2 Future Carbon Dioxide Emissions from Fossil Fuels

2.1 FUTURE PATHS OF ENERGY AND CARBON DIOXIDE EMISSIONS

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This section deals with the uncertainty about the buildup of CO_2 in the atmosphere. It attempts to provide a simple model of CO_2 emissions, identify the major uncertain variables or parameters influencing these emissions, and then estimate the best guess and inherent uncertainty about future CO_2 emissions and concentrations. Section 2.1.1 is a self-contained overview of the method, model, and results. Section 2.1.2 contains a detailed description of sources, methods, reservations, and results.

2.1.1 Overview

There is widespread agreement that anthropogenic carbon dioxide emissions have been rising steadily, primarily driven by the combustion of fossil fuels. There is, however, enormous uncertainty about the future emission rates and atmospheric concentrations beyond the year 2000; and even greater uncertainty exists about the extent of climatic change and the social and economic impacts of possible future trajectories of carbon dioxide. Yet, if the appropriate decisions are to be made, the balance of future risks and costs must be weighed, and producing best possible estimates of future emission trajectories is therefore imperative.

Many of the early analyses of the carbon dioxide problem have produced estimates of future emissions and concentrations from extrapolative techniques (see Section 2.2, the accompanying survey by Ausubel and Nordhaus). For the purposes of understanding future outcomes and policy choices, these techniques leave important questions unanswered. First, they do not allow an assessment to be made about the degree of precision with which the forecast has been constructed. Moreover, little information is generated about the underlying structure that produced the reported trajectories. It is, therefore, hard to know how changing economic structures might alter the pattern of CO_2 emissions. But information about precision and sensitivity are sometimes of critical importance to policy makers. It is critical to know not only the best scientific assessment of an event but also the extent to which that judgment is precisely or vaguely known. Particularly in cases where policy decisions are irreversible, for example, the best decision in the face of great uncertainty might be simply to gather more information. But that decision would be extremely difficult to reach without some notion of the extent of the uncertainty surrounding the projections.

In an attempt to address uncertainties, a second generation of studies, employing scenario analysis, has arisen. These studies, notable among them Limits to Growth (Meadows et al., 1972), CONAES (Modeling Resource Group, 1978), and IIASA (1981), have traced time paths for important variables with a well-defined model and specified sets of assumptions. The studies, which we call "nonprobabilistic scenario analysis," represent a marked improvement over earlier efforts. They still fall short of providing the policymaker with a precise notion of the likelihood that a particular combination of events might occur: Is the "high" scenario 1 in 10, 1 in 100, or what?

In this section an effort is made to put more definite likelihoods on alternative views of the world. The technique, called probabilistic scenario analysis, extends the scenario approach to include modern developments in aggregate energy and economic modeling in a simple and transparent model of the global economy and carbon dioxide emissions. Particular care is given not only to assure that the energy and production sectors are integrated but also to respect the cost and availability of fossil fuels.

In addition, the analysis presented here attempts to recognize the intrinsic uncertainty about future economic, energy, and carbon cycle developments. This is done by specifying the most important uncertain parameters of the model, by examining current knowledge and disagreement about these parameters, and then by specifying a range of possible outcomes for each uncertain variable or parameter. The emphasis is not to resolve uncertainties but to represent current uncertainties as accurately as possible and integrate them into the structure in a consistent fashion. The result of the entire process is the generation of a range of paths and uncertainties for major economic, energy, and carbon dioxide variables--projections of not only a "best guess" of the future paths of important variables but also a set of alternative trajectories and associated probabilities that quantify the range of possible outcomes on the basis of the current state of knowledge about the underlying uncertainty of the parameters.

It is reasonable, even at this early stage, to ask why such an elaborate effort to quantify uncertainty should be undertaken. Cannot prudent policy be written on the basis of the "best-guess" trajectories of important variables? In general, the answer is "no." To limit analysis to the best-guess path is to limit one's options. Similarly, to consider some possible path with no assessment of its likelihood relative to other possible paths is a formula for frustration, leading to endless arguments about which path should be taken most seriously. But to consider a full range of possibilities, along with each one's likelihood, allows a balanced weighing of the important and the unimportant in whatever way seems appropriate.

Armed with probabilistic scenarios, in other words, the policymaker will be able to evaluate a new dimension of his problem. He can assess not only a policy along a most likely trajectory but also along other trajectories that cannot be ruled out with some degree of statistical significance. With some knowledge of the range of uncertainty, he might decide to ask for more information to narrow the range, particularly if a policy seems to be warranted only by a few selected outcomes. Alternatively, he might choose to minimize the risk of proceeding along an undesirable set of possible paths. And finally, he might undertake a policy based simply on an expected value. Any one of these options might prove to be prudent, but none of them is possible without a quantified range of possibilities. It is toward providing such a range that this section is directed.

The plan of the overview is this. We first sketch the model that is used to relate the different variables and project future carbon dioxide emissions. We then describe the data sources and some adjustments that we have made to the data. Finally, we describe the results. It should be noted that a full description of the methods is contained in Section 2.2.

The economic and energy model is a highly aggregative model of the world economy and energy sector. It is based on the idea of a multi-input production function that represents the relationship between world Gross National Product (GNP) (the output), on the one hand, and labor, fossil fuels, and nonfossil fuels (the inputs), on the other. In addition, to reflect the likelihood that economic efficiency will continue to improve in the future, various technological parameters are included to describe the rate of growth of economic efficiency in general, as well as the extent to which that growth is more or less rapid in the energy sectors than in the nonenergy sectors.

A further important feature is the explicit incorporation of both the extent to which it is relatively easy or difficult to substitute nonenergy inputs (insulation or radial tires) for energy inputs (heating oil or gasoline) and the extent to which it is easy or difficult to substitute nonfossil energy (nuclear or solar-derived electricity or hydrogen) for fossil energy (coal-fired electricity or gasoline).

The prices of different inputs play a central role in reflecting scarcity and driving the relative quantities of different inputs. We thus introduce a cost function for fossil fuels that relates their price to their degree of exhaustion or abundance. On the other side of the market we generate an economically consistent derived demand for energy from the structure of the production function as the response of economic agents to changes in relative prices of different fuels and other inputs. Thus, if fossil fuels are scarce and costly, the system will economize on this input and use relatively more nonfossil fuels and labor inputs.

Finally, we recognize that there are a number of important uncertainties about the model and future trends. We thus incorporate 10 key uncertainties in the model. These relate to variables such as the rate of population growth, the availability and cost of fossil fuels, the rate of growth of productivity, the extent to which productivity growth will be relatively more rapid in fossil fuels versus nonfossil fuels, or in energy versus nonenergy, and so forth. A complete list of the uncertainties, with their relative importance in determining the total uncertainty is presented later in this overview.

The data are gathered from diverse sources and are of quite different levels of precision. In general, we have surveyed the recent literature on energy and economic modeling to determine what are commonly held views of such variables as future population growth or productivity growth. Other variables, such as the ease of substitution or differential productivity growth, were ones that are not the subject of common discourse; for these, we examined recent trends or results generated by disaggregated studies.

A much more difficult data problem arose from the need to estimate the uncertainty about key parameters or variables. Our starting assumption was to view the dispersion in results of published studies as a reflection of the underlying uncertainty about the variable studied. This starting point was modified in two respects. First, it is commonly observed that even trained analysts tend to cluster together excessively--that is, they tend to underestimate the degree of uncertainty about their estimates. To account for this tendency to move toward the current consensus, we have spread out some of the distributions of observations by slightly less than 50%. Second, we have also imposed our own judgments about the uncertainties in those cases where no external data or disagreement existed or where the disagreement was so small as to convince us that the predictions were not independent. We must emphasize that these judgments about the uncertainties in our understanding of the variables are only rough judgments; the methods of estimation are difficult, and they could be quite far from the estimates that would come from a more thorough study. On the other hand, however, several validation exercises revealed that our results were within the statistical realm of reason, i.e., they fell within reasonable bounds of uncertainty that could be deduced by other means on the basis of historical experience.

Using the model and data just sketched, we investigated the range of outcomes for economic, energy, and carbon dioxide variables. There were ultimately 10 uncertain variables, each of which was discretized into high, medium, and low values in such a way that the variance of the discretized variable was equal to the variance of the continuous variable. We thus ended up with 3^{10} (=59,049) different possible outcomes. Rather than do a complete description, we settled on sampling 100 or 1000 of the different possible outcomes. The results reported below, then, should be interpreted as samples of the underlying distributions (although the sampling errors are known to be quite low).

We now turn to brief descriptions of the major results of this study, with the promise that a more complete description can be found in Section 2.1.2. The first set of results pertains to the central estimates and range of estimates of the central variables, carbon dioxide emissions and concentrations. Our central estimate here is taken as the sample mean of 1000 runs.* Carbon dioxide emissions are projected to rise modestly to the end of our time horizon, the year 2100. We estimate that carbon dioxide emissions will grow at about 1.6% annually to 2025, then slow to slightly under 1% annually after 2025. Atmospheric concentrations in the average case are expected to hit the nominal doubling level (600 ppm) around the year 2070.

These results show a considerably slower emissions rate and carbon dioxide buildup than many of the earlier studies (see Ausubel and Nordhaus, Section 2.2) for two major reasons. First, the expected growth of the global economy is now thought to be slower than had earlier been generally assumed; our work includes this new expectation. Perhaps more importantly, we also include the tendency to substitute nonfossil for fossil fuels as a result of the increasing relative prices of fossil fuels. This is an important effect that has frequently been ignored.

The next result concerns our attention on the degree of uncertainty about future carbon dioxide emissions and concentrations. The range of uncertainty is shown in Figures 2.1 to 2.4. Figures 2.1 and 2.2 show 100 randomly chosen outcomes for carbon dioxide emissions and concentrations. These are shown mainly to give a visual impression of the range of outcomes. Figures 2.3 and 2.4 present the five runs that represent the 5th, 25th, 50th, 75th, and 95th percentiles of outcomes--where we measure the outcomes in terms of the cumulative carbon dioxide emissions by the year 2050. It should be emphasized that the percentiles are derived from the actual sampling distribution. They reflect, therefore, the distribution of outcomes derived from the interaction of expert opinion on the underlying random parameters and the economic model; they reflect judgment not an objectively derived distribution.

Perhaps the most useful graph to study is Figure 2.4, which shows the percentiles of carbon dioxide concentrations. For a quarter or half century, the inertia built into the economy and the carbon cycle leave an impression of relative certainty about the outcomes. After the early part of the next century, however, the degree of uncertainty becomes extremely large. In terms of our conventional doubling time, note the time at which carbon dioxide concentrations are assumed to hit 600 ppm:

Percentile	Doubling Time
5	After 2100
25	2100
50	2065
75	2050
95	2035

*More precisely, if x_j were the value assumed by run j, whose underlying sample of the 10 random variables gave it a probability of P_j, then the central estimate would be $\sum_{j=1}^{1000} P_j x_j$.

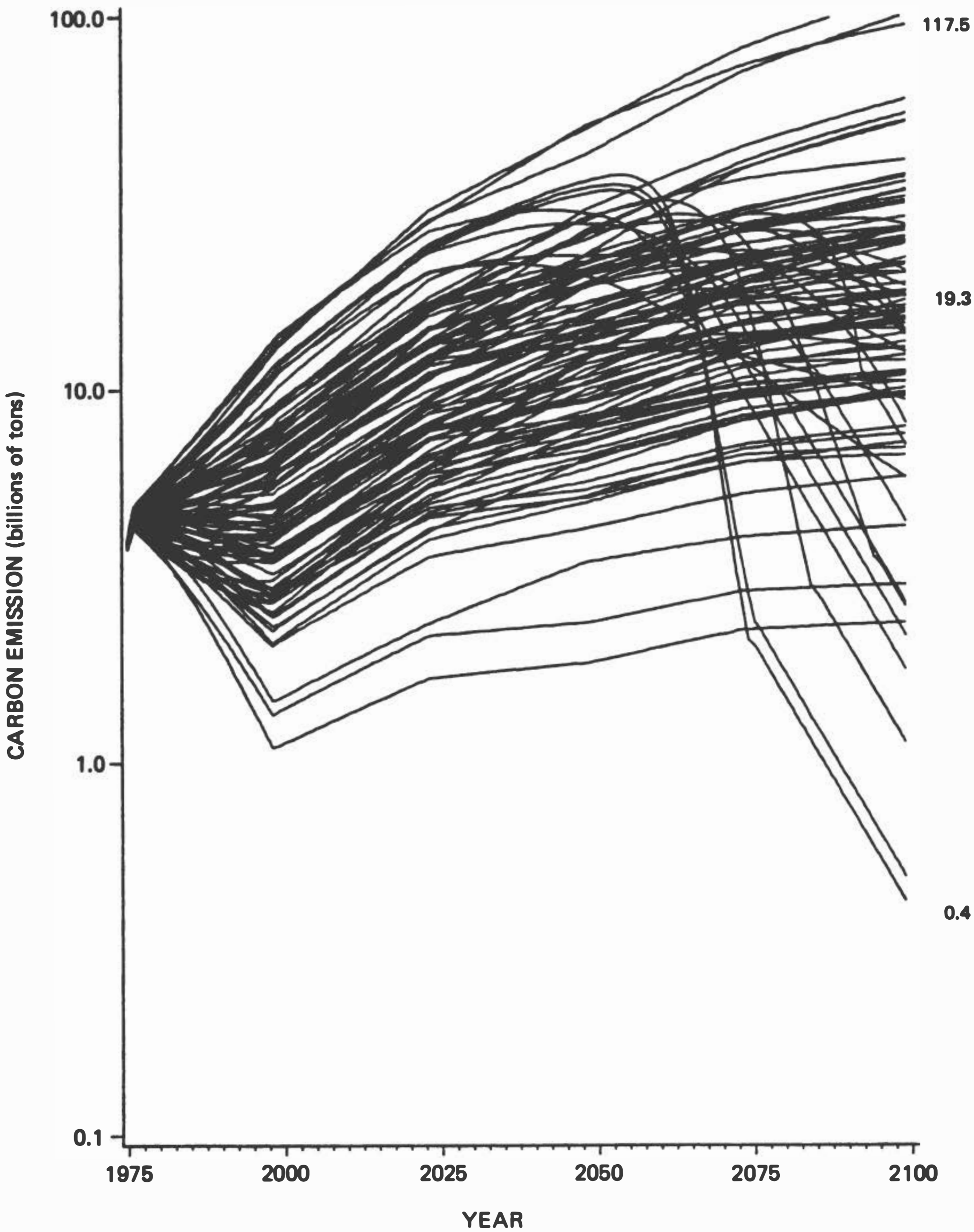

FIGURE 2.1 Carbon dioxide emissions for 100 randomly drawn runs (billions of tons of carbon per year). Outcomes of 100 randomly chosen runs; the numbers on the right-hand side indicate the mean projected yearly emission for the year 2100 and the extreme high and low outcomes.

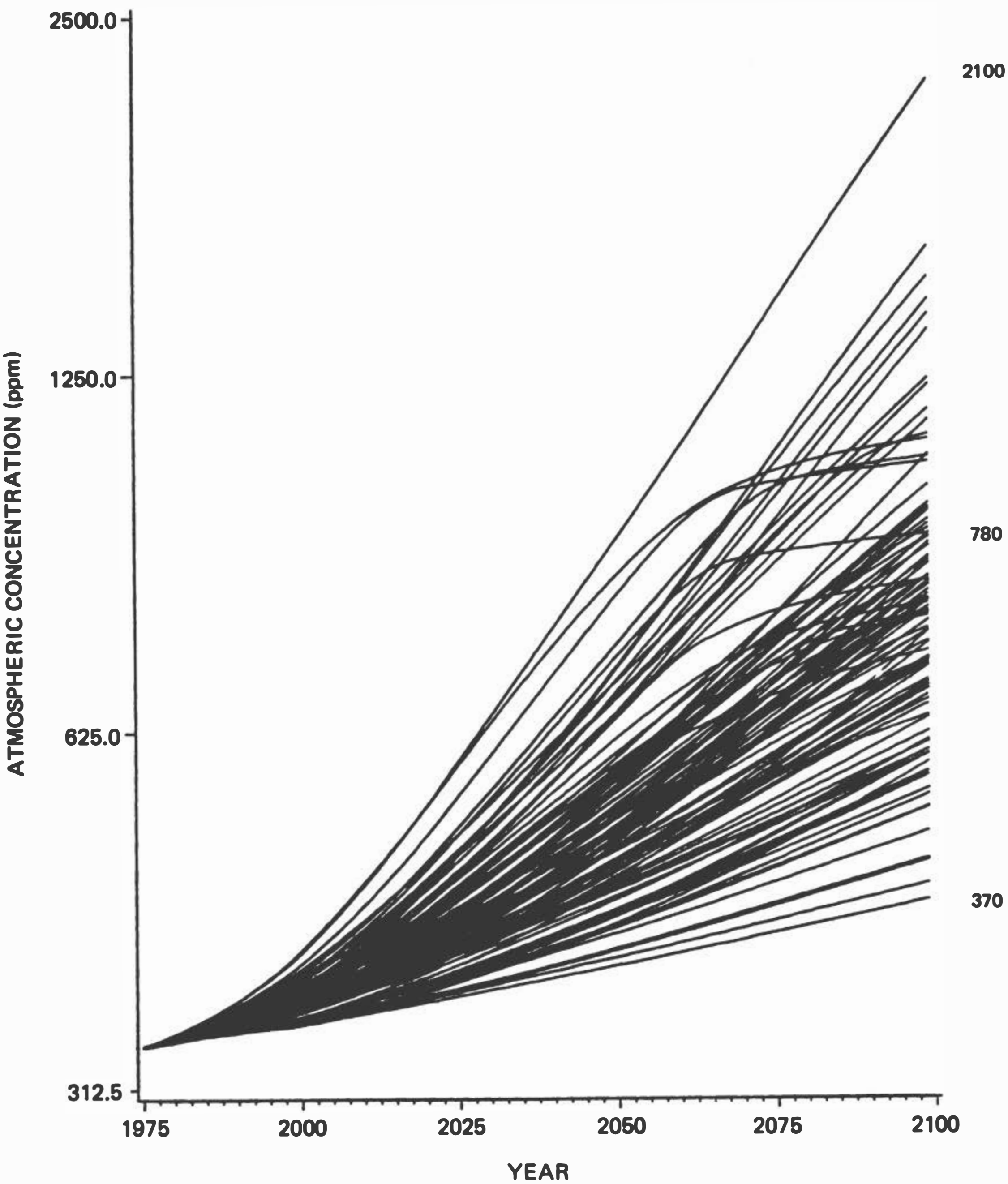

FIGURE 2.2 Atmospheric concentration of carbon dioxide (parts per million). Outcomes of 100 randomly selected runs; the numbers on the right-hand side indicate the mean concentration for the year 2100 and the extreme high and low outcomes.

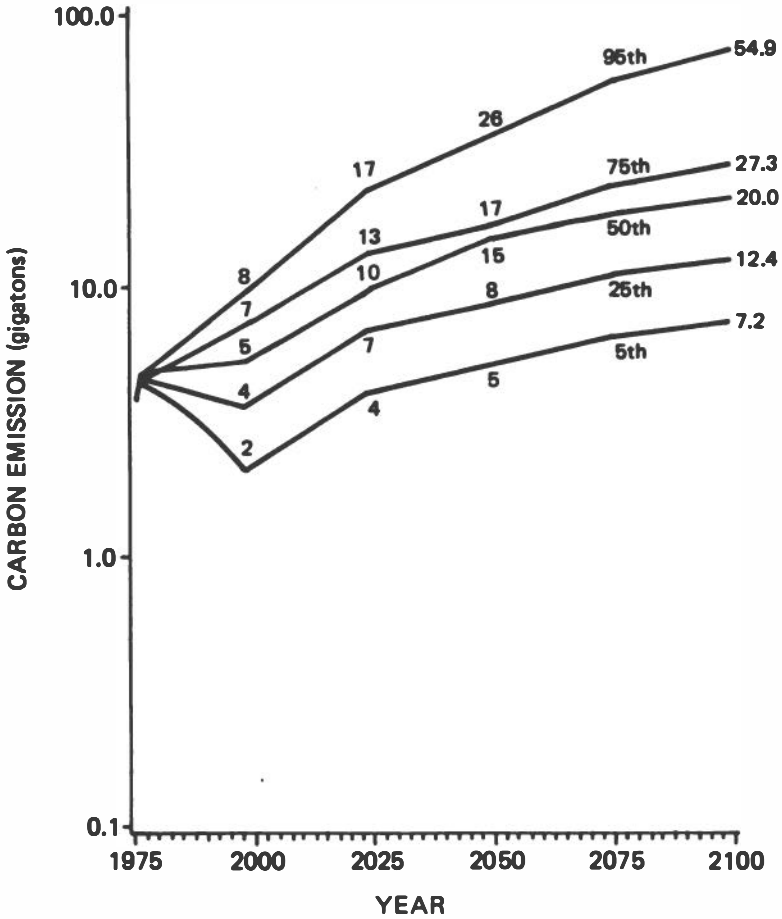

FIGURE 2.3 Carbon dioxide emissions (gigatons of carbon) from a sample of 100 randomly chosen runs. The 5th, 25th, 50th, 75th, and 95th percentile runs for yearly emissions, with emissions for years 2100, 2025, 2050, and 2100 indicated.

