributions of each of the input variables to the overall uncertainty of the output variables. Thus like Nordhaus and Yohe they produced an uncertainty range of future CO₂ emissions and ranked different parameters based on their contribution to output uncertainty.

Edmonds et al. found that in the Edmonds-Reilly model four variables played dominant roles in determining CO₂ emissions:

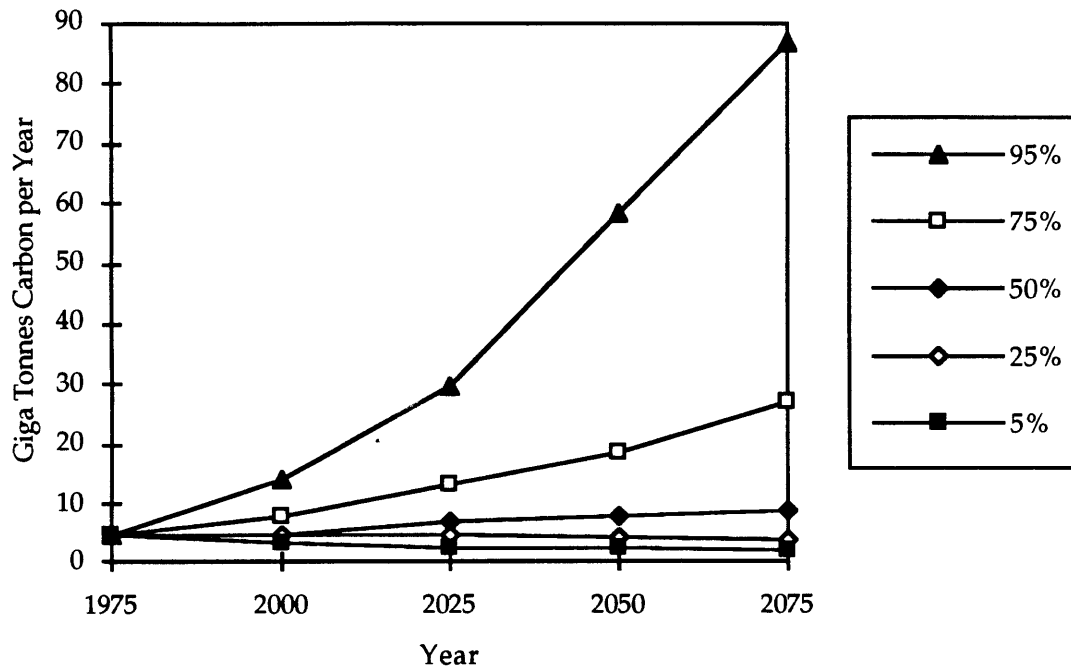
- Labor productivity growth rate in developing countries,
- Labor productivity growth rate in developed countries.
- Exogenous energy end-use efficiency improvement rate, and
- Income elasticity of demand for aggregate energy in developing regions.

And that five additional factors were important in determining CO₂ emissions:

- Biomass costs,
- Environmental costs of coal extraction in developing regions,
- Income elasticity of demand for energy in the OECD,
- Aggregate price elasticity of demand for energy, and
- Rate of technological improvement of coal production.

It is striking that the most important parameter in the Nordhaus and Yohe study, the interfuel substitution parameter, was not on the list of important

Figure 2: Carbon Emissions Percentiles from Edmonds et al. Uncertainty Analysis



Source: Edmonds and Darmstadter 1990a, 10.

parameters in the Edmonds et al. study. This difference is probably due to the increased detail included in the Edmonds-Reilly model. For example, the Edmonds-Reilly model incorporates multiple sources of energy supply and allows for interfuel substitution options. In contrast, in the Nordhaus and Yohe model there are only two sources of energy (fossil and non-fossil fuels), and substitution between these two fuels is very limited.

In their analysis Edmonds et al. concluded that future emissions of CO₂ from energy are highly uncertain. They found that a range for the average annual CO₂ emissions growth rate of 3 percent to -1.4 percent per year was needed to bracket 90 percent of the cases! Further, roughly 25 percent of the

cases resulted in constant or declining emissions. Percentiles for carbon emissions from their analysis are shown in figure 2.

Given the level of uncertainty in making long-term predictions it is not surprising that figure 2 includes a very wide range of possible future CO₂ emissions paths; however, the results of this analysis should still be viewed with caution. As stated in the report's executive summary, "The fact that uncertainty is described should not mislead the readers into concluding that whereas we do not know the future with certainty, we do know the uncertainty about the future with certainty." The results are still dependent on the accuracy of both the model and the input assumptions (including input variable distribution assumptions).

In sum, by systematically exercising their model Edmonds et al. were able to test the sensitivity of its CO₂ emissions forecasts to changes in input assumptions, explore the behavior of the model under extreme and what are currently considered to be unlikely assumptions, assess the relative importance of alternative input assumptions and present their results in terms of a best guess with confidence intervals (Edmonds 1986, 3). On the other hand in their analysis Edmonds et al. looked only at uncertainty, they did not explicitly consider policies to control emissions of CO₂.

An Alternative Approach

The approach taken in this paper uses the Edmonds-Reilly model to build on the work by Nordhaus and Yohe (1983) and Edmonds et al. (1986).

Five key uncertain parameters were chosen based on their results:

- Population growth rate,
- Labor productivity growth rate,
- Exogenous energy end-use efficiency improvement rate,
- Income elasticity of demand for aggregate energy, and

- Aggregate price elasticity of demand for energy.

Probability distributions were defined for each parameter (see next section for detailed descriptions of the distributions). Then a computer program called PRISM (developed at Oak Ridge National Laboratory) was used to sample each input distribution and generate 100 sets of parameter values. Finally the Edmonds-Reilly model was run using the PRISM generated samples to set the appropriate input parameter values.

The result of this process was a set of 100 equally probable scenarios of future CO₂ emissions (and other data) in the manner of Nordhaus and Yohe (1983) and Edmonds et al. (1986). Then the analysis was taken one step further to explore how various policies would affect the output distribution of CO₂ emissions. Before discussing the results of this analysis it would be useful to discuss how the input distributions were chosen.

Defining Uncertainty Ranges for Input Parameters

One of the first steps in the analysis involved defining uncertainty distributions for the five key input parameters. This is a highly subjective process. Triangular distributions were chosen to illustrate how one might try to do this.² As Morgan and Henrion (1990) point out there are two main reasons for choosing to represent a parameter's uncertainty with a triangular distribution: (1) it implies that values toward the middle of the defined range are more likely to occur than values near either extreme, and (2) it emphasizes the fact that the details of the shape of the distribution are not known precisely. However, the consequences of choosing to use triangular distributions are that one should not try to over-interpret or have a false

²Other possible distributions one could chose when using PRISM include: normal, log normal, uniform, loguniform, and logtriangular.

sense of confidence in the subtle details of a model's results (Morgan and Henrion 1990, 96).

A triangular distribution is parameterized by its minimum, mode, and maximum. Estimates for each of the five input variables were determined as follows.

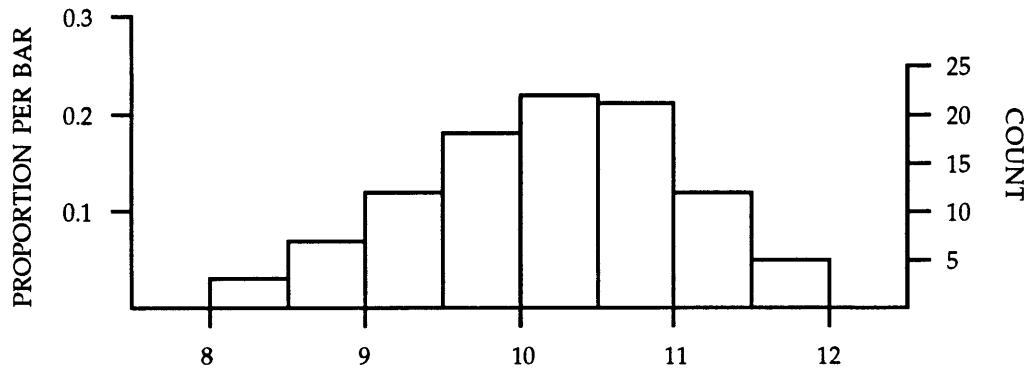
Population

Many recent analysts have utilized World Bank population projections provided by Zachariah and Vu (1988). For example, they have been used by the EPA (1989), the IPCC (1990), the Energy Modeling Forum (1991) and others. The World Bank estimate assumes that global population growth rates will slow down considerably after the year 2000, and that global population will stabilize around 10 billion after the year 2050. While this estimate may seem plausible, it is based on a set of highly subjective assumptions, and represents only one possible path. In order to capture the inherent uncertainty in future population growth rates the following triangular population distribution was used:

Region	Minimum	Mode	Maximum	
Global	8	10	12	Billion

The histogram shown in figure 3 was generated from the actual PRISM samples for the population stabilization level. As shown in figure 3, dividing 100 samples into 8 classes yields a histogram which roughly approximates a triangle. The histogram would look more like a triangle if a larger number of samples and narrower classes were used.

Figure 3: Histogram of PRISM Generated Population Stabilization Level Samples



Labor Productivity Growth Rate

The Edmonds-Reilly model disaggregates the world into nine regions. These were combined into two aggregate regions when calculating labor productivity growth rates: North (N. America, Europe, USSR, Japan and Australia) and South (Asia, Africa, L. America and Middle East). Edmonds et al. (1986) used a similar aggregation for labor productivity growth rates. In the studies conducted by the EPA (1989) and the IPCC (1990), labor productivity growth rate assumptions were extrapolated from World Bank (1987) projections for 1986-1995. Both the EPA (1989) and the IPCC (1990) used the same set of “high growth” and “low growth” labor productivity growth rate assumptions.

In the EPA (1989) and IPCC (1990) scenarios the growth rate decreases after 2000 by approximately 0.5% per 25 years. In contrast, when running the Edmonds-Reilly model the labor productivity growth rate is held constant during each model run. I chose to use growth rate distributions which would include the high and low growth assumptions of the EPA (1989) and IPCC (1990). The distributions are as follows:

Labor Productivity Growth Rate

Region	Minimum	Mode	Maximum	
North	0.0	1.5	2.5	% per year
South	1.0	2.5	3.5	% per year

Figure 4a: Histogram of PRISM Generated Labor Productivity Growth Rate Samples for the North

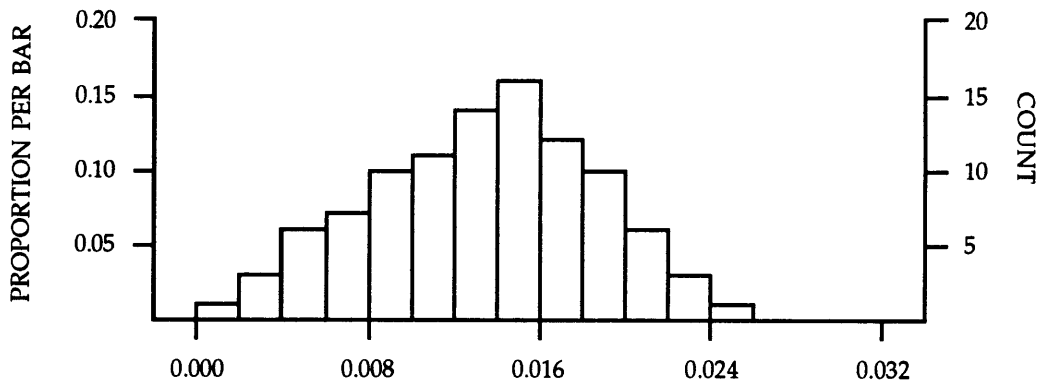
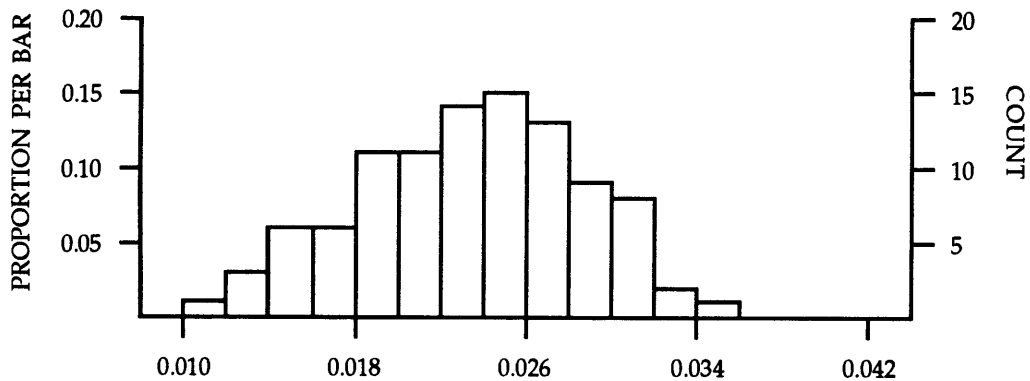


Figure 4b: Histogram of PRISM Generated Labor Productivity Growth Rate Samples for the South



Exogenous Energy End-Use Efficiency Improvement Rate

In the Edmonds-Reilly model the exogenous energy end-use efficiency improvement rate represents the rate at which energy use per unit output declines over time as a consequence of technological change. The rate is independent of population, GNP and prices. Model results are very sensitive to small changes in this value (see Edmonds et al. 1986, Edmonds and Barns 1991). As illustrated by a series of articles on CO₂ emission limits in *The Energy Journal* (Hogan 1990; Manne and Richels 1990a&b; Lave 1990; Perry 1990; and Williams 1990) there is a great deal of controversy over what is an appropriate value to use for this parameter. Analysts can not even agree on what the historical value has been. For example, Manne and Richels (1990a) and Hogan (1990) argue that there is no evidence for an exogenous energy end-use efficiency improvement rate in the post-1947 historical record. On the other hand, Williams (1990) argues that the historical rate between 1920 and 1973 averaged 0.9%.