From this result, we make the central conclusion: Given current knowledge, we find that the odds are even whether the doubling of carbon dioxide will occur in the period 2050-2100 or outside that period. We further find that it is a 1-in-4 possibility that CO_2 doubling will occur before 2050, and a 1-in-20 possibility that doubling will occur before 2035.

The next issue addressed is the question of the relative importance of different uncertainties. We have computed by two different techniques the relative importance of the ten uncertain variables discussed above, and the results are shown in Table 2.1. This table calculates the contribution to the overall uncertainty that is made by each variable taken by itself.

In one case, shown in column (2), the contribution is calculated as the uncertainty introduced when a variable takes its full range of uncertainty and all other variables are set equal to their most likely

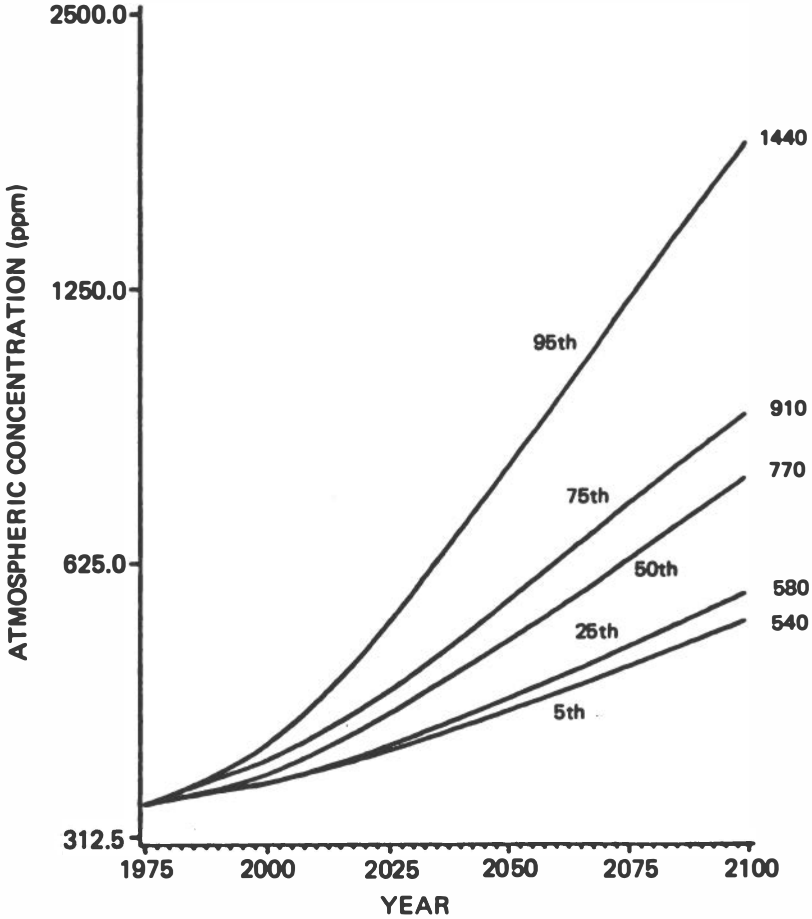

FIGURE 2.4 Atmospheric concentration of carbon dioxide (5th, 25th, 50th, 75th, and 95th percentiles; parts per million). The indicated percentile runs for concentrations; the numbers on the right-hand side indicate concentrations in the year 2100 for each run.

values. In the first column, the uncertainty is calculated from the run in which the full panoply of uncertainties is deployed--that is, when all other nine uncertain variables are allowed to take their full ranges of outcomes. In both cases, we have created index numbers with the variable that induces the most uncertainty set equal to 100, and other variables are scaled by their ratio of uncertainty added to that of the variable with the largest contribution.

The two indices are used because they convey different information. The variable in column (1) is more relevant to uncertainty reduction in the real world (because other variables do indeed have uncertainty); but the calculations in column (1) are dependent on the uncertainties assumed for the whole range of variables. The numbers in column (2) are, for that reason, more robust to misspecification in the uncertainty of other variables.

TABLE 2.1 Indices of Sensitivity of Atmospheric Concentration in 2100 to Uncertainty about Key Parameters (100 = Level of Effect of Most Important Variable[a])

Parameter[b]	(1) Marginal Variance from Full Sample[c]	(2) Marginal Variance from Most Likely Outcome[d]
Ease of substitution between fossil and nonfossil fuels [$1/(r-1)$]	100	100
General productivity growth [$A(t)$]	76	79
Ease of substitution between energy and labor [$1/(q-1)$]	56	70
Extraction costs for fossil fuels [g_1]	50	56
Trends in real costs of producing energy [$h_1(t)$]	48	73
Airborne fraction for CO_2 emission [$AF(s)$]	44	62
Fuel mix among fossil fuels [$Z(t)$]	31	24
Population growth [$L(t)$]	22	36
Trends in relative costs of fossil and nonfossil fuels [$h_2(t)$]	(3)[e]	21
Total resources of fossil fuels [$\bar{R}$]	(50)[e]	5

[a]Value of sensitivity is scaled at 100 for the variable that has the highest marginal variance.
[b]Notation in the square brackets refers to variable notation in the model presented formally in Section 2.2.
[c]"Marginal variance" from full sample equals (1) the variance in the base case (i.e., with all variables varying according to their full range of uncertainty) minus (2) the variance with listed variable set at its most likely value (but all nine other variables varying according to their full uncertainty). Note that no resampling occurs.
[d]"Marginal variance from most likely outcome" calculated as the variance when the listed variable assumes its full range of uncertainty and all nine other variables are set equal to their most likely value.
[e]Parentheses indicate that the marginal variance is negative.

The ranking of the importance of uncertainties shown in Table 2.1 contains several surprises. First, note that an unfamiliar production parameter ranks at the top of both columns--the ease of substitution between fossil and nonfossil fuels. While some studies have included substitution parameters in their model specifications (notably Edmonds and Reilly, 1983), the sensitivity of concentration projections to assumptions about substitution has not been noted earlier. A second set of variables on the list include those that have been exhaustively discussed in the carbon dioxide literature--the world resources of fossil fuels and the carbon cycle ("airborne fraction"). Our estimates indicate that these are of modest significance in the uncertainty about future carbon dioxide concentrations.

Table 2.1 is also extremely suggestive about research priorities in the carbon dioxide area. We cannot, it should be emphasized, move directly from the source of uncertainties to a budget allocation for research funds on carbon dioxide. It may be much easier, for example, to resolve uncertainties about the "depletion factor" for carbon fuels than about future "productivity growth." As a result research funds might therefore be more fruitfully deployed in the first prior area than in the second.

On the other hand, the results suggest that considerably more attention should be paid to some uncertainties that arise early in the logical chain from combustion to the carbon cycle, particularly better global modeling of energy and economy. It is striking, for example, to note that the United States supports considerable work on global carbon cycle and global general circulation (climate) models, but much less attention in the United States has been given to long-run global economic or energy modeling (see Section 2.2 for a further discussion.

Finally, it is possible to explore more fully the ramifications of Figure 2.4--the figure that indicated 5th, 25th, 50th, 75th, and 95th percentile trajectories for atmospheric concentrations of carbon dioxide. One might ask, what parameters are most influential in determining whether the concentration path deviates from the median in either direction; Table 2.1 provides the answer. If uncertainty in a parameter is significant in its effect on the overall variance of the outcome, then it follows that movement in that parameter away from its projected median would be significant in its effect on the outcome variable. Clearly, therefore, an increase (decrease) in the ease of substitution out of fossil fuel as it becomes more expensive would significantly increase the likelihood that the concentration trajectory would be lower (higher) than the 50th percentile. Similarly, slower (more rapid) productivity growth would cause slower growth in energy consumption and produce a significant lowering (raising) of the concentration trajectory.

As a final set of experiments, we have used our procedure to make extremely tentative estimates of the effect of energy-sector policies that are designed to reduce the burning of fossil fuels. The particular policy we investigate is the imposition of fossil fuel taxes, set, for illustrative purposes, at $10 per ton of coal equivalent and at a more stringent level. Taxes were not chosen for any reason other than modeling ease. Any type of emissions restraint can be represented analytically by its equivalent tax. These runs use the most likely outcome as a base case. Figure 2.5 shows the trajectory of taxes that we have investigated, while Figures 2.6 and 2.7 show the effects of the different tax policies on the level of carbon dioxide emissions and on carbon dioxide concentrations. In general, the taxes lower emissions noticeably during the period in which the taxes are in place. The effect on concentrations at the end of the twenty-first century of the $10 tax are quite modest. These examples are included here only to illustrate the nature of a problem that deserves much more attention.

They suggest, as does some other work in the literature (Edmonds and Reilly, 1983), that the use of carbon taxes (or their regulatory equivalents) will have to be quite forceful to have a marked effect on carbon concentrations, even if they are imposed worldwide. Unilateral regulations would, of course, have to be substantially more restrictive.

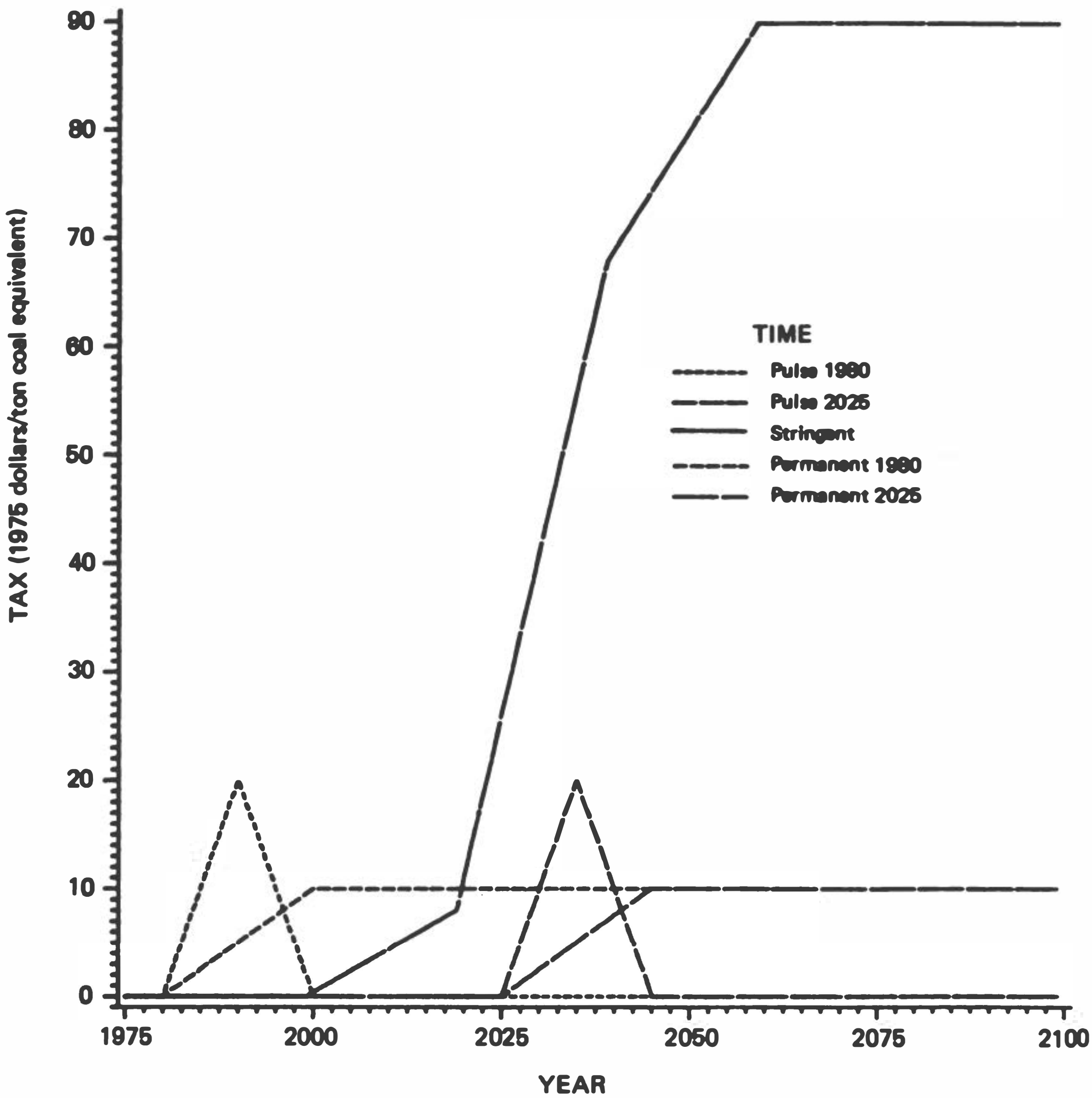

FIGURE 2.5 Taxation on carbon fuel price (1975 dollars per ton coal equivalent). The time tracks of a stringent tax and four alternative $10 per ton of coal equivalent taxes; the temporary taxes peak at $20 to accommodate the model.

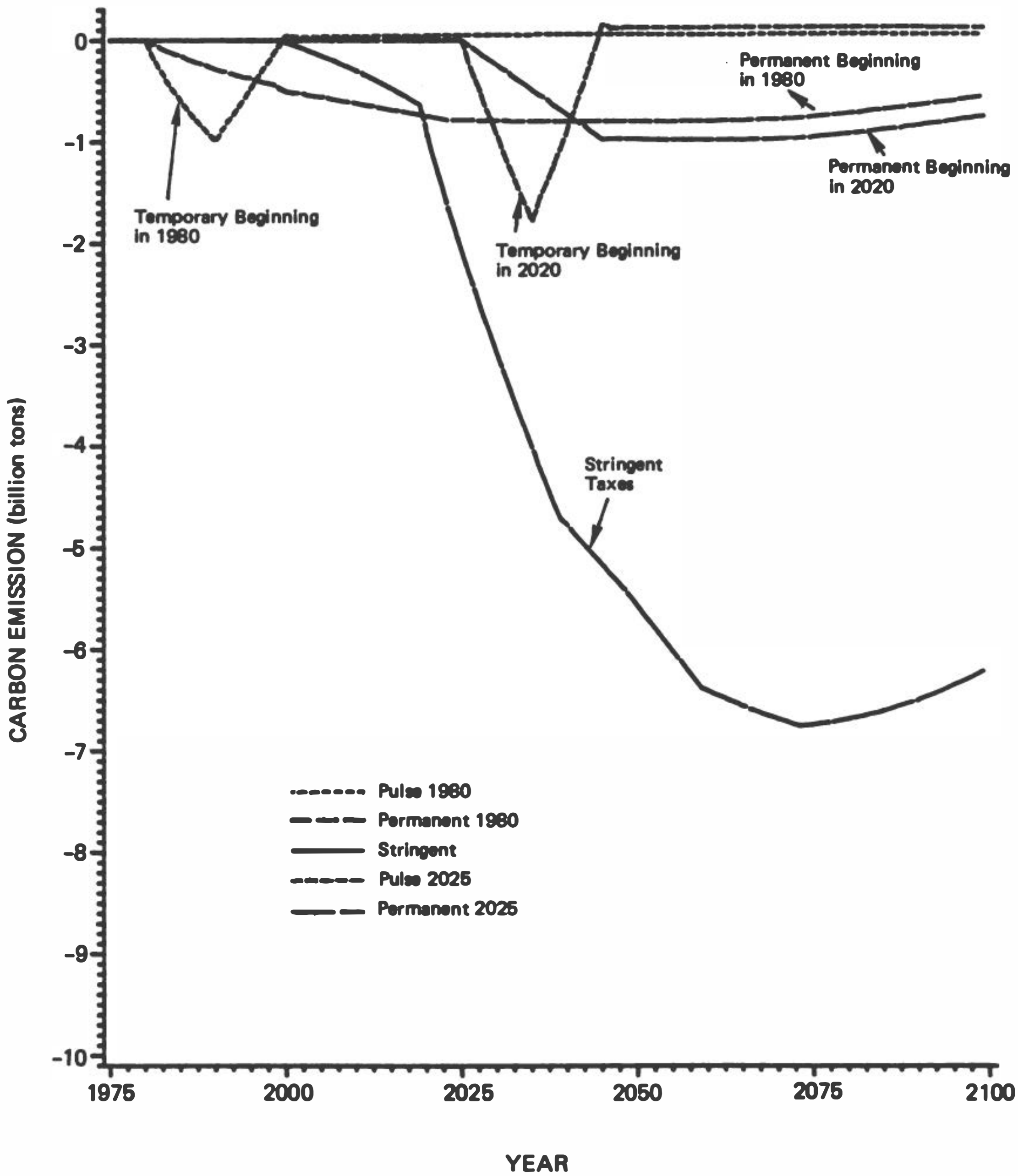

FIGURE 2.6 Plot of carbon emission versus time for taxed runs. Deviation in emissions from the base run for various taxes.

2.1.2 Detailed Description of the Model, Data, and Results

The preceding section provided an overview of the paper--its motivation, its methodology, and its results. This section will provide a more complete description of the procedures. Throughout, an attempt will be made to refrain from using economic jargon and overly technical lan-

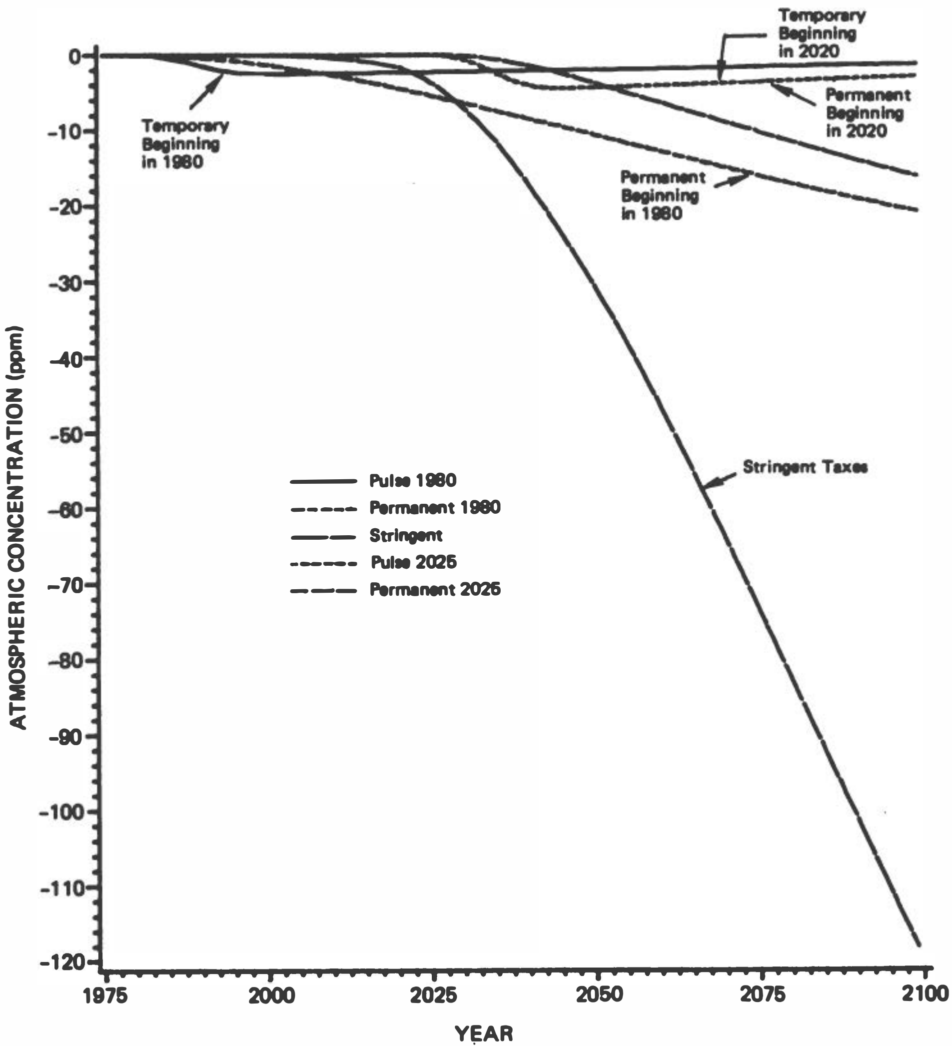

FIGURE 2.7 Effect of carbon taxes on atmospheric concentration (parts per million per year). Deviation of run from base run without carbon taxes.

guage. Where this is impossible, definitions of terms will be given in footnotes. It is hoped that the reader who is unfamiliar with the terminology will be able to follow the reasoning of the paper by referring to these notes.

2.1.2.1 The Model

2.1.2.1.1 Methodological Summary

Before we launch into a detailed description of the data and methods used in the present study, it may be useful to give a brief symbolic overview of the events to follow. We start by denoting the variables:

x_t = endogenous variables (those determined within the system), as they unfold over time;
z_t = exogenous variables (those determined outside the system), as they unfold over time;
k = parameters of the system, assumed to be constant over time;
G = a functional relation, mapping the exogenous variables and parameters into the endogenous variables.

The present study is concerned with the future evolution of CO_2 emissions and concentrations as the endogenous variables--these are the x_t variables. The key exogenous variables (or z_t) are economic "events," such as population growth or fossil fuel reserves. Parameters that relate the variables (the k's) are ones such as the airborne fraction or the emissions per unit energy produced.

We thus write our system symbolically as

$$x_t = G(z_t, k).$$

The pages that follow describe how we derive the relational function, G; how we estimate future trajectories of the exogenous variables, z_t; and how we estimate the parameters, k. The central difficulty with studies of this kind is that the system is imperfectly known. We are not able to forecast the z_t with accuracy; indeed, we may not know which are the important exogenous variables. The parameters, also, are imperfectly known.

The technique that follows uses a procedure that we have denoted probabilistic scenario analysis. We start with a simple representation of the system (the function G). We then estimate future trajectories and subjective probability distributions [denoted by g(.) and h(.)] of the exogenous variables and parameters z_t and k:

$$g(z_t),\ h(k)\ \text{(judgmental probability distributions on } z_t, k).$$

These then map through the G function to give us a conditional probability distribution--f(.)--on the variables of concern, the x_t:

$$G: [g(z_t), h(k)] \rightarrow f(x_t).$$

All of this is, unfortunately, much more easily described than accomplished. The major issues that arise are these: First, the G function is not known in advance and may be extremely complex. Second, neither the exogenous variables nor the parameters are well known. The scientific and economic literature can be used to illuminate the "best guess" about these variables or parameters, however. Third, the judgmental probability distributions are ignored in most of the applied scientific literature. Attempting to determine these distributions is the hardest part of our task. And finally, there is no established methodology for developing probabilistic scenarios. The text that follows outlines one attempt to overcome these difficulties.

An aggregate world production function sets the stage.* We chose the simplest conventional form that would allow explicit parameters for both the share of GNP devoted to energy and the ease of substituting between fossil and nonfossil fuels†:

$$X(t) = A(t)L(t)^{d(t)}[bE^c(t)^r + (1 - b)E^n(t)^r]^{[1 - d(t)]/r}, \quad (1)$$

where

$X(t)$ = world GNP at time t in constant 1975 U.S. dollars;
$L(t)$ = world population at time t;
$A(t)$ = level of labor productivity at time t in U.S. dollars of output per capita;
$(1 - d)$ = the proportion of GNP devoted to paying for energy;
$E^c(t)$ = consumption of fossil fuels at time t in metric tons of coal equivalent;
$E^n(t)$ = consumption of nonfossil fuel at time t in metric tons of coal equivalent;
r = a parameter reflecting the ease of substitution between $E^c(t)$ and $E^n(t)$; and
b = a parameter reflecting the relative levels of use of $E^c(0)$ and $E^n(0)$.

Equation (1) is not so mysterious as it might first appear. It assumes its peculiar form because of well-established techniques in micro-economics. They mandate that if a production process with certain conventional properties is to be represented mathematically, then the researcher is locked into an equation of the general type exhibited in (1). A slightly simpler form exists (the straight Cobb-Douglas form) and could have been employed, but that would have restricted the degree of substitution between the two types of energy in an arbitrary and unacceptable manner. To preserve desired flexibility in the specification of the ease of substitution, Equation (1) is the simplest option available.

Turning now to a brief discussion of some of those desirable properties, it is important to note, first, that Equation (1) displays constant returns to scale; i.e., doubling $L(t)$, $E^c(t)$, and $E^n(t)$ from any level necessarily doubles output. As growth proceeds, this

*A production function is a mathematical representation of a production process that employs a variety of inputs in a variety of combinations to manufacture some type of output. General production functions allow for substitution between any of the inputs in response to changes in input prices so that the manufacturer can maximize profits.

†The estimation of production functions is a well-developed field in economics. There have been numerous surveys, of which that by Johnston (1972) is perhaps the most comprehensive. Also see Nerlove (1965) for a careful study of the identification and estimation of the particular production function that we use, the "Cobb-Douglas" version.

feature guarantees that payments to labor employed and for energy consumed exhaust output. It should be noted, at least in passing, that almost all production relationships that spring to mind easily, and almost all that are used in existing studies, display this constant returns-to-scale property. Imposing it on our production schedule did not drive us afield of conventional economic modeling.

Note as well that Equation (1) aggregates the value of all nonenergy inputs into labor--the third factor of production. This aggregation produces a simplification that allows the model to isolate the potential substitution both between the two types of energy and between energy and other inputs without being unnecessarily cluttered by an index of what those inputs might be. No assumptions about constant capital-labor ratios are being made, and any increased productivity that might be created by this secondary substitution is captured in the A(t) parameter. Nonetheless, the substitutions of critical importance in an energy-emissions model--substitution between the two major types of energy and substitution between energy and other inputs--are both identifiable and quantifiable. We will return to them shortly.

Before doing so, however, it is convenient to discuss the derived demand for energy implicit in the functional form of Equation (1) as it stands. Since energy demand is derived entirely from production, Equation (1) imposes some unavoidable structure on the demand for energy. The share of X(t) devoted to paying for energy at any point in time is, first of all, fixed; i.e., letting $P^n(t)$ represent the real price of $E^c(t)$ at time t in 1975 U.S. dollars and $P^c(t)$ represent the real price of $E^c(t)$ at time t, then the share devoted to energy can be expressed as

$$P^n(t)E^n(t) + P^c(t)E^c(t) = (1 - d)X(t) \qquad (2a)$$

for all t. Letting

$$E^n(t) + E^c(t) = E(t)$$

represent total energy demand and

$$[P^c(t)E^c(t)/E(t)] + [P^n(t)E^n(t)/E(t)] = P(t)$$

represent the weighted aggregate price of energy, Equation (2a) can immediately be rewritten in the more convenient form:

$$E(t) = (1 - d)X(t)/P(t). \qquad (2b)$$

It becomes clear, therefore, that Equation (1) imposes unitary price and income elasticities on the aggregate energy demand equation.*

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*The price elasticity of demand is a reflection of the responsiveness of the quantity demanded to changes in the price. It is formally defined as the ratio between the percentage change in the quantity

(continued overleaf)

Additionally, the particular nested form of Equation (1) necessarily requires that the relative demand for $E^c(t)$ and $E^n(t)$ take the form

$$\frac{E^c(t)}{E^n(t)} = \left[\frac{(1-b)}{b}\ \frac{P^c(t)}{P^n(t)}\right]^{1/r-1}. \qquad (3)$$

Implicit in Equation (1), then, is the condition that a 1% increase in the energy price ratio of fossil to nonfossil fuel must always generate a $[(r-1)^{-1}]$% reduction in the ratio of fossil to nonfossil fuel use. Since the parameter r could be arbitrarily specified, however, Equation (3) is not nearly so restrictive as Equation (2b). Still, the point is this: by specifying the production function, we fully specify the underlying structure of demand for all three of our inputs--labor, fossil fuel, and nonfossil fuel.

Quantification of the ability to substitute between the two types of energy and between labor and energy now follows straightforwardly from the derived demand schedules just noted. To that end, let

$$s = \frac{d\ \ln[E^c(t)/E^n(t)]}{d\ \ln[P^c(t)/P^n(t)]}$$

represent the notion of the "elasticity of substitution" between the two types of energy; i.e., let s represent a measure of how responsive the ratio of fossil to nonfossil fuel consumed worldwide is to changes in the relative prices of the two fuels. Logarithmic differentiation of Equation (3) then reveals that

$$s = (r-1)^{-1}.$$

If r were to equal 0.5, therefore, s would equal -2.0, indicating that any 1% increase in the relative price of carbon-based fuel would

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(continued from overleaf)
demanded and the percentage change in the price that caused demand to change; i.e.,

$$(\text{price elasticity}) = d\ \ln[E(t)]/d\ \ln[P(t)].$$

Given Equation (2b), therefore, it is clear that the price elasticity of the derived demand for energy is (-1). The income elasticity of demand is similarly defined as the ratio between the percentage change in the quantity demanded and the percentage change in income. Since notationally the income elasticity of demand is $d\ \ln[E(t)]/d\ \ln[X(t)]$, it is equally clear that this elasticity must also equal 1 for the schedule listed in Equation (2b). In conclusion, therefore, the structure of the production schedule recorded in Equation (1) implies that (i) a 1% increase in the price of energy would always cause a 1% reduction in the demand for energy, while (ii) a 1% increase in world GNP would always cause a 1% increase in the demand for energy.

produce a 2% reduction in the carbon to noncarbon fuel consumption ratio. A similar computation meanwhile shows that the corresponding elasticity of substitution between either $E^c(t)$ or $E^n(t)$ and labor is unity. Thus, the unitary price and income elasticities of aggregate energy demand already noted from Equation (2b) were to be expected.

The lack of flexibility in this last elasticity was a source of concern. We were not anxious to be boxed into a structure of unitary elasticities in the demand for energy, but we were bound by a well-known result of economic theory: in maintaining the simple production structure that we felt was required to preserve the necessary transparency in the intertemporal model, we were forced to set the elasticity of substitution between energy and labor either to $s = (r - 1)^{-1}$ or to unity. Rather than loosen this theoretical binding by resorting to a more complicated production function, we chose instead to provide the desired flexibility by keeping Equation (1) as our fundamental production relationship and adjusting the share of world GNP used to pay for energy over time. To see how this was accomplished, let

$$X(t) = A(t)[mL(t)^q + (1 - m)E(t)^q]^{1/q} \qquad (1')$$

represent the next logical generalization of production. The parameter q here reflects the ease of substituting between energy and labor in the production process; it is the analog to the parameter r in Equation (1), and $(q - 1)^{-1}$ is the corresponding elasticity between energy now aggregated into one factor and labor. The resulting derived demands for labor and energy could then be combined to form the analog of Equation (3):

$$\frac{E(t)}{L(t)} = \left[\frac{(1 - m)}{m}\frac{P(t)}{w(t)}\right]^{1/(q - 1)}, \qquad (4)$$

where w(t) represents the unit price of labor. Multiplying both sides of Equation (4) by [P(t)/w(t)], a more convenient form emerges:

$$\frac{[1 - d(t)]}{d(t)} = \frac{P(t)E(t)}{w(t)L(t)} = kP(t)^{q/(q - 1)}, \qquad (4')$$

where $k = [(1 - m)/m]^{1/(q - 1)}$ and taking the approximation that w(t) = 1.* Notice that the first part of that equation simply states that the relative share of GNP devoted to paying for energy must equal the ratio of the energy bill of the world, P(t)E(t), and the global wage bill w(t)L(t). It makes the d(t) parameter defined here the precise

*Setting w(t) = 1 requires an approximation, as follows:

The model assumes that if the relative price of energy to labor, [P(t)/w(t)], is constant, then d (the share of labor) is constant. We are attempting to examine the effect of changes in P(t)/w(t) on d.

(continued overleaf)

analog of the d parameter recorded in Equation (1). Rearranging terms, then, the equation

$$d(t) = [kP(t)q/(q - 1) + 1]^{-1} \quad (5)$$

provides a means by which the share of world GNP paid to energy can be adjusted from period to period in a manner consistent with an elasticity of substitution between labor and energy equal to $(q - 1)^{-1}$. We were able, with this procedure, to approximate a more general schedule like Equation (1') with a series of simpler schedules of the type shown in Equation (1) by simply adjusting energy's share of GNP in a way that was consistent with the more complex structure that we needed. We are, in other words, out of our theoretical bind.

With this final step completed, we are able to set both the elasticity of substitution between fossil and nonfossil fuels and the elasticity of substitution between energy and labor equal to whatever the data suggested were appropriate values without overburdening the model with unnecessary complication.

To proceed from this point it is necessary to specify how A(t), L(t), and the prices of the two fuels are to be determined over time. Productivity and population are the easiest; they take the forms

$$A(t) = A_0 e^{a(t)t}$$

and

$$L(t) = L_0 e^{l(t)t},$$

where

A_0 = labor productivity at t = 0 (1975);
$a(t)$ = rate of growth of labor productivity at time t;
L_0 = world population at t = 0; and
$l(t)$ = rate of growth of population at time t;

The last three are taken to be exogenous.

(continued from overleaf)

If we were instead to set w(t) equal to its model solution, then Equation (4') could be written as

$$\lambda(t) = k\,\theta(t)^{\gamma}, \quad (4'')$$

where $\lambda = (1 - d)/d$, $\theta = P/w$, $\gamma = q/(1 - q)$. Thus the change in λ from one path to another would be

$$\Delta \ln \lambda(t) = \gamma[\Delta \ln P(t) - \Delta \ln w(t)].$$

For given L(t) and P(t), we can solve this for w(t), and $\Delta \ln w(t)$ is an order of magnitude smaller than $\Delta \ln P(t)$, because the share of E is about one tenth of the share of L. Our approximation thus misstates the change in d by about one tenth. Also note that the share of L changes only a little.

Energy prices are divided into production and distribution cost components (roughly the difference between wholesale and retail prices), and production costs are presumed to be subject to technological change. The price of noncarbon-based fuel is, more specifically, given by

$$P^n(t) = P_d^n + P_0^n e^{[h_1(t) + h_2(t)]t}, \qquad (6a)$$

where

P_d^n = distribution costs in 1975 U.S. dollars per metric ton of coal equivalent;

P_0^n = initial production costs in 1975 dollars per metric ton of coal;

$-h_1(t)$ = rate of technological change in the energy industry at time t; and

$-h_2(t)$ = bias of technological change toward noncarbon energy at time t

are all exogenous. The last two entries in the list may require a little explanation. The rate of technological change in the energy industry is the rate at which the efficiency in the industry is improving; conversely, it can be viewed as the inverse of the rate of change in the real price of energy. If, for example, the price of energy were decreasing at a rate of 1% per year, this would be consistent only with a rate of technological change of 1% per year. The bias in the rate of technological change reflects the possibility that technical change and innovation will not proceed at the same rate in both energy sectors. If innovation were more rapid in the nonfossil fuel sector, for instance, then the bias would favor that sector, and $h_2(t)$ would be positive.

The price equation for fossil fuel takes similar form. The only complicating element here is the implicit inclusion of a depletion factor--a reflection of the usual expectation that the price of fossil fuel should increase over time as the world's resources of fossil fuels are used up. We do not, here, necessarily include supply and demand effects.* The depletion factor represents, more accurately, the notion

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*The model has one theoretical flaw from the point of view of the economics of exhaustible resources. This is that there are no rents charged to scarce fossil fuels. The economics and some estimates of such scarcity rents are provided in Nordhaus (1979) for a model without uncertainty.

There is a very great difficulty in the present model, however, in calculating the appropriate scarcity rents. This difficulty arises because the appropriate scarcity rents will be different in each of the 3^{10} possible trajectories. And the actual rent at each point of time will depend on the way that the uncertainties are revealed over time.

(continued overleaf)

that the price of fossil fuel must increase as the cheaper wells are drilled or mines are exhausted and as more expensive sources come on line. Depletion is represented as follows:

$$P^c(t) = P_d^c + \left(g_0 + g_1 \left\{R(t)/[\bar{R} - R(t)]\right\}^{g_2}\right) e^{h_1(t)t} + T(t - \bar{t}), \quad (6b)$$

where

P_d^c = distribution costs in 1975 U.S. dollars per metric ton of coal equivalent;

g_0 = initial production costs in 1975 dollars per metric ton of coal equivalent;

R = a measure of the world's remaining carbon-based fuel reserves in metric tons of coal equivalent in 1975;

$T(t - \bar{t})$ = a tax policy parameter used to reflect taxation of fossil fuels;

$R(t)$ = $[E^c(0) + \ldots + E^c(t - 1)]$ = total carbon-based fuel consumed since 1975 in metric tons of coal equivalent; and

$g_i (i = 1,2)$ = depletion parameters.

In this list, of course, all but R(t) are taken to be exogenous.

At this point, then, only three parameters remain to be determined: b, A, and m. These are specified, given assumed values for s, r, q, d, L_0, $E^c(0)$, $E^n(0)$, $(p_0^n + P_d^n)$, and $(g_0 + P_d^c)$, so that the entire set of parameters satisfied Equations (1), (3), and (5) at time zero. No further data are necessary.

Special mention needs to be made of the policy variable $T(t - \bar{t})$. It is included to reflect any policy that might be designed to reduce carbon dioxide concentrations either directly by taxes or indirectly by discouraging the consumption of fossil fuels. Since either type of policy would make it more expensive to burn these fuels, either would be captured by the tax $T(t - \bar{t})$ that increased the price of $E^c(\bar{t})$. The parameter t simply denotes the lag between the imposition of a CO_2 reduction policy and its effect on the day-to-day operations of fuel burners. The use of a tax to summarize even quantity-based restrictions is widespread in the economic literature and is supported by the following equivalence theorem: for any targeted quantity restriction on, for example, carbon-based fuels, there exists a tax to

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After some thought about the best way to calculate the rents, we finally gave it up as hopelessly complicated.

In reality, it seems that, except for oil and gas, the scarcity rents are likely to be quite small for most of the time. This conclusion is based on a reading of the estimates from Nordhaus (1979). However, it should be noted that omission of the scarcity rent leads to a downward bias in the market price of fossil fuels and consequently in an upward bias in the estimate of CO_2 emissions and concentrations. We expect that this bias is likely to be on the order of 0 to 2% during the period under consideration.

be added to the price of carbon-based fuels such that consumers, in their own best interest, will undertake actions to lower their consumption to the prescribed target level.* Either tool, properly computed, can therefore achieve any arbitrary policy objective, and the generality of the tax approach is assured.

Some have noted that the two alternatives need not be equivalent, in terms of their efficiency, under uncertainty. A similar theorem exists, however, when the comparison is conducted between alternatives computed to generate the same expected result. Others have worried that the equivalent tax might, in practice, be difficult to compute. Whether that is true or not, of course, this purported difficulty does not damage the treatment in the present paper.

Returning now to the model, Equations (1) and (6) complete a simple, economically consistent vehicle with which to project the driving force of industrial CO_2 emissions. Only a link to the atmosphere is required; that link is represented by

$$C(t) = \left[Z_0 e^{z(t)t} \right] \left[E^c(t) \right],$$

where

$C(t)$ = emissions of carbon in gigatons per year;

Z_0 = the "emissions factor," equal to the initial ratio of carbon emissions to fossil fuel consumption in 1975; and

$z(t)$ = the rate of growth of the emissions factor.

The last two are, of course, exogenous. The ratio $z(t)$ is, moreover, presumed to increase over time because of a supply-induced change in the fuel mix (i.e., toward coal and shales). Nonfossil fuels are presumed to provide energy without adding to carbon emissions.

An airborne fraction approach to link emissions to atmospheric concentrations is finally employed to complete the model. Formally,

$$M(t) = M(t - 1) + AF(s)[0.471\ C(t)] - sM(t - 1), \tag{7}$$

where

s = a seepage factor reflecting the slow absorption of airborne carbon dioxide into the deep oceans;

$AF(s)$ = the marginal airborne fraction of carbon dioxide; and

$M(t)$ = carbon mass in the atmosphere in period t measured in parts per million.

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*See Yohe (1979) for a survey of the literature on this point.