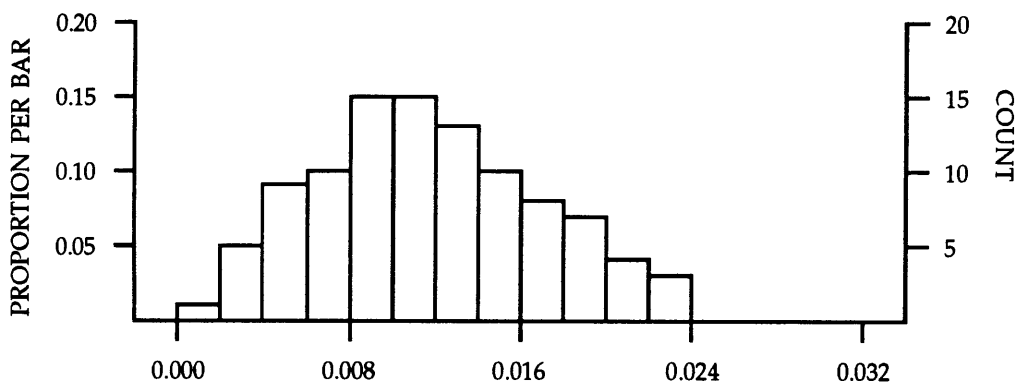
There is also a great deal of disagreement about whether or not policies can be used to increase the rate of exogenous energy end-use efficiency improvement in the future. This parameter is at the heart of the technical optimist vs. pessimist debate, and the economic vs. technological modeling approaches. It is sometimes treated as a policy parameter; however, it is not really a policy parameter. Instead it can be argued that there are policy changes which could affect it such as: regulatory changes in the electric power sector, increases in CAFE standards, appliance efficiency standards, increased government funding of energy efficiency R&D, etc.

In my analysis I defined the exogenous energy end-use efficiency improvement rate distribution based largely on work by Edmonds et al. (1986) and Edmonds and Barns (1991). I am going to come back to this parameter

later, and look at how one might treat it as a policy parameter. I used the following triangular distributions for exogenous energy end-use efficiency improvement rate:

Exogenous Energy End-Use Efficiency Improvement Rate				
Region	Minimum	Mode	Maximum	
Global	0.0	1.0	2.5	% per year

Figure 5: Histogram of PRISM Generated Exogenous Energy End-Use Efficiency Improvement Rate Samples



Income and Price Elasticities of Demand for Aggregate Energy

Typically values chosen by analysts for price and income elasticities are treated as if they are defined constants. In reality they are empirical functions with a great deal of uncertainty associated with them. Uncertainty about income and price elasticities arise primarily from subjective judgment and disagreement about how much the future is likely to be like the past. In my analysis using the Edmonds-Reilly model, income elasticity is aggregated into

North and South (same as labor productivity) while price elasticity is set globally. Both parameters are held constant during each model run.

In my analysis I defined the elasticity distributions based largely on work by Edmonds et al. (1986) and Edmonds and Barns (1991). I used the following triangular distributions for income and price elasticities:

Income Elasticity of Demand for Aggregate Energy			
Region	Minimum	Mode	Maximum
North	0.5	1.0	1.3
South	0.6	1.2	2.0

Figure 6a: Histogram of PRISM Generated Income Elasticity of Demand for Aggregate Energy Samples for the North

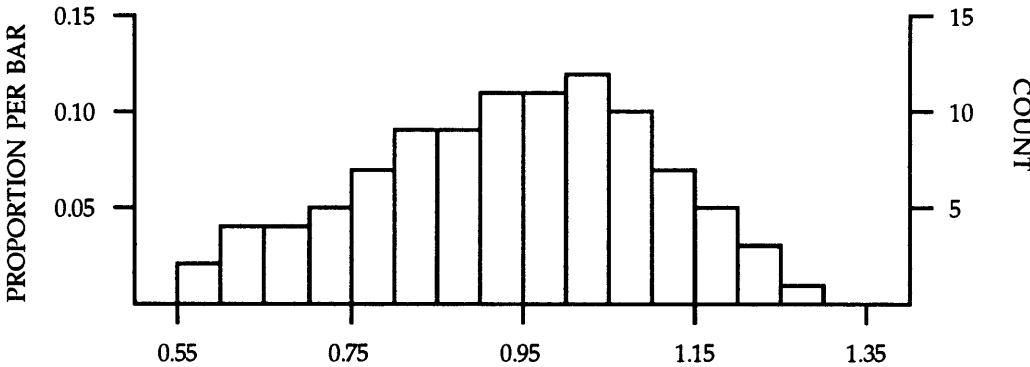
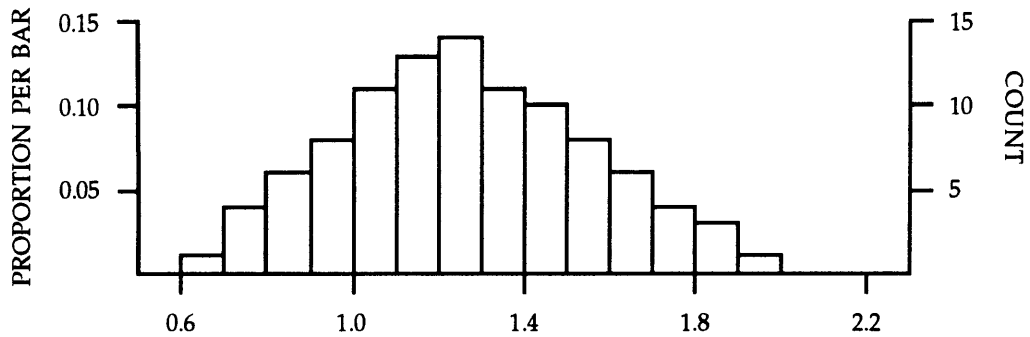


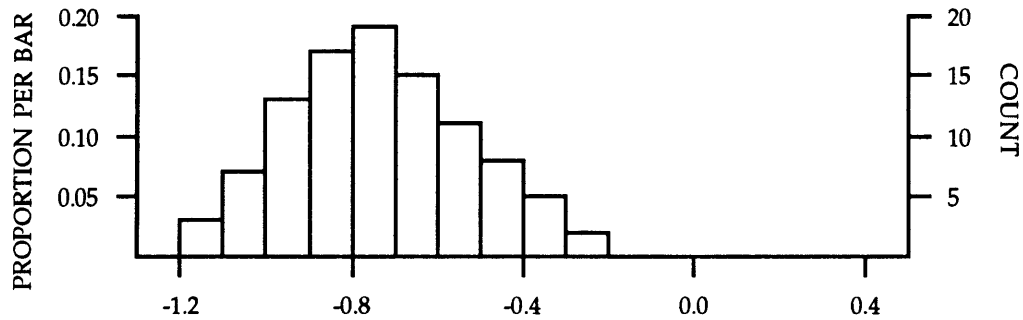
Figure 6b: Histogram of PRISM Generated Income Elasticity of Demand for Aggregate Energy Samples for the South



Aggregate Price Elasticity of Demand for Energy

Region	Minimum	Mode	Maximum
Global	-1.2	-0.8	-0.2

Figure 7: Histogram of PRISM Generated Aggregate Price Elasticity of Demand for Energy Samples



Generation of Samples Using PRISM

After defining the input distribution as described above PRISM was used to generate samples to be used when running the Edmonds-Reilly model. The technique for generating samples used by PRISM is called Latin-

Hypercube sampling. In Latin-Hypercube sampling, to generate n samples, each input distribution is divided up into n equiprobable intervals. Then a single value is sampled (at random) from within each of the intervals. Thus for each input distribution a sample of n values is produced that is more uniformly distributed than random sampling. Then n sets of samples are generated by selecting one value at random from each of the input samples, without replacement. The result is n sets of samples, in which each value from each input is used only once (Morgan and Henrion 1990, 204-5). In my analysis I set n equal to 100. Thus PRISM was used to generate 100 sets of samples.

Base Output Distribution

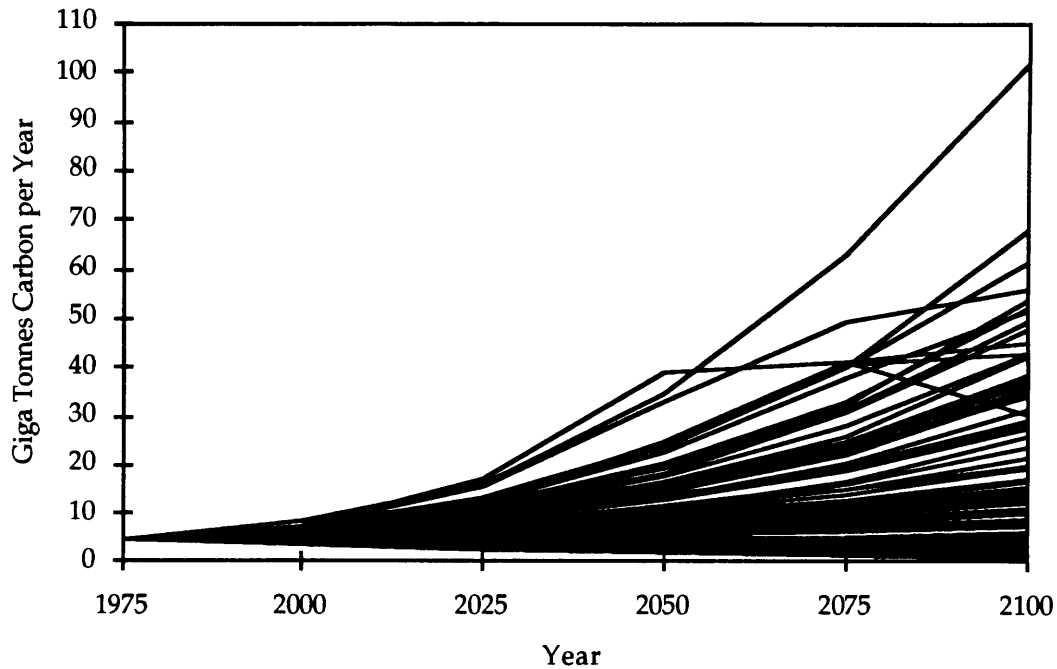
I ran the Edmonds-Reilly model with the PRISM generated sets of samples and produced a set of 100 scenarios.³ The 100 scenarios are shown in Figure 8. I will refer to them as my “base output distribution.” Figure 9 shows the percentiles for carbon emissions in a similar format to Nordhaus and Yohe (figure 1) and Edmonds et al. (figure 2).⁴ My results fall between the results of these two earlier studies.

In 2075 the Edmonds et al. (1986) study shows a range of 2 to 87 GtC/yr for the 5th to 95th percentiles, and a range of 4 to 27 GtC/yr for the 25th to 75th percentiles; meanwhile, in 2075 my base output distribution shows a range of 1.6 to 40 GtC/yr for the 5th to 95th percentiles, and a range of 4.6 to 19

³I modified version 2.50 of the Edmonds-Reilly model to automatically run 100 times using the PRISM generated data file. The modified version of the Edmonds-Reilly model and PRISM were both run on a Micro Vax 3400 using Vax/VMS V 5.4-3.

⁴The percentiles are determined from the actual sampling distribution. In other words, they are derived from the output distribution which is generated by the set of parameter input distributions described above. Determining percentiles for a set of 100 scenarios involves a straight forward procedure. First sort the carbon emissions in each period, then by definition the 5th, 25th, etc. sample from each ordered set corresponds to the 5th, 25th, etc. percentile.

Figure 8: Carbon Emissions for 100 Base Output Scenarios

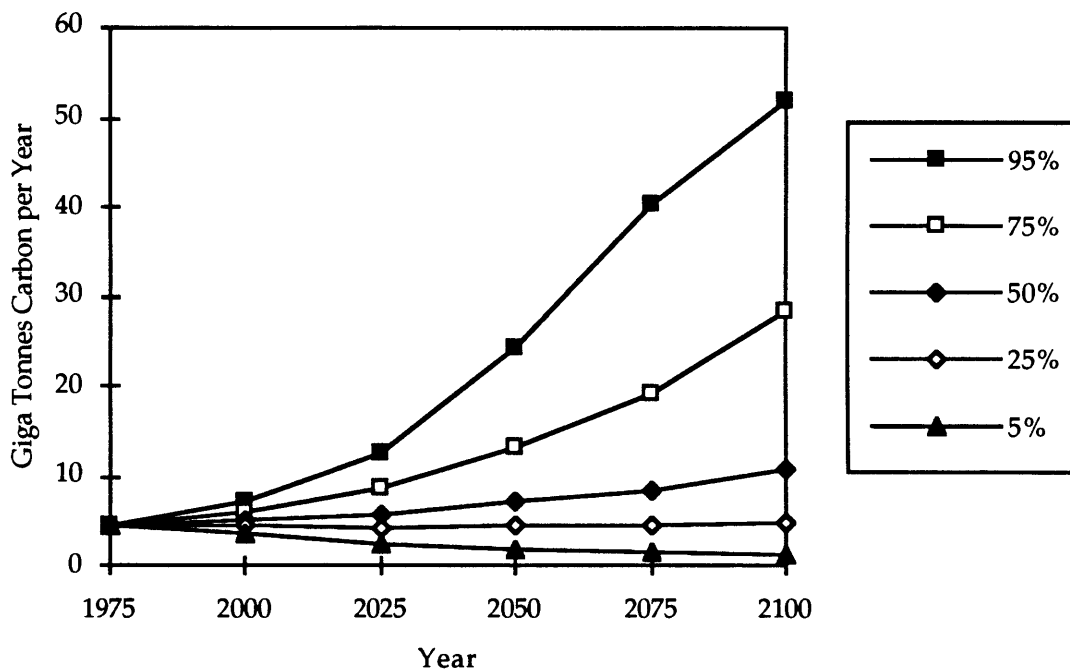


GtC/yr for the 25th to 75th percentiles. It is not surprising that my results span a narrower range than the results presented by Edmonds et al., because Edmonds et al. were varying 79 variables in their analysis while I was varying 5 variables with similar ranges. In fact it is interesting how much of the uncertainty is produced by the 5 variables I chose to vary.⁵

In comparison to the Nordhaus and Yohe study, in 2100 my base output distribution shows a range of 1.4 to 52 GtC/yr for the 5th to 95th percentiles, and a range of 4.9 to 28 GtC/yr for the 25th to 75th percentiles; meanwhile, the Nordhaus and Yohe (1983) study shows a range of 7.2 to 55 GtC/yr for the 5th to 95th percentiles, and a range of 12 to 27 GtC/yr for the 25th to 75th percentiles.