Equation (7) is a standard representation of the complex workings of the atmosphere, frequently used in the carbon cycle literature.* The coefficient 0.471 preceding C(t) simply converts gigatons of carbon into the appropriate atmospheric units of parts per million. The seepage factor is a subject of current debate among researchers (see Brewer, this volume, Chapter 3, Section 3.2); in separate work, we have shown that the maximum likelihood estimate of the airborne fraction is quite sensitive to the specification of s; thus, the AF(s) notation.

In summary, then, the model operates with the demands for fossil and nonfossil fuel being derived entirely from a production function that, for any year, assumes the form

$$X(t) = A(t)L(t)^{d(t)}[bE^c(t)^r + (1 - b)E^n(t)^r]^{[1 - d(t)]/r}. \quad (1)$$

They emerge summarized by

$$P^n(t)E^n(t) + P^c(t)E^c(t) = [1 - d(t)]X(t) \quad (2a)$$

and

$$\frac{E^c(t)}{E^n(t)} = \left[\frac{(1 - b)}{b} \; \frac{P^c(t)}{P^n(t)}\right]^{1/r - 1} \quad (3)$$

with

$$d(t) = [kP(t)q/(q - 1) + 1]^{-1}. \quad (5)$$

Furthermore, the neutral productivity growth factor and labor growth component of Equation (1) are given exogenously by

$$A(t) = A_0e^{a(t)t}$$

and

$$L(t) = L_0e^{l(t)t},$$

respectively. The supply conditions from fossil and nonfossil fuels are meanwhile determined by

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*See Bolin (1981) for a complete discussion of the concentration model. Our modification of that work specifies a marginal airborne fraction--the fraction of period t emissions that remain in the atmosphere on the margin (i.e., in period t). Whenever the seepage factor is nonzero, the marginal fraction does not equal the average fraction that most of the previous studies have employed.

$$P^n(t) = P_d^n + P_0^n e^{[h_1(t) + h_2(t)]t} \quad (6a)$$

and

$$P^c(t) = P_d^c + \left(g_0 + g_1\{R(t)/[\bar{R} - R(t)]\}^{g_2}\right) e^{h_1(t)t} + T(t - \bar{t}) \quad (6b)$$

with $R(t) = E^c(0) + \ldots + E^c(t - 1)$.

Emissions are then recorded according to

$$C(t) = \left[z_0 e^{z(t)t}\right] E^c(t)$$

and atmospheric concentrations according to

$$M(t) = M(t - 1) + AF(s)[0.471\ C(t)] - sM(t - 1). \quad (7)$$

Figure 2.8 represents a geometric interpretation of this process.

2.1.2.2 The Data

Two kinds of data are required. Initial conditions are, first of all, required. Table 2.2 records the estimates for world GNP, world population, and world fossil and nonfossil fuel in 1975. Since these initial conditions are based on historical evidence, consensus is not difficult to achieve. Existing studies and comparison with published data are sufficient to generate consistent estimates for these parameters. Initial energy prices are a bit more problematical. We want aggregate prices based on the historical distribution of, for example, fossil fuels between coal, oil, and gas. Table 2.3 records both the necessary raw data and their sources. Table 2.4 produces the aggregates and illustrates the procedure that is employed in their construction. Table 2.5 registers the emissions ratios of the various types of fossil fuels from which the initial value for the aggregate emissions ratio is computed. Table 2.4 also records that aggregation procedure. Finally, an initial level of atmospheric carbon concentration is required; current measures set the 1975 value at 331 parts per million (ppm) (see Keeling et al. in Clark, 1982, Table 1, page 378).

Data are also required to set the long-term context of the study--a more difficult problem. Projections of various important parameters into the near and distant future were compared, but the uncertainties inherent in such projection made consensus impossible. Existing studies provide ranges for variables like world population growth, world productivity growth, energy prices, and the emissions factor, but no generally accepted paths emerge. The observed ranges are, however, viewed as more than spurious disagreement among researchers. They are, instead, viewed as a reflection of the inherent uncertainty about the variables.

A more precise description of the technique we use is the following: we assume that the published estimates for each of the random variables

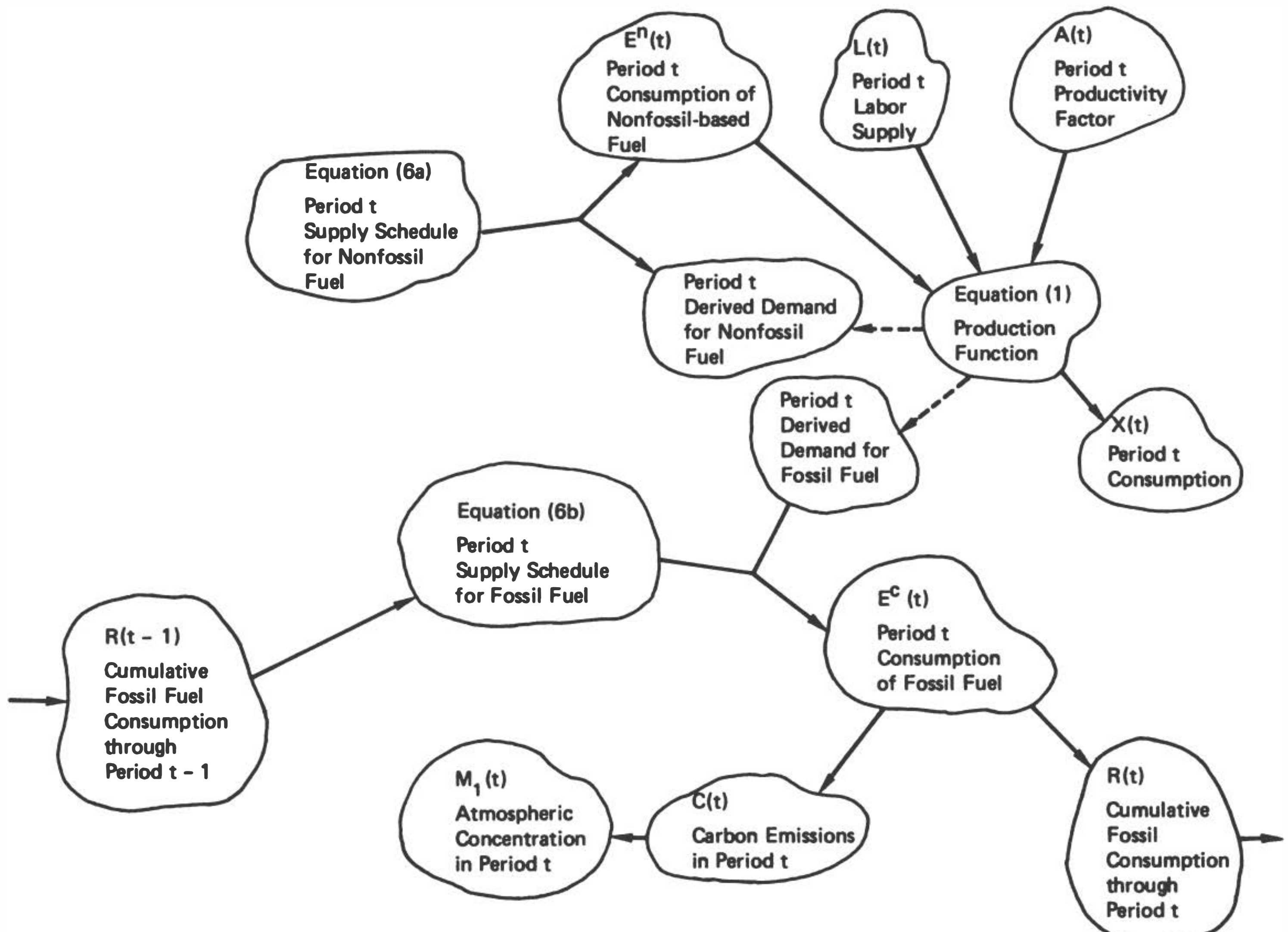


FIGURE 2.8 Iteration with the model.

TABLE 2.2 Initial Conditions for Population, GNP, and Aggregate Fuel Consumption

A. World Population in 1975	
IIASA (1981, p. 133)	4×10^9
Ridker and Watson (1980, p. 45)	3.8×10^9
Keyfitz (1982)	3.98×10^9
Value employed: $L(0)$	4×10^9
B. World GNP in 1975	
IIASA (1981, p. 457)	$\$ 6.4 \times 10^{12}$
Ridker and Watson (1980, p. 45)	$\$ 4.5 \times 10^{12}$
Report of the President (1980)	$\$ 6.53 \times 10^{12}$
Value employed: $X(0)$[a]	$\$ 6.4 \times 10^{12}$
C. Fossil Fuel Consumption in 1975	
IIASA (1981, p. 136)	8.127×10^9 mtce
Ridker and Watson (1980, p. 185)	8.114×10^9 mtce
Value employed: $E^c(0)$	8.1×10^9 mtce
D. Nonfossil fuel Consumption in 1975	
IIASA (1981, p. 136)	0.67×10^9 mtce
Ridker and Watson (1980, p. 185)	0.69×10^9 mtce
Value employed: $E^n(0)$	0.7×10^9 mtce

[a]The Ridker and Watson estimate was ignored because it was built around an estimate of per capita income that appeared to be low relative to other published data.

identified in our model is an unbiased, but not necessarily independent, estimate of that variable. We use the means and variances of those estimates as a basis for constructing judgmental probability distributions for each variable. To obtain a manageable number of alternatives from which to sample, we assume that each judgmental probability distribution is normally distributed. We then take high, middle, and low values (corresponding to 25, 50, and 25%, respectively) that maintain the same means and variances as the estimated normal distributions.

To put it more intuitively, we have constructed discrete distributions to mirror the level of uncertainty at present surrounding the various analysts' published projections. In deference to the tendency of individuals to underestimate uncertainty, however, the procedure for reflecting uncertainty does not stop there. Particularly when the estimated variances declined over time, future variances are expanded beyond their computed ranges to correct for systematic underestimation of uncertainty. Section 2.1.2.2.1 is devoted to a thorough exploration of this second procedural phase; the remainder of this section will concentrate on applying the first phase to the critical parameters.

In passing, though, it should be noted that our procedure produces more than a purely subjective view of the future paths of some complicated variables. It produces a "judgmental" view that weighs the expert opinions of many researchers as expressed in their published

TABLE 2.3 Energy Price and Disaggregate Consumption Data

A. Consumption Patterns (1975)[a]		
I. Fossil Fuel		
Coal	2.42×10^9 mtce	30%
Oil	4.10×10^9 mtce	50%
Gas	1.61×10^9 mtce	20%
Total	8.13×10^9 mtce	100%
II. Nonfossil Fuel		
Hydro	0.53×10^9 mtce	81%
Nuclear	0.13×10^9 mtce	19%
Total	0.66×10^9 mtce	100%
B. Energy Prices (1975)[b]		
I. Primary[c]		
Coal	$ 15/mtce	
Oil	$ 54/mtce	
Gas	$ 19/mtce	
Electricity	$118/mtce	
II. Secondary[d]		
Coal	$ 23/mtce	
Oil	$ 98/mtce	
Gas	$ 28/mtce	
Electricty	$255/mtce	
C. Energy Prices (1981)[e]		
I. Primary[c]		
Coal	$ 15/mtce	
Oil	$108/mtce	
Gas	$ 86/mtce	
Electricty	$118/mtce	
II. Secondary[d]		
Coal	$ 23/mtce	
Oil	$171/mtce	
Gas	$116/mtce	
Electricty	$255/mtce	

[a]Source: IIASA (1981), p. 471.
[b]Measured in 1975 United States dollars. Source: Reilly et al. (1981).
[c]These are wholesale prices.
[d]These are retail prices.
[e]Measured in 1975 United States dollars. They are derived from the 1975 prices to reflect the impact of the 1979 Iran-Iraq war as follows. The June 10, 1982, issue of Blue Chip Indicators provided an estimate for the 1981 wholesale oil price of $34.00 (current dollars) per barrel. That translates into $22.50 per barrel in 1975 dollars, or $108/mtce. The btu equivalent price for gas was then computed to equal [0.8($108/mtce)] = $86/mtce. Coal and electricity (generated from nonfossil fuels) were assumed to remain constant over the 6-year period. The secondary prices for oil and gas were then computed by adding the reported consensus differences between wholesale and retail prices: $13/barrel or $63/mtce for oil and $30/mtce for oil. Thus, secondary prices of [$108 + $63] = $171/mtce and [$86 + $30] = $116/mtce were recorded, respectively.

TABLE 2.4 Aggregate Prices and Emissions

A. Energy Prices in 1975[a]	
I. Primary	
Fossil fuel[b]	$ 35/mtce
Nonfossil fuel[c]	$ 118/mtce
II. Secondary	
Fossil fuel[b]	$ 62/mtce
Nonfossil fuel[c]	$ 255/mtce
B. Energy Prices in 1981[a]	
I. Primary	
Fossil fuel[d]	$ 76/mtce
Nonfossil fuel[c]	$ 118/mtce
II. Secondary	
Fossil fuel[d]	$ 116/mtce
Nonfossil fuel[c]	$ 255/mtce
C. Emissions Ratio in 1975[e]: Z(0)	580 g of C/mtce

[a]Measured in constant 1975 dollars.
[b]Computed using the prices and weights recorded in Table 2.3. In 1975, for example, coal amounted to 30% of the total fossil fuel consumed and cost $15/mtce, oil amounted to 50% of the total and cost $54/mtce, and gas amounted to 20% at a cost of $19/mtce. Thus, the aggregate price of fossil fuel in 1975 was 0.3($15) + 0.5($54) + 0.2($19) = $35/mtce.
[c]The price of nonfossil fuel was taken to be the price of electricity generated from nonfossil sources.
[d]Computed using the weights and prices recorded in Table 2.3. The weights employed were the 1975 numbers because it was unlikely that major substitutions could have occurred in the 6 years from 1975 and 1981. This presumption is borne out by data published in the *BP Statistical Review of the World Oil Industry, 1980*, p. 16.
[e]The ratio of grams of carbon emitted per mtce of fuel consumed. The 1975 consumption weights of Table 2.3 were combined with the emission data of Table 2.5 to produce Z(0); i.e., Z(0) = 0.3(700) + 0.5(577) + 0.2(404) = 580 g of C/mtce.

work. The data for obtaining parameter estimates are not, in other words, anonymous and private. They are public and thus presumably derived with the care that scientists use in producing work attached to their names. And they are judgmental views about nonelemental variables--not variables like GNP growth or energy growth that depend

TABLE 2.5 Carbon Emissions from Fossil Fuels[a]

Fuel	kg of C/10^9 J	kg of C/mtce[b]
Petroleum	19.7	577
Gas	13.8	404
Coal	23.9	700
Shale oil[c]	41.8	1224

[a]Source: Marland (1982).
[b]Conversion based on 1 mtce = 29.29 x 10^9 J; kg of C, kilograms of carbon.
[c]Includes carbon dioxide emissions due to shale oil mining and extraction.

on a host of known and unknown effects, but variables like population growth and resource availability that depend on fewer things.*

Beginning once again with population numbers, Table 2.6 shows that a variety of growth projections have been made for at least the next 50 years. Each assumes no major catastrophes; and while the general trend in each calls for a steady decline in the rate of growth, there is some disagreement. Differences are to be expected, of course, but it is interesting to note that these differences found their source in the assumptions made about the less-developed countries; the historical experience of the LDCs has been so widely varied that a common expectation would, of course, have been surprising. The full effect of that disagreement is not reflected in the world projections, however, because the larger, more-developed countries have displayed low, stable growth rates over the past few decades.

Of further interest was the marked reduction in the variance of projections beyond the year 2025; most researchers predict that the world's population will stabilize sometime after the first third of the twenty-

*Two technical points might be raised:

First, are the estimates independent? It is likely that some of the figures depend on previous estimates--indeed, they might all go back to a single careful study. We have been unable to check for such an occurrence in every case, but in some we are confident that the outcomes are truly independent, even competitive.

Second, are the underlying judgmental probability distributions independent? While some lingering correlations probably exist, we took care to construct our random variables so that the correlations were low--that is, the variables are intended to be orthogonal. Thus, the rate of productivity growth in energy is thought to be independent of the difference in productivity growth between fossil and nonfossil fuels.

TABLE 2.6 Projected Trends in the Growth Rates of World Population[a]

Source of Estimate[b]	1975-2000	2000-2025	2025 and beyond
OECD	1.6%	--	--
IIASA[c]	1.7%	0.9%	[d]
RFF (high)	1.9%	1.52%	[d]
RFF (low)	1.4%	0.75%	[d]
Hudson Institute	2.0%	1.4%	--
Keyfitz[c]	1.6%	0.9%	0.3%
Mean	1.7%	1.1%	0.3%
Standard deviation	0.2%	0.36%	n.a.
Cell extremes	1.4%; 2.0%	0.6%; 1.6%	n.a.

[a]Estimates of the l(t) parameters of population growth equation.
[b]Sources: OECD Interfutures Project (1979), IIASA (1981), Ridker and Watson (1980), Kahn et al. (1976), and Keyfitz (1982).
[c]The IIASA projections were based on an earlier set of estimates by Keyfitz.
[d]The IIASA and RFF studies report the expectation of stable world population some time after the first third of the twenty-first century.

first century. Sometimes they have reached that conclusion because they believe that by then the volatile LDC behavior will have evolved into the predictable model of the developed countries; sometimes their predicted stability was based on some other presumption. In either case, their behavioral hypothesis was as much of a guess about the unknown future as any other growth path, and it is hard to see why uncertainty should diminish as time goes forward. The observed reduction in range of population growth projections beyond 2025 is thus a likely candidate for the adjustment discussed further in the next section.

As troublesome as the later estimates might have been, however, the earlier ranges provided excellent arenas for illustrating the summarizing procedure for the observed variation. The various estimates, ranging from 1.4% growth per year up to 2.0% for 1975-2000 are, for example, assumed to be observations drawn from an underlying normal distribution of the true uncertainty. These observations (X_i) are then used to compute estimates of the mean (μ_x) and variance (σ^2) of that distribution:

$$\mu_x = \bar{X} = \frac{1}{n}\left\{X_1 + \dots + X_n\right\}$$

and

$$\sigma^2 \approx s^2 = \frac{1}{n-1}\left\{(X_1 - \bar{X})^2 + \dots + (X_n - \bar{X})^2\right\},$$

where n represents the number of observations. To discretize the distribution defined by $\bar{X}$ and S^2 into three cells of probabilities 0.25, 0.50, and 0.25, therefore, $\bar{X}$ is assigned a probability of 0.5 and $(\bar{X} \pm s\sqrt{2})$ probabilities of 0.25. In this way, mean and variance $[s^2 = 0.25(2s^2) + 0.25(2s^2)]$ are both preserved. For the 1975-2000 range, therefore, 1.7% is the "middle" estimate, while 1.4% and 2.0% represent the extremes. Under this procedure, roughly 8% of the underlying probability is left beyond the extremes on both sides. Similarly, 1.0% is the middle estimate for the period 2000-2025, with 0.5% and 1.5% catching the 0.25 probability tails.

Estimates of growth in world productivity are recorded in Table 2.7. They are, for the most part, based on a somewhat surprising assumption about the growth of world trade over the next several decades. Each researcher found that the growth of the world economy will be bounded by growth in the largest markets--the developed countries. Many studies have identified productivity growth as a critical parameter for energy and carbon dioxide projections. The common presumption about the growth of world trade, ironically, has caused otherwise independent studies to project estimates of output growth that converge over time. Of particular note is the decline in the variance in projected growth rates beyond the year 2025. It may have been caused more by a dearth of estimates than anything else, but its range includes only the lower tail of the long-run historical experience of the United States, and it misses the Japanese experience completely. These ranges, too, are subject to revision later.

TABLE 2.7 Projections of the Rate of Growth of World Productivity[a]

Source of Estimate[b]	1975-2000	2000-2025	2025 and beyond
OECD (high)	3.4%	--	--
OECD (mid)	2.8%	--	--
OECD (mid)	1.9%	--	--
OECD (low)	2.7%	--	--
IIASA (high)	2.3%	0.9%	--
IIASA (low)	1.2%	1.9%	--
Hudson	2.8%	1.4%	1.2%
RFF (high)	2.4%	2.1%	--
RFF (low)	1.6%	1.8%	--
Hudson (low)	--	--	0.75%
Mean	2.3%	1.6%	1.0%
Standard deviation	0.7%	0.5%	0.3%
Cell extremes	1.2%; 3.4%	0.9%; 2.3%	0.5%; 1.5%

[a]Estimates of the a(t) parameter in the productivity growth expression.
[b]Sources: OECD Interfutures Project (1979), IIASA (1981), Ridker and Watson (1980), and Kahn et al. (1976).