⁵The 5 variables I chose to vary include 6 out of 9 of the variables found to be most important in terms of contributing to uncertainty in the 1986 Edmonds et al. study.

Figure 9: Carbon Emissions Percentiles for Base Output Scenarios



Thus my base output distribution is in line with previous work done by Edmonds et al. (1986), and Nordhaus and Yohe (1983). However, these two previous studies focused their uncertainty analysis on defining base output distributions. I extended this work to policy analysis by using the Edmonds-Reilly model to explore how policy changes, like carbon taxes, might be analyzed in the context of uncertainty. This approach to analysis I call conducting probabilistic policy experiments.

Implementing Policies in the Context of Uncertainty

The use of probabilistic scenario analysis explicitly acknowledges that there is uncertainty in a model's structure and in parameters which drive a model. These two inherent uncertainties mean that a model's output will also be uncertain. This is true when using a model to generate a base output

distribution, as described above, and when conducting policy experiments with a model. In fact, because of the inherent uncertainty in model generated results, instead of testing policy options on a single future it makes sense to investigate the effectiveness of various policy options across an entire set of possible futures. After all, what we really ought to be concerned about is how a particular set of policies will effect the distribution of possible futures instead of how they will effect a specific future.

I used the Edmonds-Reilly model to conduct 5 probabilistic policy experiments: 3 experiments used different levels of carbon taxes based on a fuel's carbon content, and 2 experiments explored the effects of changing the input distribution for the exogenous energy end-use efficiency improvement rate. Thus 6 sets of scenarios (1 base and 5 policy) were generated using the Edmonds-Reilly model. Since each set of scenarios contains 100 individual scenarios, a total of 600 scenarios were generated. Next I will discuss both how each policy was implemented and the results of each probabilistic policy experiment.

Carbon Tax Based on a Fuel's Carbon Content

The most commonly discussed policy with respect to climate change is a carbon tax based on a fuel's carbon content. Typically, such a tax is only applied to fossil fuels and is based on the carbon emission coefficients for each fuel. Table 1 shows typical values for carbon emission coefficients.

Using the emission coefficients shown in table 1 would imply that a \$100/tC tax would be equivalent to a \$1.92/gJ tax on oil, \$1.37/gJ tax on gas, \$2.38/gJ tax on coal, and \$2.79/gJ tax on shale oil (from carbonic rock).⁶ Thus a \$100/tC tax applied in 1990 would have increased the cost of minemouth

⁶All prices in this chapter are in 1990 prices unless other wise noted.

coal by almost 250%, crude oil by over 70% and wellhead natural gas by about 80% (DOE 1991, 63).⁷

Table 1: Carbon Emissions Coefficients

Fuel	Carbon Emissions
Liquids	19.2 TgC/EJ
Gases	13.7 TgC/EJ
Solids	23.8 TgC/EJ
Carbonic Rock Mining	27.9 TgC/EJ

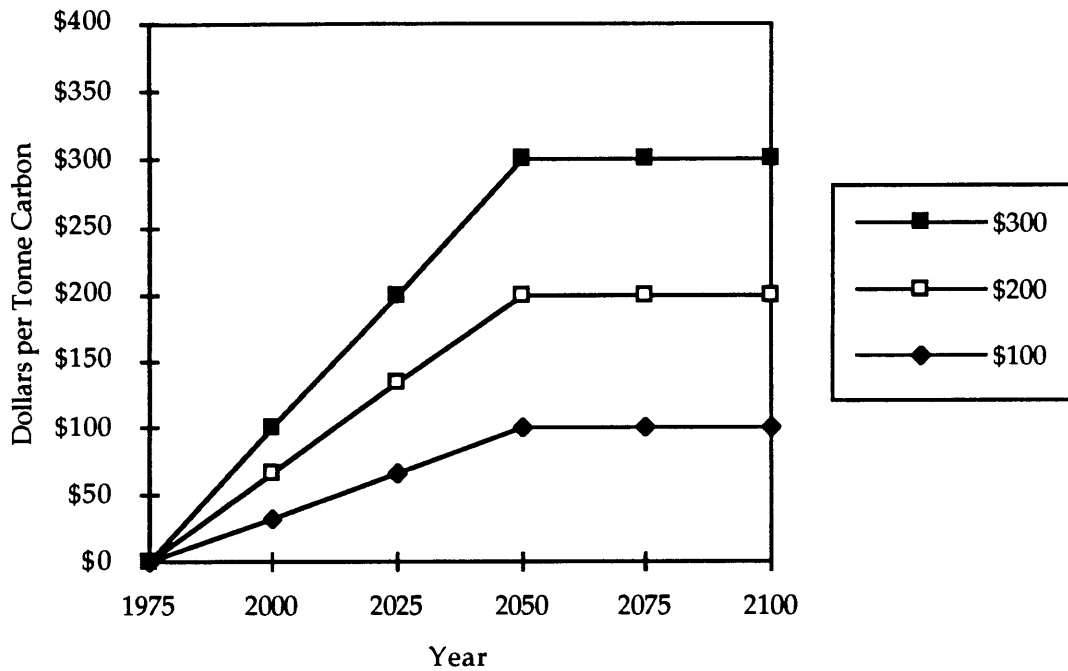
Source: Edmonds and Barns 1991.

During the past couple of years, analysts have explored a wide range of carbon taxes. For example, Montgomery (1992) reviewed the results of 4 studies using different energy models (Global 2100, Jorgenson-Wilcoxon, Edmonds-Reilly, and DRI) and found that taxes ranging from \$60/tC to \$427/tC were required in order to stabilize carbon emissions in 2020 at 80% of 1988 levels (Montgomery 1992, 11). In my analysis I looked at carbon taxes up to \$300/tC.

The Edmonds-Reilly model does not contain a parameter for taxes based on carbon content. However, the model does contain a parameter for the "Environmental Cost of Energy." I used this parameter to simulate a carbon tax. This is a reasonable approach since the environmental cost parameter is applied as an add on cost to all grades of a given fuel (i.e., it is equivalent to a tax). Thus using the carbon emission coefficients given in table 1, I was able to translate a given carbon tax into equivalent environmental costs for oil, gas, coal, and shale oil.

⁷Assumes a base cost, in 1989\$, for coal of \$23.02/short ton, for oil of \$16.81/bbl, and for natural gas of \$1.81/tcf (DOE 1991, 63).

Figure 10: Carbon Tax Trajectories for Various Tax Levels



I ran the model with 3 different levels of carbon taxes: \$100/tC, \$200/tC, and \$300/tC. The trajectories for how these taxes were applied over time are shown in figure 10. In all cases the carbon tax started at \$0/tC and increased linearly to its final value in 2050. After 2050 the tax remained constant. Thus the taxes were phased in over a 75 year period. This is a very long phase in time for a tax. One could argue that it would be possible to phase in a carbon tax (even a very large one) over a much shorter time period, say 20 or 25 years.