TABLE 2.8 Projections of the Rate of Growth of Noncarbon Energy Prices[a]

Source of Estimate[b]	1975-2000	2000-2025	2025 and beyond
IEA	0.0%	0.0%	0.0%
RFF (DH NU)[c]	1.0%	0.6%	--
RFF (DHP1)[c]	0.7%	-0.1%	--
RFF (DHP2)[c]	1.0%	-0.4%	--
Mean	0.6%	0.0%	0.0%
Standard deviation	0.5%	0.4%	n.a.
Cell extremes	-0.1%; 1.3%	-0.5%; 0.5%	n.a.

[a]Estimates of the $h_1(t)$ and $h_2(t)$ parameters of the energy price (supply) equations.
[b]Sources: Reilly et al. (1981), Ridker and Watson (1980).
[c]The difference between these three scenarios is essentially a difference in the assumption about solar and nuclear development. The particulars are not so important, for our purpose, as the spread of uncertainty.

Table 2.8 records projected future adjustments in the primary real price of noncarbon-based energy--electricity not derived from burning carbon-based fuel. These trends can, however, be interpreted as the inverse of the rate of technological change in the energy sector, i.e., in the notation of the previous section, $h_1(t)$. Since technological change can continue in the fossil fuel sector as well, these estimates are also used to frame the difference in the rate of advance between the two sectors [$h_2(t)$]. These estimates, then, are clearly dependent not only on growth assumptions (and thus the need for new technology) but also about the future contributions of sources like nuclear, fusion, and solar-generating facilities. Despite the obvious uncertainties involved in projecting either factor into the twenty-first century, the estimates recorded in Table 2.8 again converge. The Reilly et al. (1982) view of constant real prices is therefore included as the middle case, and the ultimate variation around that case expanded.

Estimates of the emissions factor are based both on the unit emissions for each source recorded in Table 2.5 and on projected mixes of carbon-based fuels in the future. For each case, the mix of oil, gas, coal, and shale oil is computed and used to weight the unit emissions in computing an aggregate. The procedure has already been illustrated in the calculation of $Z(0)$ for Table 2.4. Results of the other computations are noted in Table 2.9. The summarizing procedure is applied across the ranges of emissions for each period to produce high, medium, and low trends. Notice that the high trend includes a 31% contribution from shales (as projected by RFF) by the year 2050. The lower two paths stabilized at 100% coal, or 700 g of C/mtce by 2075. The three possibilities are illustrated in Figure 2.9.

TABLE 2.9 Aggregate Carbon Emissions

A. Fuel Proportions

Year	Source[a]	Proportions Oil	Gas	Coal	Shale	Carbon Emissions
1975	Table 2.3	0.50	0.20	0.30	0.00	580
2025	IIASA (high)	0.33	0.29	0.38	0.00	580
	IIASA (low)	0.34	0.23	0.43	0.00	590
	IEA	0.28	0.18	0.54	0.00	612
	RFF	0.28	0.23	0.37	0.06	607
2050	IIASA (high)	0.25	0.10	0.65	0.00	604
	IIASA (low)	0.28	0.19	0.53	0.00	598
	IEA	0.26	0.08	0.66	0.00	644
	RFF	0.02	0.02	0.65	0.31	854

B. Projected Growth in Emissions--Z(t)

Year	Emissions Mean	Std.Dev.	Extremes	Growth Mean	Extremes
1995-2025	597	15	582; 612	0.05%	0.0%; 0.1%
2025-2050[b]	627	25	602; 799	0.2%	0.1%; 1.1%
2050-2075[c]	n.a.	n.a.	700; 700; 854	0.4%	0.6%; 0.3%
2075-2100[c]	n.a.	n.a.	700; 700; 854	0.0%	0.0%; 0.0%

[a]Sources: IIASA (1981), Reilly et al. (1982), Ridker and Watson (1980).
[b]The mean and standard deviation reported here excludes the shale estimate to generate the low extreme and the middle growth paths. The higher extreme includes the shale estimate in both computations.
[c]The two lower runs exclude shale; the high extreme converges to a 30% shale share of carbon-based fuel.

Elasticities of substitution between energy and labor, on the one hand, and between the two types of energy, on the other, are estimated on the basis of the literature on price elasticities of demand. In the former case, for example, it is noted that many would put the overall price elasticity of demand for energy somewhere in the inelastic range, i.e., they would expect a 1% price increase to reduce consumption by something less than 1%. A range for $s' = (q - 1)^{-1}$, the elasticity of substitution between $E(t)$ and $L(t)$, that select -0.4 and -1.2 for the 25% probability extremes and -0.7 for the mean is therefore employed. Similar reasoning puts the extremes for $s = (r - 1)^{-1}$, the elasticity between $E^c(t)$ and $E^n(t)$, at -0.5 and -2.0 around the middle run of -1.2.

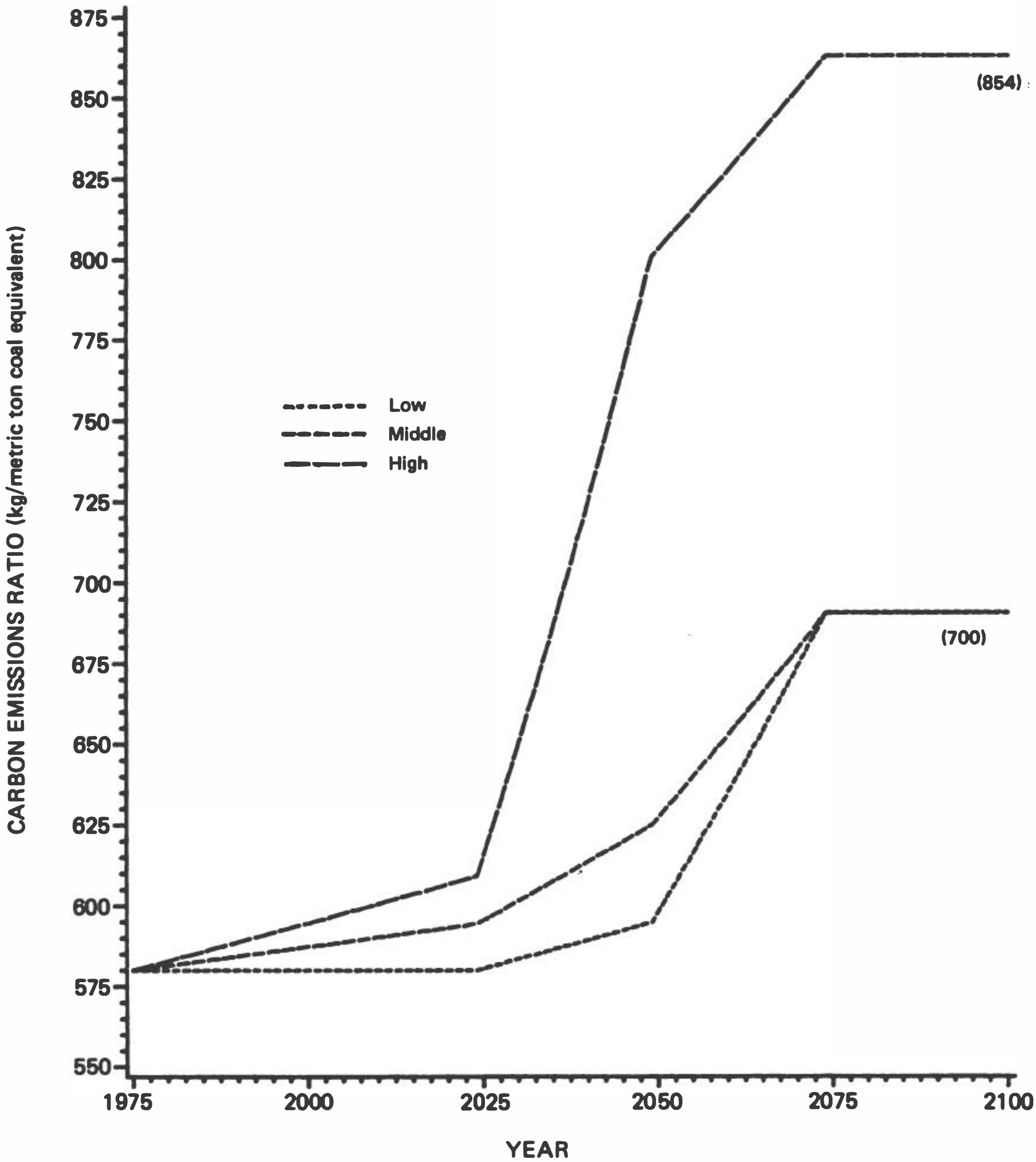


FIGURE 2.9 Carbon emissions ratio.

There are by now a wide variety of studies of the elasticity of substitution between energy and nonenergy inputs. To a first approximation, this parameter is equal to the price elasticity of the derived demand for energy [this is shown in Nordhaus (1980a)]. Table 2.10, drawn from Nordhaus (1980a), gives central estimates and ranges for the price elasticity of the demand for energy.

TABLE 2.10 Range of Estimated Final Demand Elasticities[a]

Sector	Hogan	Nordhaus	Best Guess	Implicit Elasticity for Primary Energy
Residential	-0.28 to -1.10	-0.71 to -1.14	-0.9	-0.3
Transport	-0.22 to -1.30	-0.36 to -1.28	-0.8	-0.2
Industrial	-0.49 to -0.90	-0.30 to -0.52	-0.7	-0.4
Aggregate	--	-0.66 to -1.15	-0.8	-0.3

[a]Sources: The first column is from Hogan (1980); the second column, from Nordhaus (1977); the third column is Nordhaus's judgmental weighting of various studies. To obtain an estimate of the crude price elasticity in the fourth column, the final demand price elasticity in the third column is divided by the ratio of retail price to crude price.

For use in the present study we lowered the elasticity to 0.7 because of some suggestion that price elasticities are lower in less-developed countries than in developed countries. In addition, note that, while the price elasticities may appear high, they are not for two reasons. First, they are long-run rather short-run elasticities. And, second, they relate to the elasticity for final energy demand, not for primary energy. As is shown in the last column of Table 2.10, price elasticities for primary energy are considerably lower than the figures we use.

The elasticity of substitution between carbon- and noncarbon-based fuels was derived as follows. We examined the effects of different CO_2 taxes on the ratio of carbon to noncarbon fuels in the runs presented in Nordhaus (1979), Chapter 8. The logarithmic derivative of the ratio of the two fuels to the ratio of their prices was somewhat greater than 1.5 in absolute value. We reduced the elasticity to 1.2 to allow for the tendency of LP models to "overoptimize." The alternatives were set above and below the important boundary elasticity of 1. It must be noted that the empirical basis for this parameter is as weak as any we rely on.

Turning now to the parameters in Equation (6b), estimates for g_1, g_2, and R are required. Estimates of world fossil fuel reserves vary widely according to the assumptions that are made about economic feasibility. Table 2.11 registers the variety from which our estimates were drawn. The low range includes only proven reserves that will certainly become economically feasible in the foreseeable future. The middle range captures a large increment of reserves that most researchers think will become feasible in that time span; it quadruples the low range by including difficult oil deposits and extensive use of cleansed coal. The upper range adds a small percentage of potential shale availability to the supply and puts world resources well beyond quantities that will be consumed over the span of our study--the next 125 years.

TABLE 2.11 World Resources of Fossil Fuels[a]

A. Certain Economic Feasibility (low R)[b]	
IIASA	2.7×10^{12} mtce
WAES	3.2×10^{12} mtce
Value employed for low R	3×10^{12} mtce
B. Probable Economic Feasibility (middle R)	
IIASA	11×10^{12} mtce
IEA (high)	12.2×10^{12} mtce
IEA (low)	12.0×10^{12} mtce
Value employed for middle R	12×10^{12} mtce
C. Including Shale Estimate (high R)	
Total deposits--Duncan and Swanson	144×10^{12} mtce
Value employed for high R (= middle R + 0.07 shale)	22×10^{12} mtce

[a]Sources: IIASA (1981); Energy: Global Prospects, Workshop on Alternative Energy Strategies (WAES) (1977); Reilly et al. (1982); Duncan and Swanson (1965).
[b]These numbers are consistent, component by component, with other incomplete data found in Moody and Geiger (1975), and World Energy Conference (1978).
[c]The inclusion of shale allows for incredible availability of fossil fuel. The 7% utilization rate, chosen rather arbitrarily, generated a resource constraint that was always nonbinding through the year 2100.

The procedure for computing g_1 and g_2 is more involved. For simplicity, first of all, g_2 is set equal to 1; manipulating g_1 provides more than enough flexibility. A range of prices for fossil fuel in some future time after an arbitrary R_1 mtce of fossil fuel had been consumed, is then constructed. Denoting those prices by P_j and the various reserve estimates cited above by $\bar{R}_k$, a collection of g_1 values, now clearly dependent on both P_j and $\bar{R}_k$, are computed according to

$$P_j = g_0 + g_1(j,k)[R_1/(\bar{R}_k - R_1)], \qquad (8)$$

where j and k index high, middle, and low values for P_j and $\bar{R}_k$, respectively. Figure 2.10 shows that this procedure generated three possible paths for each of the three $\bar{R}_k$; i.e., nine separate specifications of the $g_1(j,k)$ and thus nine specifications of Equation (6b). Table 2.12 meanwhile records the prices estimated by several studies for $R_1 = 1100 \times 10^9$ mtce. It is a value chosen because of the availability of these price projections, and the table shows how the necessary aggregate prices are computed. Several other studies cited either prices without aggregation weights or consumption mixes without prices, so they were of little use. It is, nonetheless,

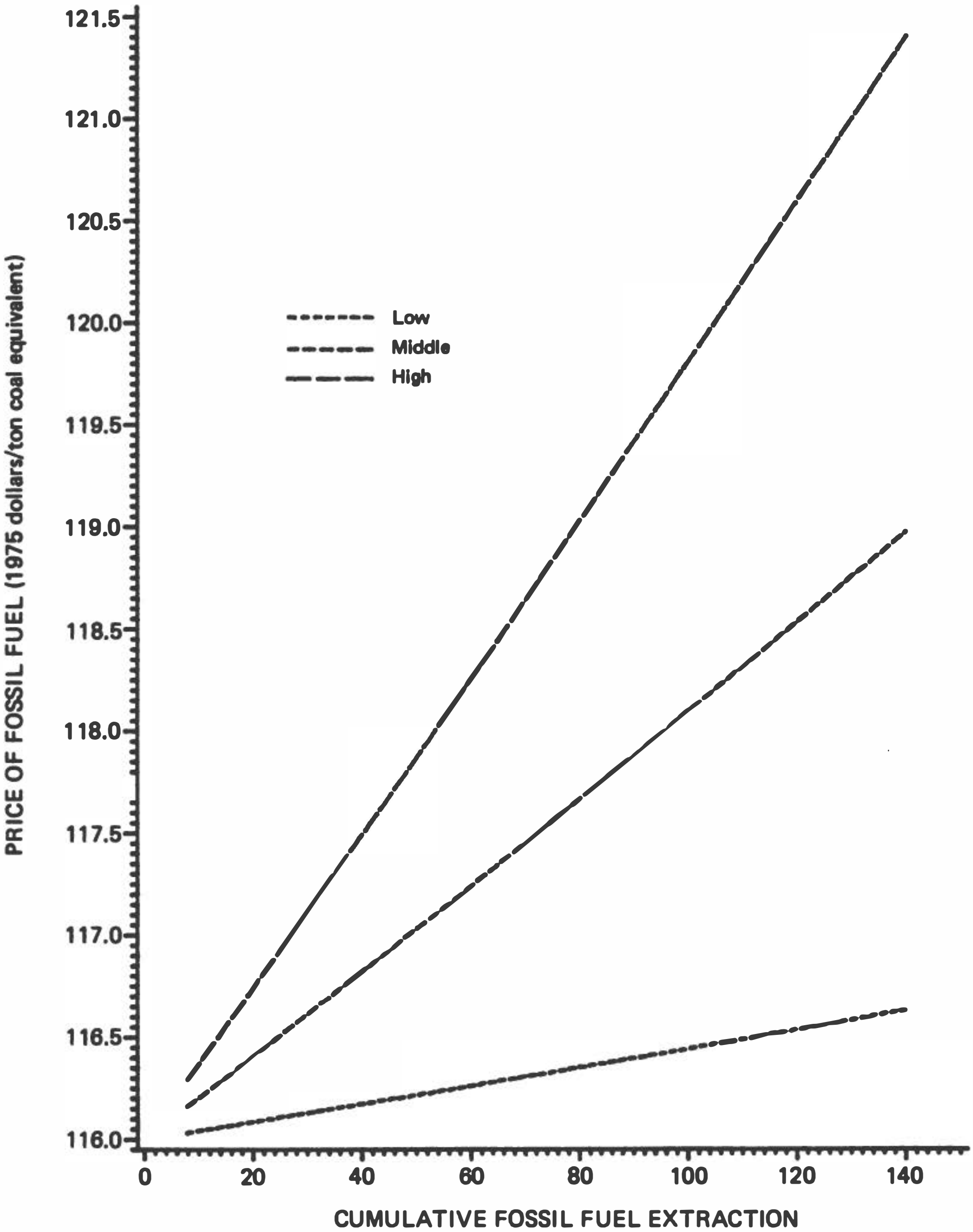


FIGURE 2.10 Secondary (retail) price of fossil fuel as a function of cumulative fossil fuel extraction. Prices are 1975 dollars per metric ton of coal equivalent. Cumulative extraction is measured from 1975 in billion metric tons of coal equivalent. In the terms of this section, these are price paths for a given $\bar{R}_k$ and $P_j = (P_l, P_M, P_H)$ for R_1.

TABLE 2.12 Primary (Wholesale) Fossil Fuel Prices when Cumulative Extraction from 1975 (R_1) = 1100 x 10^9 mtce

Source of Projection[a]	Oil[b]	Gas[b]	Coal[b]	Aggregate Price[c, d]
IIASA (high)	$130(0.33)	$70(0.29)	$25(0.39)	$73/mtce
IIASA (low)	$150(0.34)	$65(0.23)	$25(0.43)	$76/mtce
IEA (low)	$140(0.28)	$65(0.18)	$25(0.54)	$64/mtce
IEA (high)	$140(0.34)	$65(0.18)	$25(0.47)	$71/mtce
RFF	$123(0.38)	$75(0.27)	$40(0.35)	$81/mtce
Mean				$73/mtce
Standard deviation				$5.7/mtce
Cell extremes				$65; $81/mtce

[a]Sources: IIASA (1981), Reilly et al. (1982).
[b]The proportions of each source in the total consumption are given in the parentheses.
[c]Aggregate prices are computed as weighted sums of the components, with the weights being the proportions noted in the parentheses. Thus, for IIASA (high) (0.33)($130) + (0.29)($70) + (0.39)($25) = $73/mtce.
[d]Many studies did not provide a full range of necessary data. A compilation of 23 surveys of projected oil prices produced during the 1981 Stanford International Energy Workshop did, however, provide a good sample of oil price expectations through the year 2000. Extrapolating those data through 2030 [the year when most studies see R(t) = 1100 x 10^9 mtce] using the range of weights listed here produced a much wider range extending from $43/mtce to $106/mtce. These are rough estimates, of course, but lead to some widening later.

interesting to note that interpolating between the estimated oil prices used in this study for 2025 (and contained in Table 2.12) and the 1981 oil prices provides us a benchmark for comparison. This benchmark fell in the third decile of 23 studies (i.e., lower end) compiled during the Stanford International Energy Workshop of 1981 (Energy Modeling Forum, Stanford University).

Even with these data collected, our work on the price equation for fossil fuel is not completed. Section 2.1.2.1 outlines an approximation procedure that allowed both the simplicity of the nested production function recorded in Equation (1) and the flexibility of being able to vary the elasticity of substitution between energy and labor across time. It was an adjustment made necessary by a desire to incorporate a source of dynamic uncertainty into the model that could well loom large in the balance of this century. Much in the same spirit, we now need two similar adjustments in the fossil fuel equation. The first is designed to preserve the structure of Equation (3) even as the short-term effects of restricted oil supplies were recognized. The second gives society enough foresight to prepare for the imminent exhaustion of fossil fuel supplies.