Graphs of carbon emissions percentiles for a \$100/tC tax, \$200/tC tax, and \$300/tC tax are shown figures 11, 12, and 13. Note that the scales are not the same on each of these figures. Also, in order to be able to compare the results more easily, a box plot of carbon emissions in 2075 for the base output

distribution, and the three tax levels is shown in figure 14. Table 2 contains a basic description of how to interpret box plots.

As one would expect, larger carbon taxes lead to lower carbon emissions. Thus a \$100/tC tax keeps carbon emissions nearly constant for the 50th percentile through 2100, a \$200/tC tax stabilizes carbon emissions for the 75th percentile by 2075, and a \$300/tC tax comes very close to stabilizing carbon emissions for the 95th percentile by 2075. These results show that imposing a carbon tax based on carbon content can have a significant effect on carbon emissions.

Figure 11: Carbon Emissions Percentiles With a \$100/tC Tax

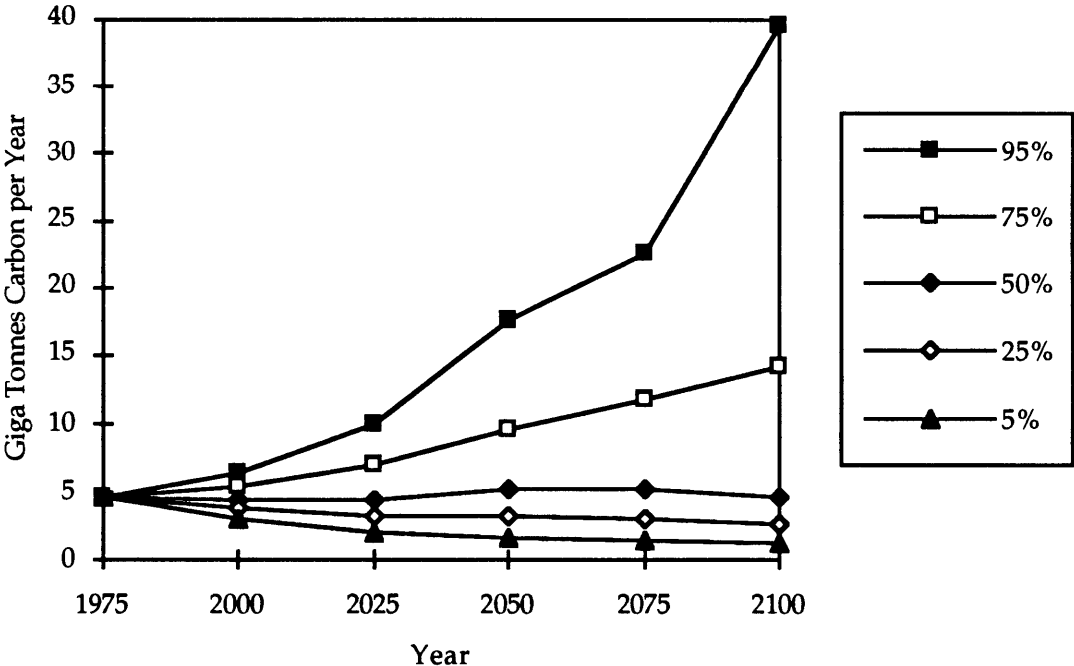


Figure 12: Carbon Emissions Percentiles With a \$200/tC Tax

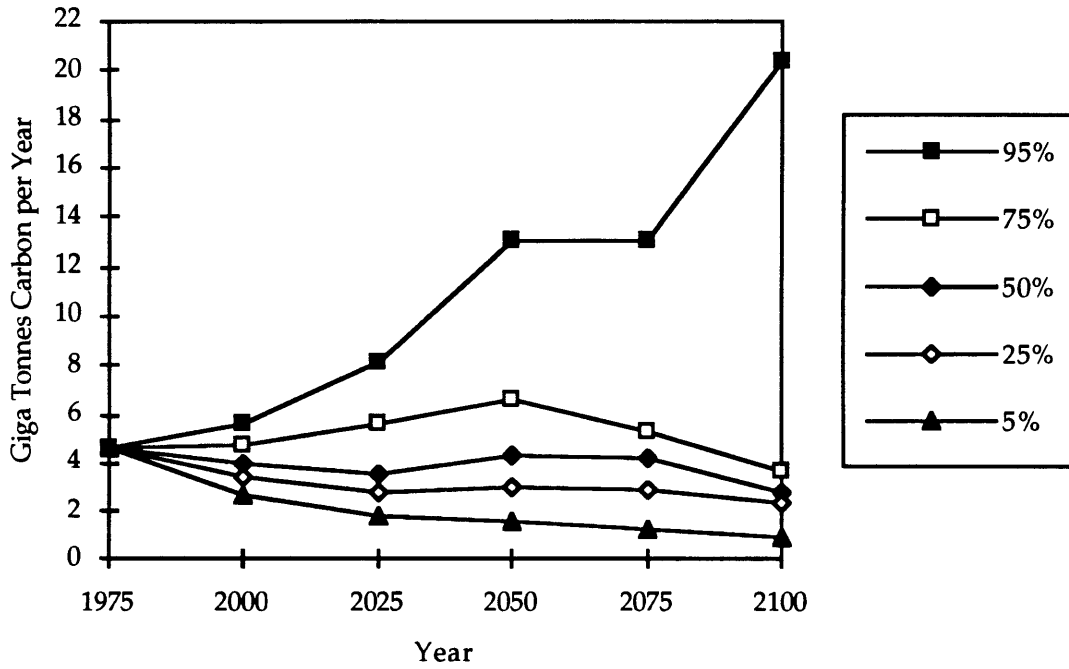


Figure 13: Carbon Emissions Percentiles With a \$300/tC Tax

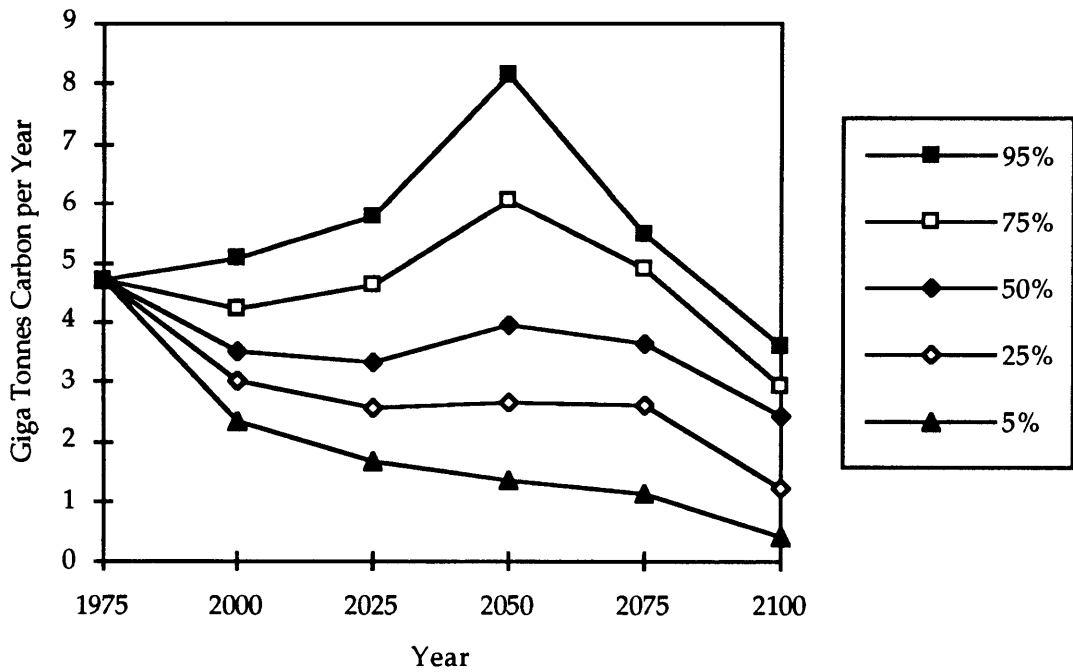


Figure 14: Box Plot for Base Output Distribution, and Three Tax Levels (in 2075)

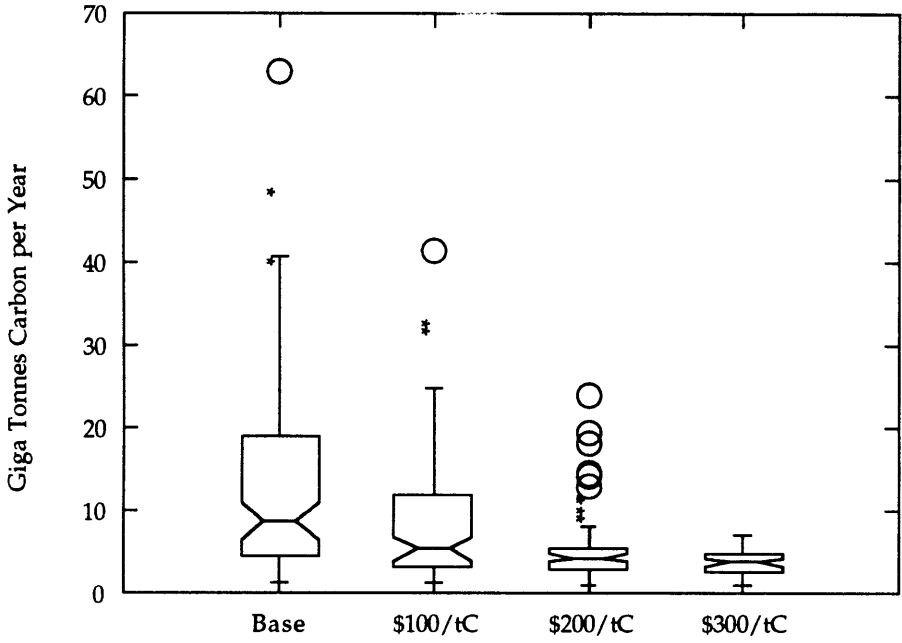


Table 2: Interpreting Box Plots

- The line in the middle of each box is the median value (i.e., the 50th percentile).
- The edges of each box are defined as the upper and lower hinges (i.e., the 75th and 25th percentiles respectively).
- Hspread is defined as the difference between the upper and lower hinges (i.e., the interquartile range).
- The inner fences are defined as:
 lower inner fence = lower hinge - (1.5Hspread), and
 upper inner fence = upper hinge + (1.5Hspread).
The lines from each end of a box to the upper and lower inner fences are called whiskers. Values outside the inner fences are plotted with asterisks.
- The outer fences are defined as:
 lower outer fence = lower hinge - (3Hspread), and
 upper outer fence = upper hinge + (3Hspread).
Values outside the outer fences are plotted as empty circles.
- Boxes are notched at the median and return to full width at the upper and lower confidence intervals.

Source: Wilkinson 1989, 182-6.

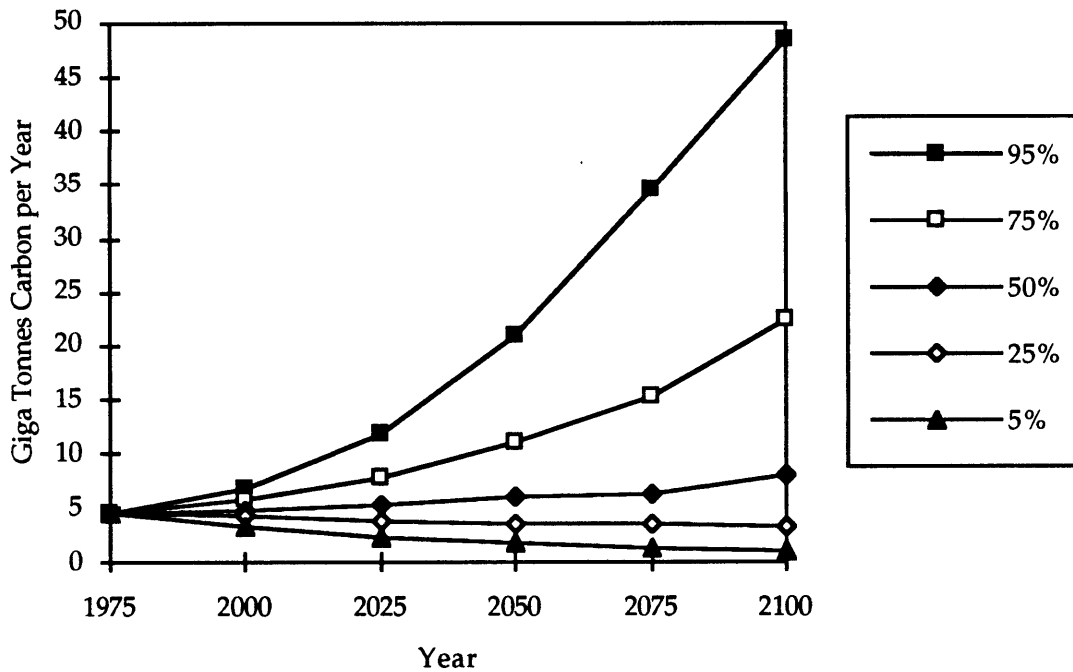
Changing Efficiency Assumptions

Typically, as above, policy experiments using energy models focus on the use of carbon taxes to reduce future carbon emissions. In this study, in addition to looking at the effects of carbon taxes, I explored how changing the exogenous energy end-use efficiency improvement rate assumptions would effect the base output distribution. In order to simulate higher efficiency improvement rates I conducted two experiments: (1) shifting the mode of the input distribution +0.5% (to 1.5%), and (2) shifting the entire input

distribution +0.5% (mode and end points). PRISM was used to generate two new sets of samples, and the samples were used to run the Edmonds-Reilly model.⁸

Graphs of carbon emissions percentiles for the results of these two experiments are shown in figure 18 & 19. In addition, figure 20 shows a box plot of carbon emissions in 2075 for the base output distribution, the mode of the efficiency distribution shifted +0.5%, and the entire efficiency distribution shifted +0.5%. All three of these graphs show relatively small shifts downward, from the base distribution, in carbon emissions. Here as one would expect, shifting the entire distribution leads to a larger decrease than shifting only the mode of the distribution.