The need for the first adjustment can be seen by looking at the very recent past. The model, as presented above, allows instantaneous substitution into and out of aggregate energy and between its carbon and noncarbon components each year in response to changes in relative input prices. While this is a conventional assumption for long-range growth models in which people are presumed to predict price movements accurately and plan accordingly, it does not conform well to the uncertain world that has confronted energy consumers since 1975. The dramatic disruption in world oil supplies caused by the advent of OPEC in 1973, the events in Iran, the oil glut, and the decontrol of gas and oil prices in the United States are all examples of factors that have contributed to the uncertainty; and their net effect has been to increase the primary price of carbon-based fuel from $35/mtce in 1975 to $76/mtce in 1981. Investment decisions taken in 1975 were, however, made in response to 1975 prices and 1975 expectations. Much of the world's present capital stock was, in fact, put into place before the oil shocks of 1973. The decisions that produced these investments were clearly not made with the type of accurate foresight required in the model. Nor can it be presumed that instantaneous substitution would have brought all the existing capital up to date relative to current energy prices. Thus, there exists a need to provide a longer reaction time at the beginning of the model to reflect the difficulty faced by most consumers in responding to such enormous price changes.

One possible adjustment would involve making alterations in the production function, but that course is again rejected to avoid complexity. Rather than produce the complications of more complex intertemporal substitution, we modify the early fossil fuel prices against which consumption decisions would be made. For the first 25 years of each run, in particular, a linear combination of projected current fossil fuel prices (computed from 1981 prices) and the lower 1975 prices is employed to slow the rate of growth of fossil fuel prices; the result is a reduction in the reaction to higher fossil fuel prices mandated by Equation (3). After the year 2000, however, this delayed reaction is stopped and decisions are assumed to be made on the basis of prevailing fuel prices.

More specifically, the 1975 primary price of fossil fuel ($35/mtce) is used in conjunction with the price ranges computed for $R_1 = 1100 \times 10^9$ mtce to compute the appropriate g_1 coefficients. They are recorded here in Table 2.13. This computation, with the R_1 price range expanded to $43, $73, and $103 per mtce to reflect the larger dispersion of the Stanford estimates of oil prices, is appropriate because the price estimates on which the range was based were made under 1975 expections. Nonetheless, the primary price of fossil fuel did reach $76/mtce by 1981, and distribution costs did rise by $40/mtce from 1975 through 1981. These figures, therefore, are used as initial conditions for the long-term supply equation; i.e., the equation

$$P^c(t) = \left(76 + g_1\left\{R(t)/[\bar{R} - R(t)]\right\}^{g_2}\right)\exp[h_1(t)t] + 40 \qquad (9)$$

fully specifies the long-term price equation for fossil fuel. Still, the point of this adjustment is that imposing these inflated prices in

TABLE 2.13 The g_1 Parameters of $P^c(t)$[a]

R	Price at R_1[b]	g_1	Probability
3200×10^9 mtce	$43/mtce	13.8	0.06
3200×10^9 mtce	$73/mtce	65	0.13
3200×10^9 mtce	$103/mtce	118	0.06
11000×10^9 mtce	$43/mtce	72	0.13
11000×10^9 mtce	$73/mtce	342	0.24
11000×10^9 mtce	$103/mtce	612	0.13
21000×10^9 mtce	$43/mtce	145	0.06
21000×10^9 mtce	$73/mtce	687	0.13
21000×10^9 mtce	$103/mtce	1230	0.06

[a]Source: Tables 2.11 and 2.14, Equation (6b), and the text of this section.
[b]In 1975 U.S. dollars.

1981 would not have been consistent with the spontaneous flexibility of the production function. Since the relevant secondary price of fossil fuel in 1975 is $62/mtce and not $116/mtce, the operative fossil fuel price for the first 25 years is adjusted linearly according to

$$[P^c(t)]' = [(25 - t)/25]62 + [t/25]P^c(t).$$

Notice, as illustrated in Figure 2.11, that $[P^c(t)]'$ and $P^c(t)$ are therefore coincident only after the year 2000.

The second adjustment is necessary to preclude the possibility that the world would unexpectedly exhaust all of its fossil fuel reserves. The notion here is that there exists a "backstop" technology (such as solar or fusion) that should become economically feasible before exhaustion and that entrepreneurs would provide that technology before the economic effects, perhaps collapse, that unexpected exhaustion would create. For our purposes, we model the backstop as a gradual contraction of reliance on fossil fuel once its price climbed to levels in excess of four times the price of nonfossil fuel. The multiple is selected to match current estimates of the cost of generating hydrogen from conventional sources; the subsequent rate of decline of fossil fuel consumption is assumed to be roughly 6% per year and is estimated from preliminary runs in which the supply of fossil fuel was exhausted in the absence of the backstop.

Consideration of the airborne fraction is the final order of business. Estimates from a variety of experts are cited in Clark (1982), but we found that they were mostly the products of statistically inefficient estimation procedures and highly sensitive to assumptions made about the contribution of carbon dioxide to the atmosphere from the biosphere. The latter sensitivity reflected misspecification of

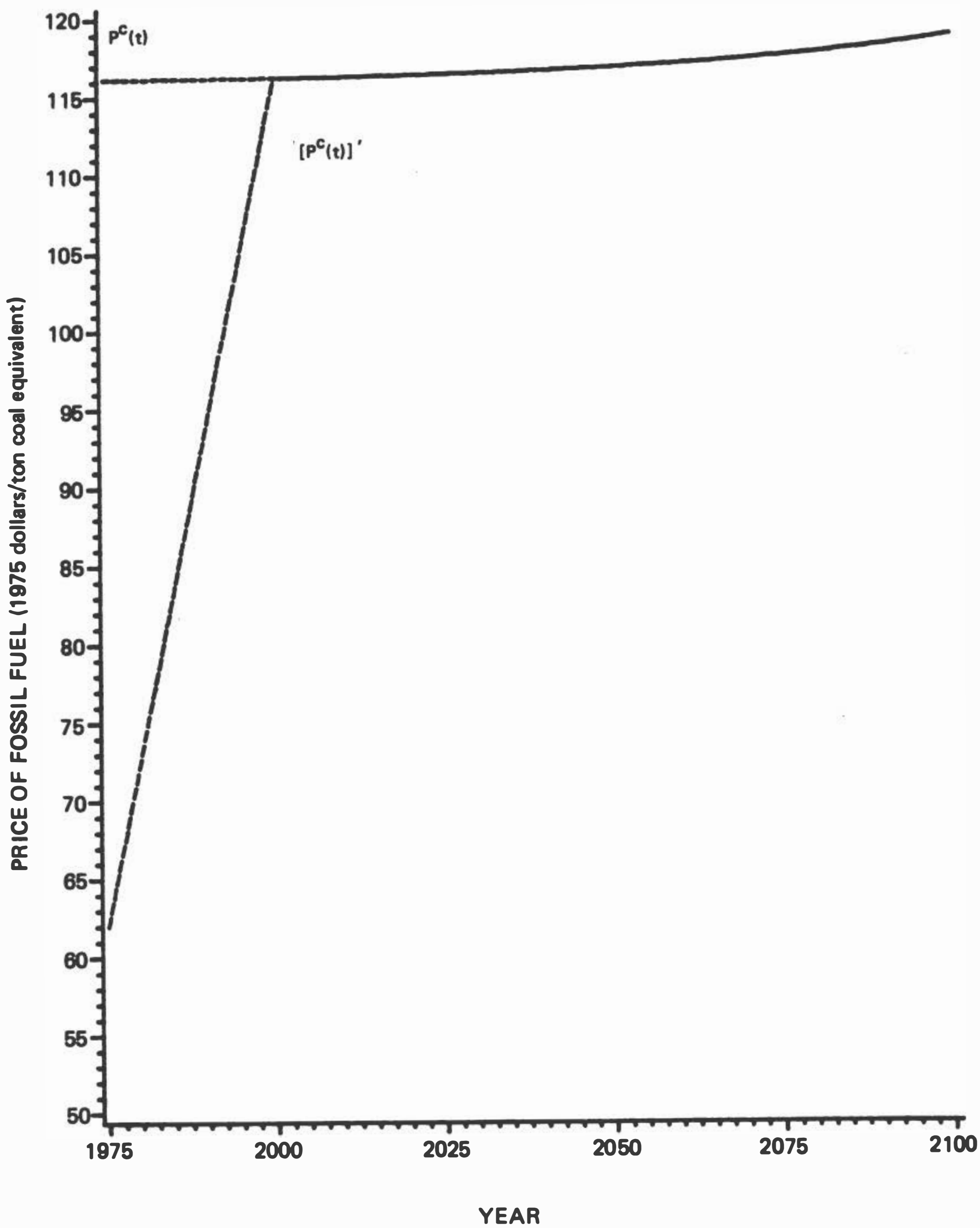


FIGURE 2.11 Price of fossil fuel (1975 dollars per ton of coal equivalent). A comparison of $P^C(t)$ and $[P^C(t)]'$--the adjustment required to accommodate the rapid increase in fossil fuel prices from 1975 through 1981.

the appropriate estimating equation and led us to our own study. At this point, we advance a maximum likelihood estimate of the marginal airborne fraction equal to 0.47, given an average seepage of 0.1% of ambient carbon dioxide into the oceans and an annual contribution from the biosphere of 1 Gt of C (the mean estimate). We differentiate between a marginal airborne fraction (the fraction of current emissions that remain in the atmosphere during their first year) and an average airborne fraction because of the seepage factor. The contribution of each year's emissions decays over time in our model, and that decay will have implications later when we turn to consider emission taxes as policies with which to address the carbon dioxide problem. The extreme cell estimates of the marginal fraction are also computed to discretize the usual normal distribution around a regression coefficient; 0.38 emerges as the low estimate, and 0.59 is the upper extreme.

2.1.2.2.1 Adjustment of Subjective Uncertainty

The inability of individuals, even those with statistical training, to deal efficiently with uncertainty about the future has come under increasing scrutiny. Studies in both the economic and psychological literature have argued, in particular, that individuals tend to underestimate the uncertainty about events.* For present purposes, two reasons for these systematic errors are relevant. First, when people look to previous studies in seeking guidance for their own views, they may place too much weight on the early studies. If one were then to view the range of resulting estimates as an indication of the true uncertainty, the computed variance would be too small.

A simple illustration of this phenomenon, sometimes known as the wine-tasting problem, can make this point. Suppose that a sample of two independent observations, x_1 and x_2, were taken from the same distribution, and let that distribution be normal with mean κ and variance σ^2. Each x_i would therefore be independently, normally distributed with mean κ and variance σ^2. The sample mean, $\overline{x} = (x_1 + x_2)/2$ would then be an unbiased estimate of κ, and $S^2 = (x_1 - \overline{x})^2 + (x_2 - x)^2$ would be an unbiased estimate of σ^2 (i.e., $\{E[S^2]\} = \sigma^2$). If, however, the second scientist looks over the shoulder of the first, he might allow his judgment to be influenced. Say that the reports of observation x_2 were weighted by x_1 so that reported values (y) are $y_1 = x_1$ and $y_2 = ax_2 + (1 - a)x_1$. The reported variance would decline. The reason is that the y_2 would display a variance

$$\sigma^2(y_2) = a^2\sigma^2 + (1 - a)^2\sigma^2 = [1 + 2(a^2 - a)]\sigma^2 < \sigma^2, \text{ for } 0 < a < 1.$$

*See Arrow (1982) for a summarizing review of both.

So, the variance of the reported values is biased downward from σ^2. The infusion of judgment allows the first researcher's result to influence the second, and the observed variance is smaller than the underlying variance.

Second, people seem reluctant to accept the true uncertainty inherent in small samples. Several studies report that individuals frequently base their expectations on one observation even when they are aware that historical experience has been widely varied.* The estimates for the more distant periods recorded in this section seem to suggest such a telescoping of uncertainty. In some cases, the range of estimates declined as the forecast period increased, even though the passage of time should have increased the uncertainties. It appears that, in the face of higher uncertainty, scientists may look to each other for guidance.

To correct for the resulting tendencies to underestimate the degree of uncertainty, estimate ranges are expanded around the computed means; i.e., the ranges are adjusted either to keep the ranges from contracting over time or to make them consistent with historical experience. The adjustments are based on our judgment but are undertaken only if they could be justified by one of these two rationales.

Table 2.14 presents the results of this procedure. The population growth ranges after the year 2025 are, for example, expanded to maintain the 0.5% deviation computed for the 2000-2025 period. The later productivity ranges are similarly expanded to match the uncertainty found in the first two periods. Energy price ranges are, finally, widened in response to the enormous political and economic uncertainties inherent in the world energy market. The survey of 23 projections for oil prices collected during the 1981 Stanford International Energy Workshop (ranging from 10% reductions to 100% increases in the price of imported crude oil) provide some very rough guidance for our energy price uncertainty (Manne, 1982).

2.1.2.3 Results

2.1.2.3.1 Levels and Uncertainties of Major Variables

Four types of experiments are conducted with the fully specified model. In the first, we investigate not only the most likely paths of emissions and concentrations but also the inherent uncertainty that surround those projections. This is accomplished by taking 1000 random samples from the 3^{10} different trajectories. The results of a sample of 1000 runs are recorded in Table 2.15. Figures 2.12 through 2.16 plot the first 100 of those runs for some of the more important variables. And Table 2.16 records the annual growth rates of the most likely path for those variables. Notice that these rates of growth, particularly those for energy consumption and GNP, conform well with

*See Arrow (1982) and the sources cited therein.

TABLE 2.14 Adjusted Ranges[a]

	1975-2000	2000-2025	2025 and Beyond
A. Population Growth			
High	2.0%	1.6%	0.8%
Middle	1.7%	1.1%	0.3%
Low	1.4%	0.6%	-0.2%
B. Productivity Growth			
High	3.4%	0.9%	0.1% (0.5%)
Middle	2.3%	1.6%	1.0%
Low	1.2%	2.3%	1.9% (1.5%)
C. Nonfossil Fuel Price Growth			
High	2.0% (1.3%)	1.0% (0.5%)	1.0% (n.a.)
Middle	0.5%	0.0%	0.0%
Low	-1.5% (-0.2%)	-1.0% (-0.5%)	-1.0% (n.a.)
D. Aggregate Carbon Emissions--no change			
E. Fossil Fuel Prices for $R_1 = 1100 \times 10^9$ mtce			
High	\$103/mtce (\$81/mtce)		
Middle	\$ 73/mtce		
Low	\$ 43/mtce (\$65/mtce)		
F. Airborne Fraction--no change[b]			

[a]Source: Previous tables and the present text. Unadjusted figures are indicated in parentheses when adjustments to widen the ranges have been made.
[b]The uncertainties cited were measurement problems and were biometrically evaluated from the carbon dioxide literature; they were not subject to the types of underestimation cited here.

the averages of the projections cited in Ausubel and Nordhaus (Section 2.2) through the year 2025. The 50-year averages predicted by the 1000 runs are, in fact, 2.1% and 3.3% for energy and GNP; the averages for the previous studies are 2.4% and 3.4%, respectively. The results presented here should not, therefore, be considered to be the products of a model that embodies radically different expectations about economic growth than the consensus of professional opinion.

The uncertainty surrounding the average path is, however, quite striking. The measured standard deviations of all variables expand over time, and that expansion is sometimes dramatic. For carbon emissions and concentrations, in particular, a fair amount of certainty through the year 2000 balloons to the point where, by 2100, standard deviations of their projections equal 60% and 23% of their means, respectively. Put another way, the extreme values for concentrations run from 377 ppm to 581 ppm in the year 2025, and from 465 ppm to 2212 ppm in the year 2100! Those interested in the actual distributions of

TABLE 2.15 Results of a Sample of 1000 Runs (Probability Weighted Means and Standard Deviations)

	1975	2000	2025	2050	2075	2100
Means						
Energy consumption	8.71	12.49	24.47	32.89	43.34	57.90
CO_2 emissions	4.59	5.37	10.21	13.94	17.55	19.39
Atmospheric concentration	340.	367.	425.	515.	634.	779.
Price of fossil fuel	0.067	0.133	0.144	0.163	0.207	0.274
Price of nonfossil fuel	0.257	0.295	0.299	0.303	0.309	0.315
Fossil consumption	7.90	9.14	17.09	21.2	24.2	26.
Nonfossil consumption	0.81	3.35	7.38	11.7	19.1	31.2
Output	6.93	17.8	36.8	53.49	77.94	113.
Alpha	0.894	0.881	0.880	0.877	0.874	0.870
Standard Deviations						
Energy consumption	0.18	3.70	8.45	13.5	21.3	36.5
CO_2 emissions	0.12	2.06	4.31	6.69	8.84	11.72
Atmospheric concentration	0.29	6.60	25.9	61.4	112.	181.
Price of fossil fuel	0.00011	0.0185	0.0253	0.0373	0.145	0.232
Price of nonfossil fuel	0.00300	0.0502	0.0633	0.078	0.094	0.113
Fossil consumption	0.216	3.50	7.22	9.81	11.73	15.81
Nonfossil consumption	0.055	1.92	4.96	9.15	17.6	32.0
Output	0.101	3.33	8.90	16.6	29.9	53.1

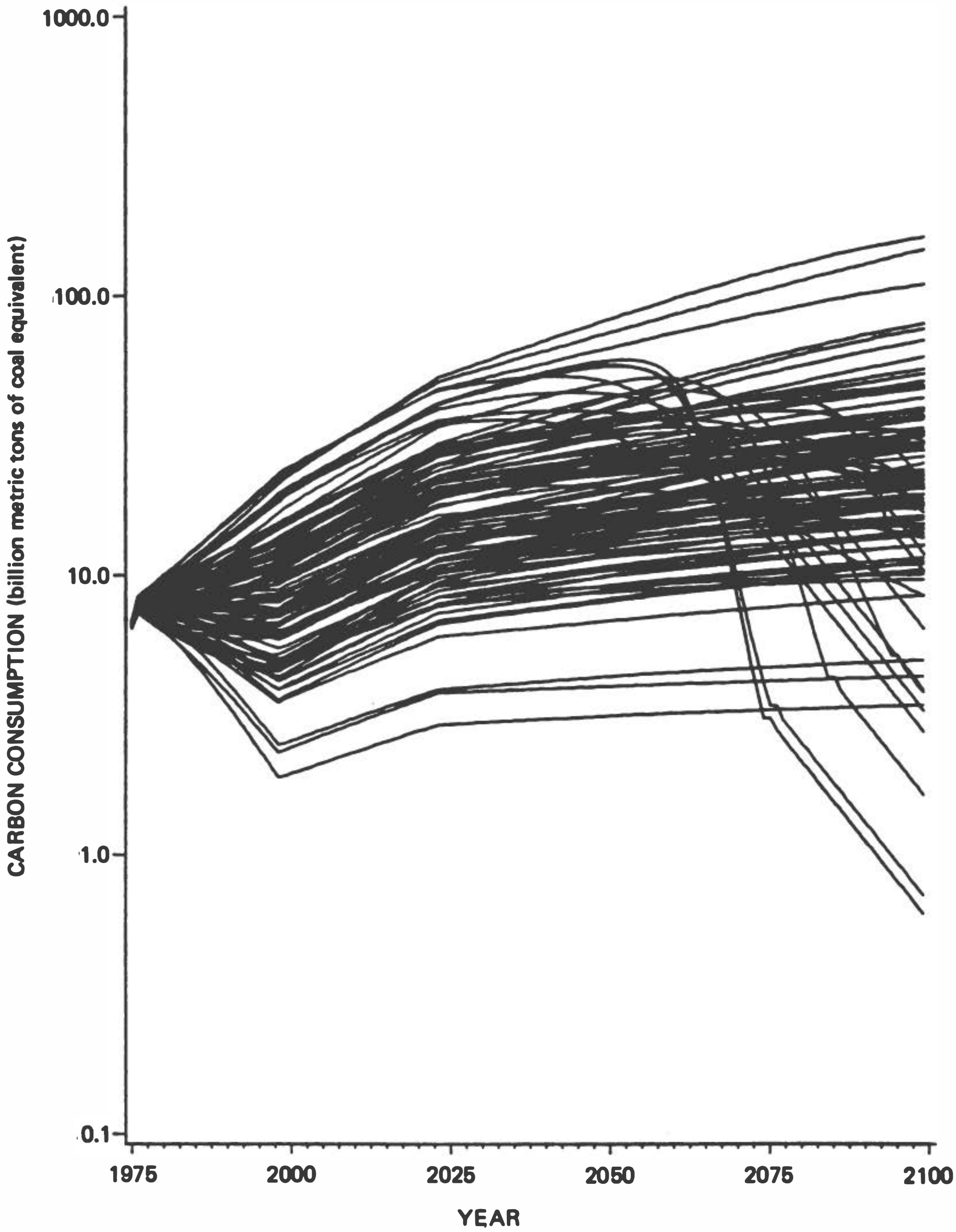


FIGURE 2.12 Fossil fuel consumption for 100 randomly drawn runs (billion metric tons of coal equivalent per year).