Figure 18: Carbon Emissions Percentiles Shifting the Mode of the Efficiency Improvement Rate +0.5%



⁸In order to ensure that the efficiency improvement rates were the only parameters to change, the same random number seed was used when re-running PRISM.

Figure 19: Carbon Emissions Percentiles Shifting the Entire Efficiency Improvement Rate Distribution +0.5%

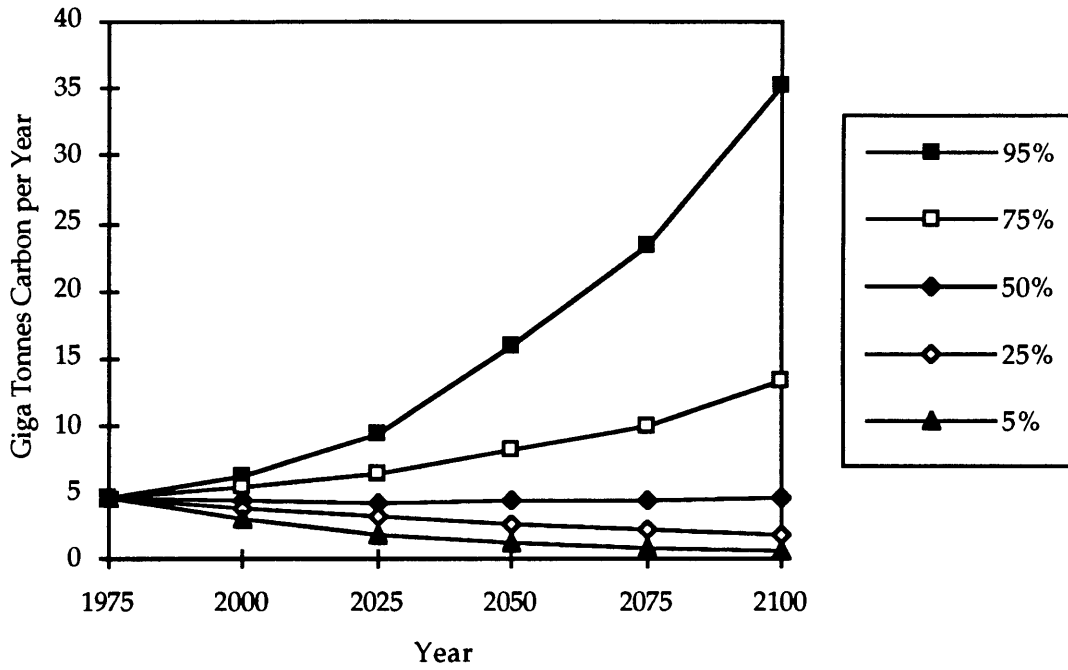
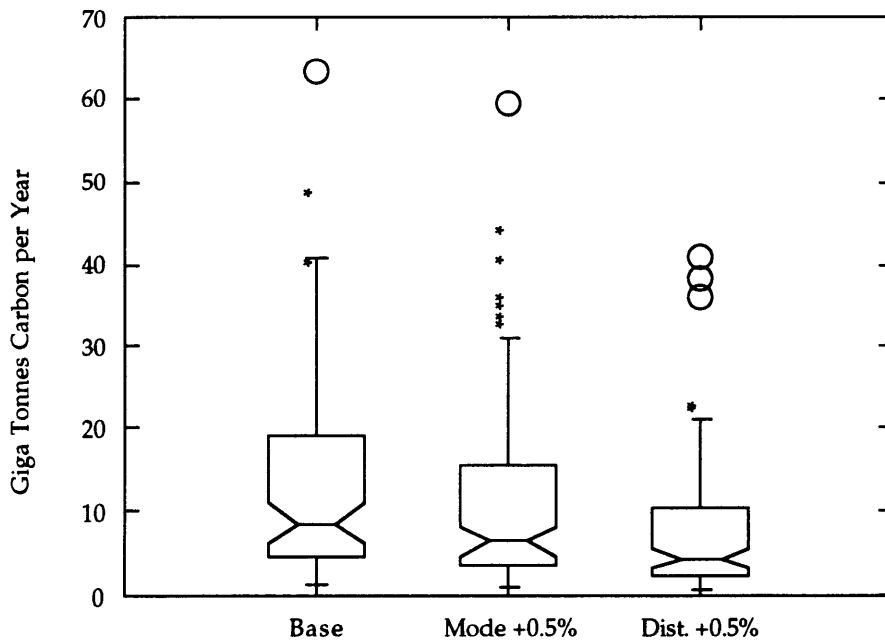


Figure 20: Box Plot for Base Output Distribution, Efficiency Mode Shifted +0.5%, and Efficiency Distribution Shifted +0.5% (in 2075)



These experiments were not intended to determine whether or not policies aimed at increasing efficiency improvement rates would be effective; instead, they were intended to highlight some of the issues that arise when trying to model policies other than carbon taxes. For example, in the first experiment I shifted the mode of the distribution, but not the end points. This was done to highlight the fact that there is uncertainty in implementing policies aimed at increasing efficiency improvement rates. In fact, the relationship between policies (such as R&D spending) and efficiency improvement rates is very uncertain.

Finally, these two experiments highlight the need to design models with “policy levers” that translate potential policies, other than carbon taxes, into model inputs in a clear and defensible manner. This is a difficult task because the relationship between policy actions and changes in a model’s parameters are often unclear.

Conclusions:

The analysis described above explores a methodology for using long-term energy-economic-environmental models for evaluating the effects of policies in the context of uncertainty. It builds on the previous studies conducted by Nordhaus and Yohe (1983) and Edmonds et al. (1986). Since the analysis focuses on methodology its numerical results should not be taken too seriously. Further it is important to understand that conducting probabilistic policy experiments, to explore the effectiveness of various policies on reducing future carbon emissions from energy use, is a significant departure from previous approaches to analysis. However, given the inherent uncertainty in any long-term energy-economic-environmental

model's structure and parameters, these more traditional scenario analyses can be misleading.

In addition, using a probabilistic approach, as demonstrated above, offers both analysts and policymakers an opportunity to move beyond arguing about which is the "right" best guess scenario. Using this type of approach can be somewhat humbling for analysts because it forces them to admit that they have limited knowledge. However, it enables policymakers to consider a full range of possible futures along with each one's likelihood. Thus by using a probabilistic approach, policymakers can concentrate on the real questions at the heart of the climate change issue:

- Should we focus our attention on narrowing the range of uncertainty?
- Should we minimize the risk of following a set of undesirable future paths? Or,
- Should we act based on expected value?

In essence, by using a probabilistic approach analysts can focus on using energy-economic-environmental models to help participants in the policy process learn about how different components of the overall energy-economic-environmental system interact with each other, gain insight into the limitations of the models themselves, identify important uncertainties in the models, and evaluate potential policy options over a range of possible futures.

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