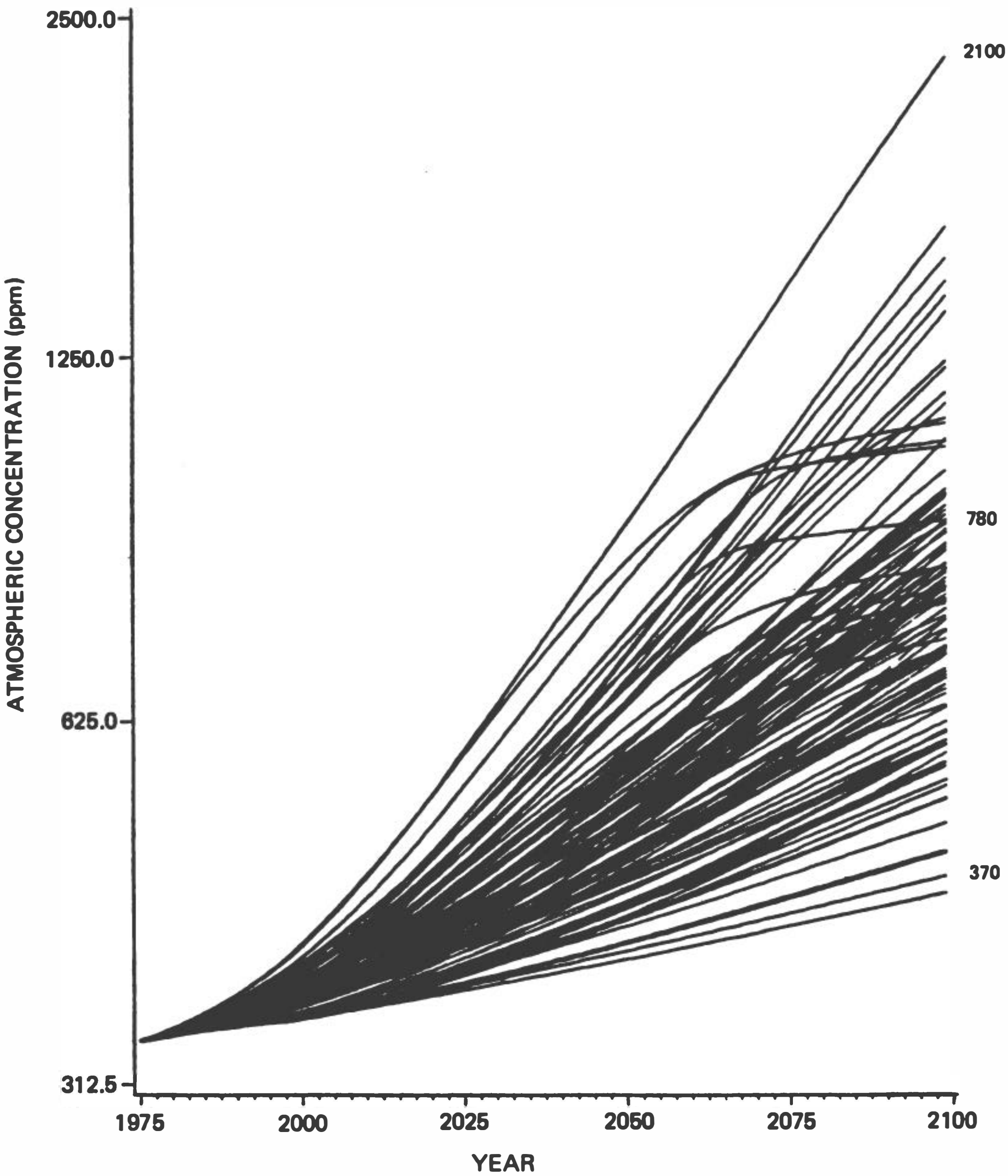


FIGURE 2.13 Atmospheric concentration (parts per million) of carbon dioxide for 100 randomly drawn emission runs. The numbers on the right-hand side indicate the mean concentration for the year 2100 and the extreme high and low outcomes.

emissions and concentrations for critical years are referred to Figures 2.17 and 2.18.

The model presented here finds that carbon dioxide emissions are likely to grow steadily over the next century or so, with an atmospheric concentration reaching 600 ppm, in our most likely case, shortly after 2065. If we call attainment of 600 ppm a "doubling," our

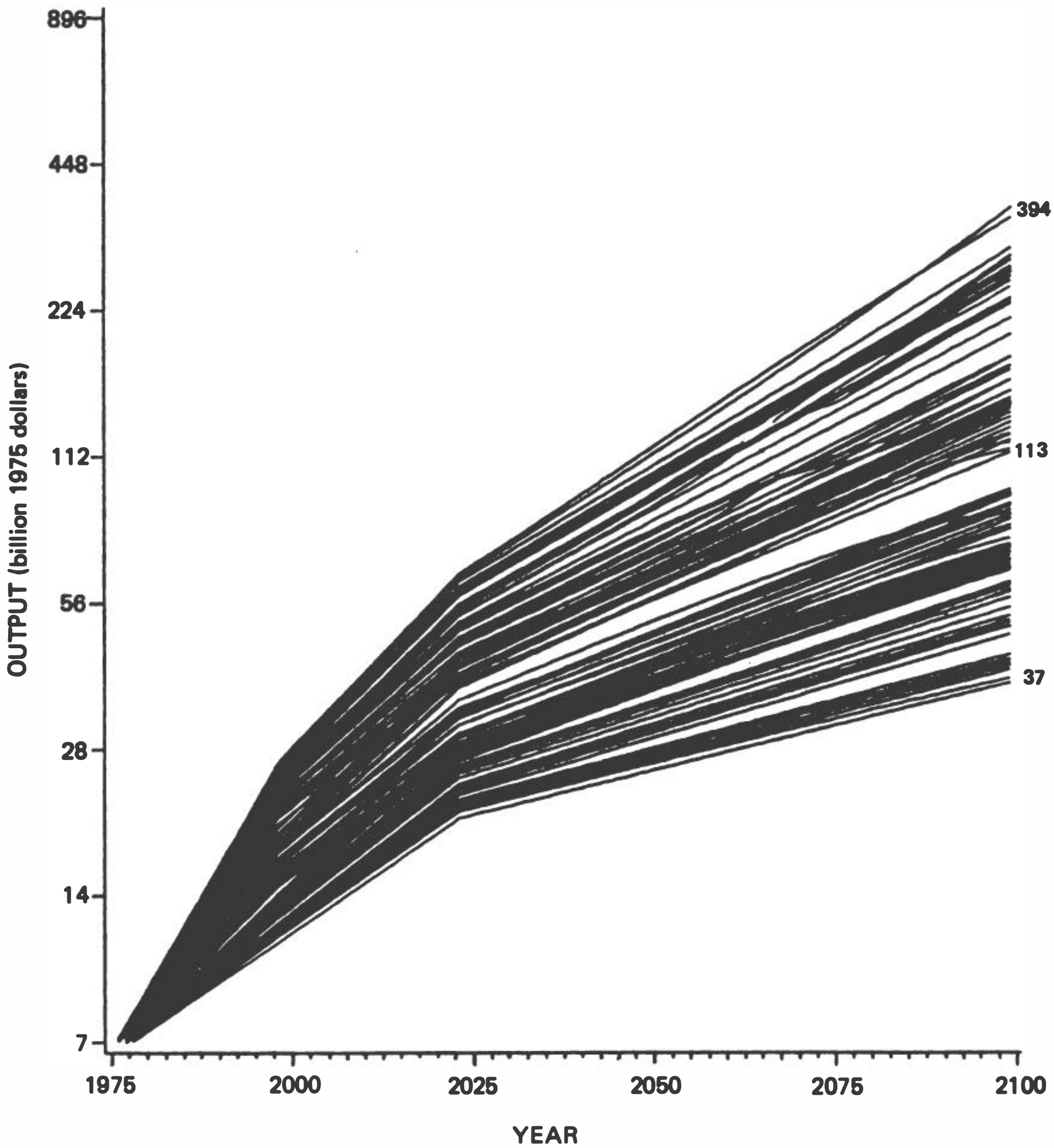


FIGURE 2.14 Gross world product for 100 randomly drawn runs (trillion 1975 dollars).

estimates indicate a doubling time longer than some earlier studies. This slower buildup arises primarily because we estimate a greater sensitivity of fossil fuel consumption to rising fossil fuel prices. But while this average result suggests a considerable time before a CO_2 doubling, our analysis also shows a substantial probability that doubling will occur much more quickly. Looking at the distribution for the year 2050, in fact, our results show a 27% chance that doubling will already have occurred. Unless this uncertainty can be reduced by

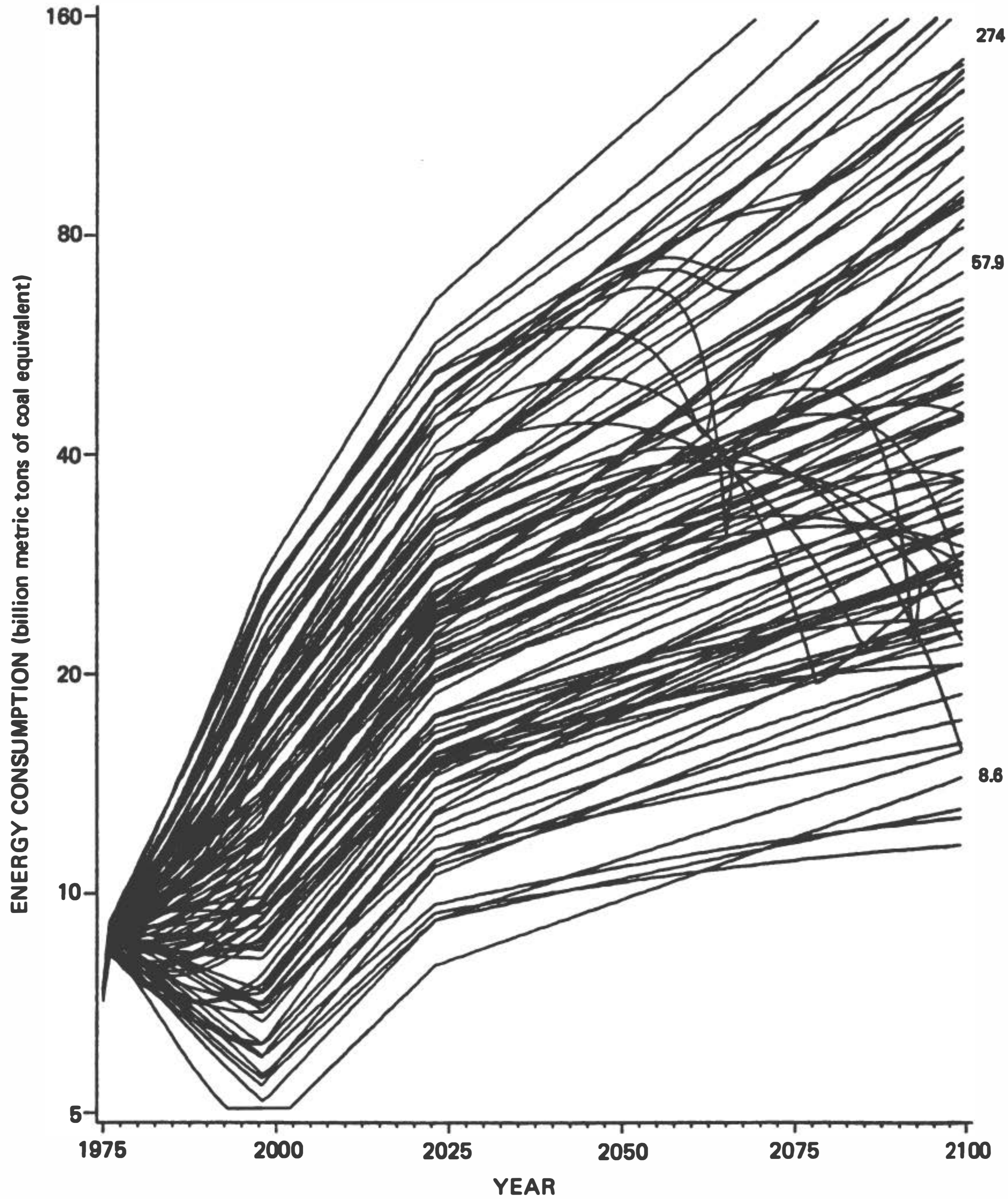


FIGURE 2.15 Energy consumption for 100 randomly drawn runs (billion metric tons of coal equivalent per year).

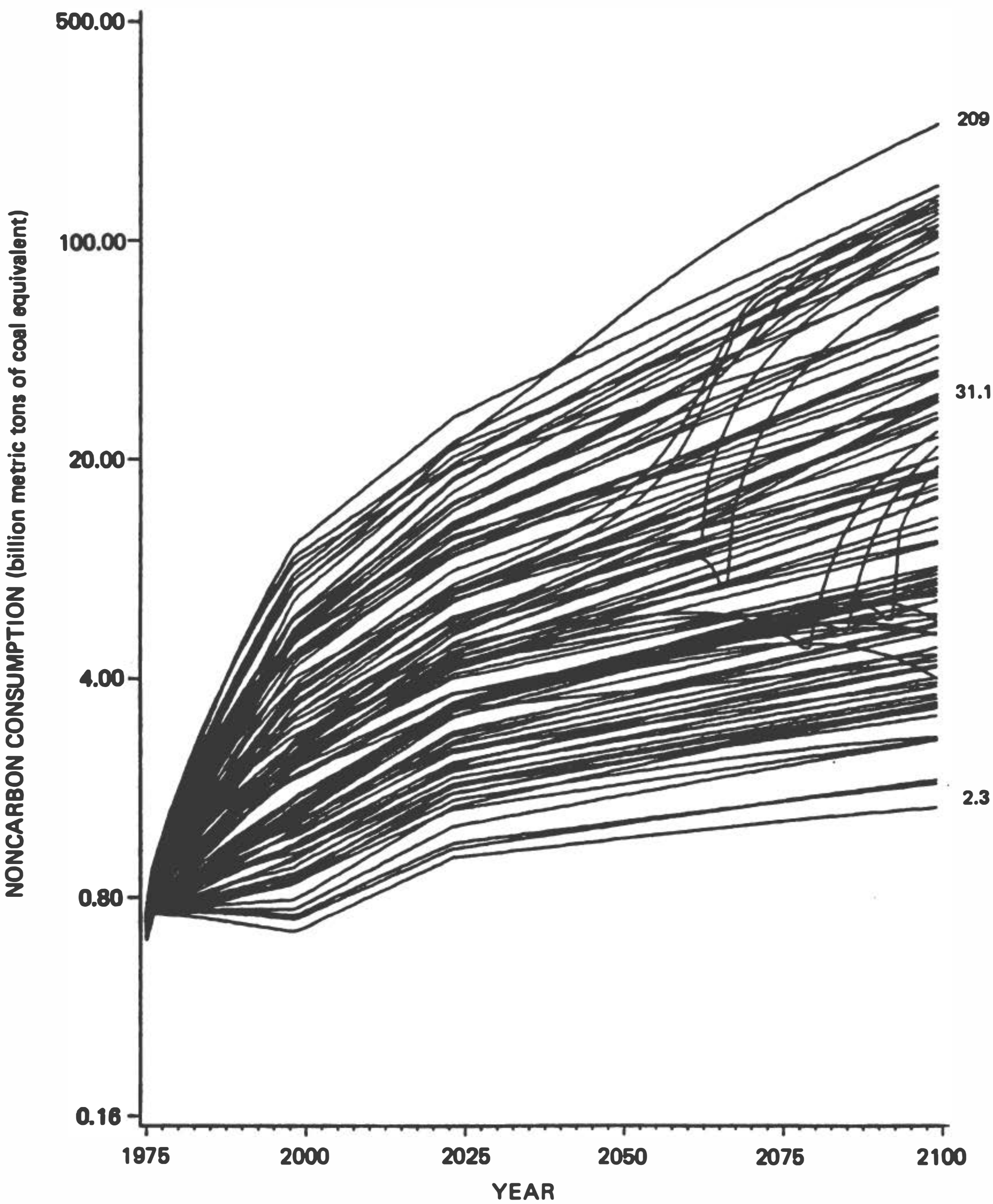


FIGURE 2.16 Nonfossil fuel consumption for 100 randomly drawn runs (billion metric tons of coal equivalent per year).

TABLE 2.16 Annual Growth Rates of Critical Variables (percent per annum)[a]

Variable	1975–2000	2000–2025	2025–2050	2050–2075	2075–2100
GNP	3.7	2.9	1.5	1.5	1.5
Energy consumption	1.4	2.7	1.2	1.1	1.2
Fossil fuel consumption	0.6	2.5	0.9	0.5	0.4
Nonfossil fuel consumption	5.6	3.1	1.8	2.0	2.0
Price of fossil fuel	2.8	0.3	1.2	2.9	1.1
Price of nonfossil fuel	0.5	0.1	0.1	0.1	0.1
CO_2 emissions	0.6	2.6	1.2	0.9	0.4
Concentrations	0.3	0.6	0.8	0.8	0.8

[a]These are calculated as the probability weighted means of the 100 random runs.

further research, it would appear to be unwise to dismiss the possibility that a CO_2 doubling may occur in the first half of the twenty-first century. Perhaps the best way to see this point is to refer back to Figure 2.4. There, only five paths are drawn, but it is clear that doubling occurs before the year 2050 along two of them, the 95th and 75th percentile paths.

Finally, it is surprising that the backstop technology comes into play on 11% of the runs, with the earliest transition occurring in year 2054. Recall that a backstop technology is invoked when fossil fuels are almost completely exhausted. Exhaustion (and appearance of the backstop) usually requires a combination of variables that include low fossil fuel reserves, high productivity growth, high population growth, and small substitution possibilities out of carbon-based fuel. The share of GNP devoted to energy always rises sharply during the period immediately preceding transition to the backstop and thus conforms well to the notion that the conversion to a backstop technology will be expensive. Transition to the backstop then causes carbon emissions to fall to roughly 5% of their peak over the next 25 years.

2.1.2.3.2 Sources of Uncertainty

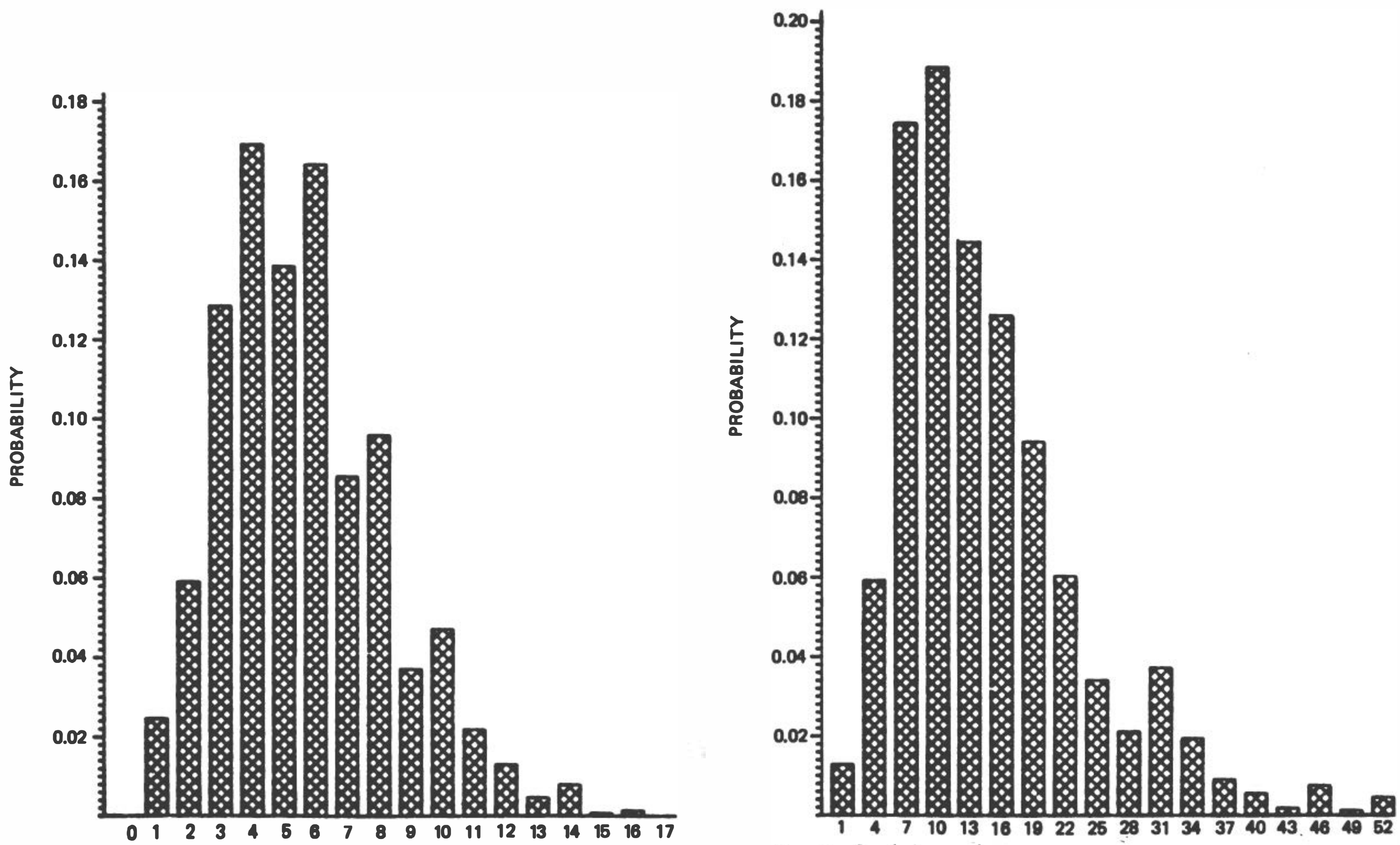
A second experiment is designed to determine which of the 10 sources of uncertainty was most important in producing the ranges that have just been noted; it was conducted in two ways. In the first, each of the 10 random variables are, in turn, set equal to their two extreme values while all the others are fixed at their middle setting. In that way, the individual contributions of each source to the overall uncertainty of the projections is measured and compared. The second column of Table 2.1 records an index of the individual standard deviations that emerged. The second method is, in effect, the converse of the first. Each random variable is, in turn, held at its most likely (or "middle") value while random samples are taken across the other nine; the resulting reduction in the uncertainty is then taken to be a reflection of the marginal or incremental contribution of the fixed variable to overall uncertainty. The first column of Table 2.1 records an index of this measure.

Notice that both measures produce similar rankings. The ease of substitution between fossil fuels and nonfossil fuels rank first in both; this is an area that has thus far been almost ignored in prior study of the carbon dioxide problem. Second in both lists is the rate of productivity growth, but the importance of this variable is intuitively clear and has been apparent for some time. Below these two, a second echelon grouping of four variables appears in both columns: ease of substitution between labor and energy, extraction costs of fossil fuels, technological change in the energy sector, and the airborne fraction. The last member of this list has been heavily studied over the past few years, but even our wide range of uncertainty only pushed it into the middle of the ranking according to either scale. The fuel mix and the rate of growth in the population form a third grouping.

The bottom factors in terms of contribution to uncertainty are trends in relative energy costs and world fossil fuel resources. Holding these last two fixed actually produced higher variation in concentrations in 2100. The cost variable effect is small and probably cannot be statistically distinguished from zero, but the resources effect is pronounced. It is, however, easily explained. The backstop technology is invoked only when world resources are set at their lowest value. And when the backstop is imposed, emissions fall quickly to zero and concentrations tend toward roughly the same number. Removing the backstop as a possibility by removing the possibility that world fossil fuel resources might be quite small therefore removes circumstances that have a serious dampening effect on the range of possible atmospheric concentration. An expanded variance should therefore be expected.

2.1.2.3.3 Validation

Our third area of experimentation poses the problem of validating our results. Validation is, of course, a major issue arising in the estimation and use of very-long-run economic and energy models where the time period over which the data are available is typically much too short to permit testing and validating by usual statistical techniques. Moreover, economic systems evolve and mutate over time, so even models that use classical statistical time series tests would be suspect. Our time frame--125 years--clearly heightens concerns about these concerns. This raises the question of whether we have accurately estimated the uncertainty of future events by looking at each of the variables individually, imposing distributions on them and expanding those distributions to account for the likelihood that scientists systematically overestimate the confidence in their results. Two types of tests are run to attempt to answer this question.



EMISSIONS (billions of tons/yr)

YEAR 2000

(a)

EMISSIONS (billions of tons/yr)

YEAR 2050

(b)

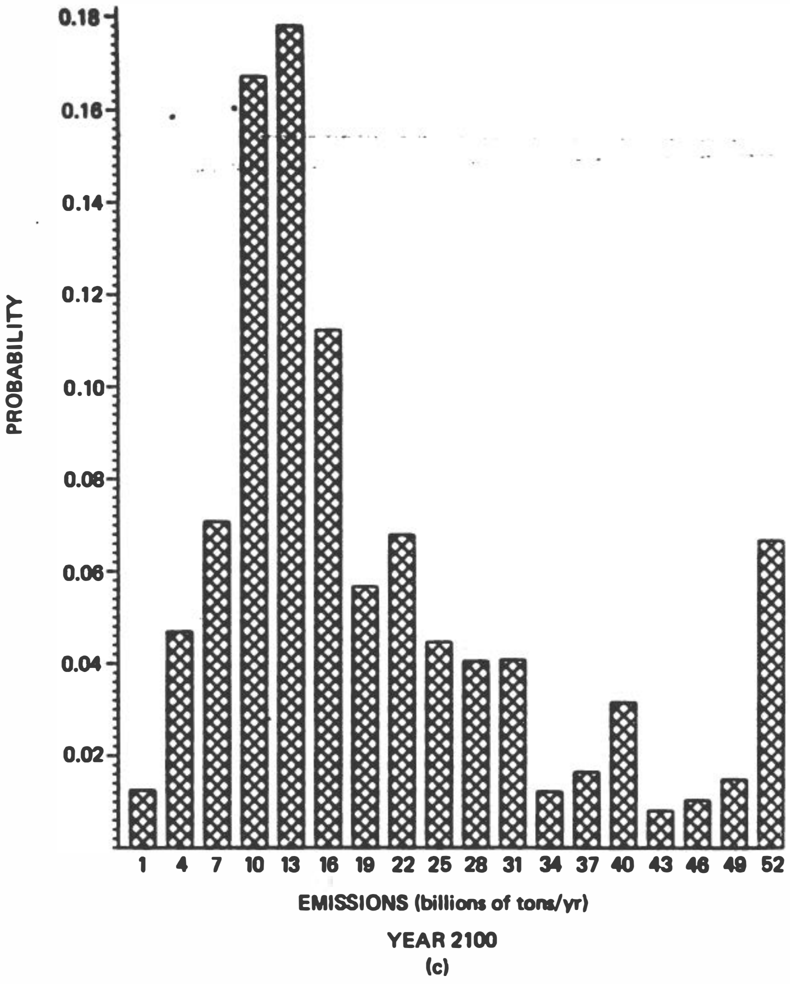
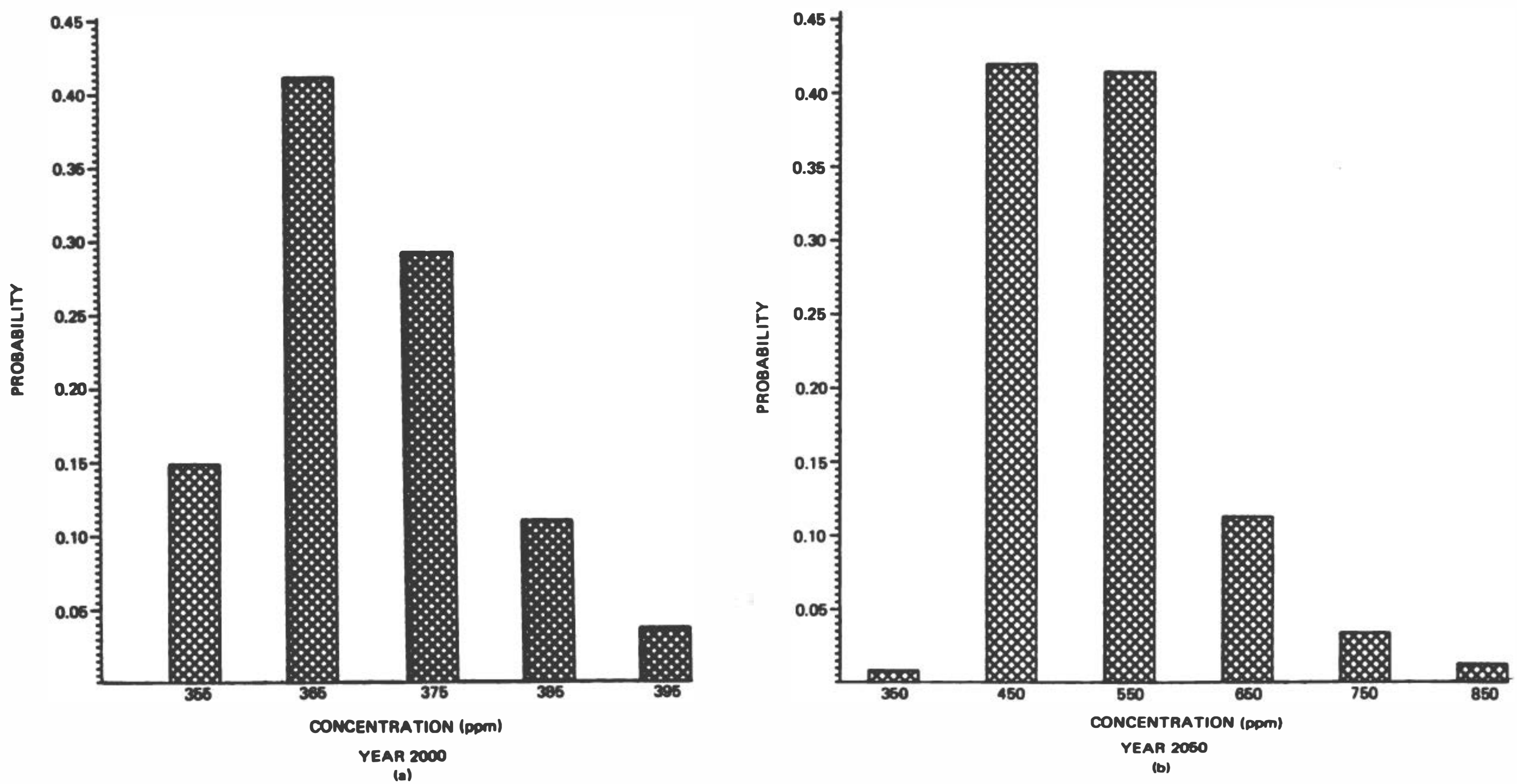


FIGURE 2.17 (a) Distribution of carbon emissions in the year 2000 (weighted sample of 1000 runs). (b) Distribution of carbon emissions in the year 2050 (weighted sample of 1000 runs). (c) Distribution of carbon emissions in the year 2100 (weighted sample of 1000 runs).


PROBABILITY
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
355
365
375
385
395
CONCENTRATION (ppm)
YEAR 2000
(a)
PROBABILITY
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
350
450
550
650
750
850
CONCENTRATION (ppm)
YEAR 2050
(b)

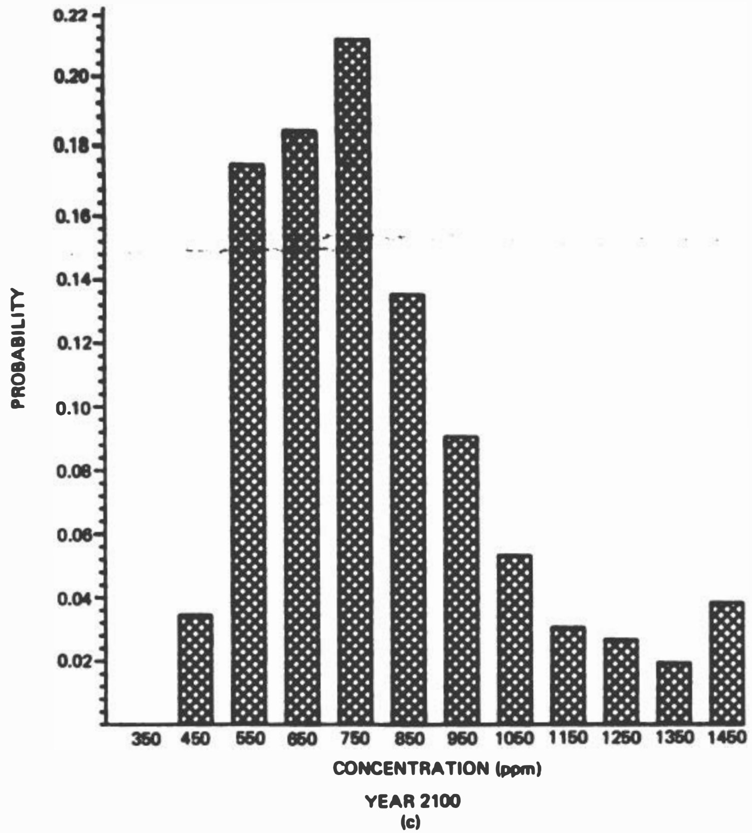


FIGURE 2.18 (a) Distribution of atmospheric concentrations in the year 2000 (weighted sample of 1000 runs). (b) Distribution of atmospheric concentrations in the year 2050 (weighted sample of 1000 runs). (c) Distribution of atmospheric concentrations in the year 2100 (weighted sample of 1000 runs).

TABLE 2.17 Alternative Estimates of the Uncertainty of Carbon Dioxide Emissions (Calculated as the Standard Deviation of the Logarithm of Emissions)

Time from Last Data (t)	Statistical (Calculated from Historical Data) Static[a]	Dynamic[b]	Model[c]
0	0.005	0.06	0.04
25	0.14	0.50	0.56
50	0.28	0.75	0.61
75	0.42	0.76	0.67
100	0.56	0.99	0.68
125	0.70	n.a.	0.85

[a]Calculated as t x se(g), where t is time in future and se(g) is the standard error of g in a regression log (emissions) = a + gt, over the sample period 1960-1980. The equation was estimated assuming first-order autocorrelation of residuals.
[b]Calculated as the standard deviation of a forecast of log (emissions) t periods in the future or past. The number of nonoverlapping samples were 10 for t = 0, 9 for t = 25, 6 for t = 50, 4 for t = 75, and 2 for t = 100.
[c]Calculated as the standard deviation of log (emissions) for 100 randomly selected runs.

We first use classical prediction theory to estimate the prediction errors that are consistent with the data over the period 1960-1980 (see, for example, Johnston, 1972; or Malinvaud, 1980). Under this approach, we assume that there was a "true" growth rate of emissions, g, and that the data over the 1960-1980 period are an unbiased sample of that true growth rate. The mean growth rate over this period is 3.67% per annum, and the standard deviation of the growth rate is 0.561% per annum. Using this approach, we show in column 2 of Table 2.17 the estimated standard errors of emissions that would be expected over forecast periods extending further and further into the future.

In the second approach, the historical data are used to provide out-of-sample forecasts. (This technique has been used infrequently. For an example as well as further discussion, see Fair, 1978.) Under this approach, we estimate a growth trend for each of five 21-year periods (1860-1880, 1880-1900, 1900-1920, 1920-1940, 1940-1960). On the basis of the estimated trend functions, we then forecast into the future (unknown then but known now) through 1980. Thus we obtain, respectively, 100, 80, 60, 40, and 20 years of out-of-sample forecasts. The same procedure is then used to "backcast," that is, to fit functions to recent data and then to project backward into time what emissions should have been. In the backcast exercises, for example, we fit a trend function to the data for 1960-1980, then use that estimated relation to calculate emissions over the period 1860-1960. Again, five 21-year trends are estimated and five different sets of backcasts are constructed.

From the 10 sets of forecasts and backcasts, we construct a set of out-of-sample errors, 0, 25, 50, 75, and 100 years away from the sample--future or past. The root-mean-squared errors are then calculated; they are labeled as "dynamic" statistical error forecasts and are shown in column 3 of Table 2.17.

The backcast procedure may at first appear bizarre. It is an implication of the model we are using, however, that estimates of the structure are equally valid forward and backward into time. This implication arises because the trend model has no explanatory variable but time, as well as because the trend model assumes that there is no change in the underlying economic structure. It should be emphasized, however, that use of this type of trend extrapolation model to forecast emissions in no way is an endorsement of such a technique for all purposes. We are employing it here only for validation purposes.

The results of this validation test indicate that the error bounds for emissions estimated by the model, recorded in column 4 of Table 2.17, are within the bounds generated by the two historical error estimation procedures. In general, the model produces error bounds greater than the classical statistical technique shown in column 2, but smaller than the dynamic estimates shown in column 3.

If we were to choose between procedures for estimating errors, we would be inclined toward the dynamic rather than the static as a realistic estimate of forecasting uncertainty. The reason for this inclination is that the static estimate assumes that there is no change in the underlying structure of the economy, so that future growth rates are drawn from the probability distribution generated by the in-sample growth rates. The dynamic model, on the other hand, recognizes that there is evolution in the structure of the economy, so that the distribution from which we draw observations is likely to drift around over time. Assuming that the pace of economic structural change over the next 100 years will be about as rapid as that over the last 100 years, the dynamic estimates give a better estimate of the realistic error bounds for a forecast of the future. To the extent that careful structural modeling allows us to improve on a naive extrapolation of trends--which is after all the major point of economic and energy models of the kind we introduce here--the error bounds of the model should be an improvement over the dynamic error bounds. And, finally, it should be noted that these exercises were conducted after the model had been constructed and estimated; no tuning of the model has been undertaken to bring it in line with either series recorded in Table 2.17.

2.1.2.3.4 Policy Experiments

Our final set of experiments considers the possibility that governments will intervene to curtail CO_2 emissions. There are clearly a wide variety of approaches to discouraging fossil fuel combustion and CO_2 emissions. Some might take the form of taxes on production or consumption of carbon-based fuels; nonfossil sources might be encouraged; countries that have large coal reserves might place export limitations or heavy taxes on coal exports. Government might agree to national CO_2 emissions quotas and then enforce these in a wide variety of ways. At this point, we do not pass on the likelihood or desirability of these different policies--rather, we attempt to investigate their impacts.

For purposes of analysis, it is convenient to convert all policies that discourage use of CO_2 into the carbon-equivalent taxes. As an example, say that a 2x% tax on carbon fuels would always produce an x% reduction in their use. We would then use this hypothetical formula as a way of representing any quantitative restriction on carbon-based fuels. Whatever the set of policies, we can derive the tax rate on fossil fuels that would produce the same restraint on CO_2 emissions. This equivalent tax is the carbon-equivalent tax investigated here. We consider only the most likely run--the case in which all the random variables are set equal to their middle values. Because of the crudeness of the policy, the results quoted below should be viewed as being extremely tentative.

Five different taxes are imposed on the supply equation for fossil fuel. Two are taxes increasing from zero to $20 per mtce over the course of 10 years and then declining back to zero over the next decade; one pulse begins in the year 1980, and the other begins in the year 2025. For a second set of runs, permanent taxes of $10 per ton are introduced linearly over the first 20 years. One begins in the year 1980, and the other begins in the year 2025. A final tax, modeled after the 100% control case presented in Nordhaus (1979) and called the "stringent tax," imposes a permanent tax that rose linearly beginning in the year 2000 from zero to $6 per mtce by the year 2020, then to $68 per mtce by the year 2040, and finally to $90 per mtce by the year 2060. These are all illustrated in Figure 2.19.

Table 2.18 and Figures 2.20 and 2.21 show the results of the tax runs. Notice there that while the pulse taxes accomplish very little, the permanent tax initiated in 2025 is the most effective among the first four alternatives. This paradox is explained as follows: burning more fossil fuel early and postponing CO_2 reductions lowers the eventual CO_2 concentration because it allows the atmosphere to cleanse itself slowly. To see this, recall that our model allows for a slow seepage (1 part per 1000 per year) of ambient carbon dioxide into the deep oceans. Earlier emissions, therefore, gradually disperse into the deep oceans and produce end-of-period concentrations that are somewhat lower.

The major conclusion concerns the extent to which concentrations appear to respond to taxes. As can be seen, a $10 per ton tax accomplishes only a modest reduction in CO_2 concentrations. Should emissions restraint become desirable, it will take extremely forceful policies to make a big dent in the problem. Even the "stringent"

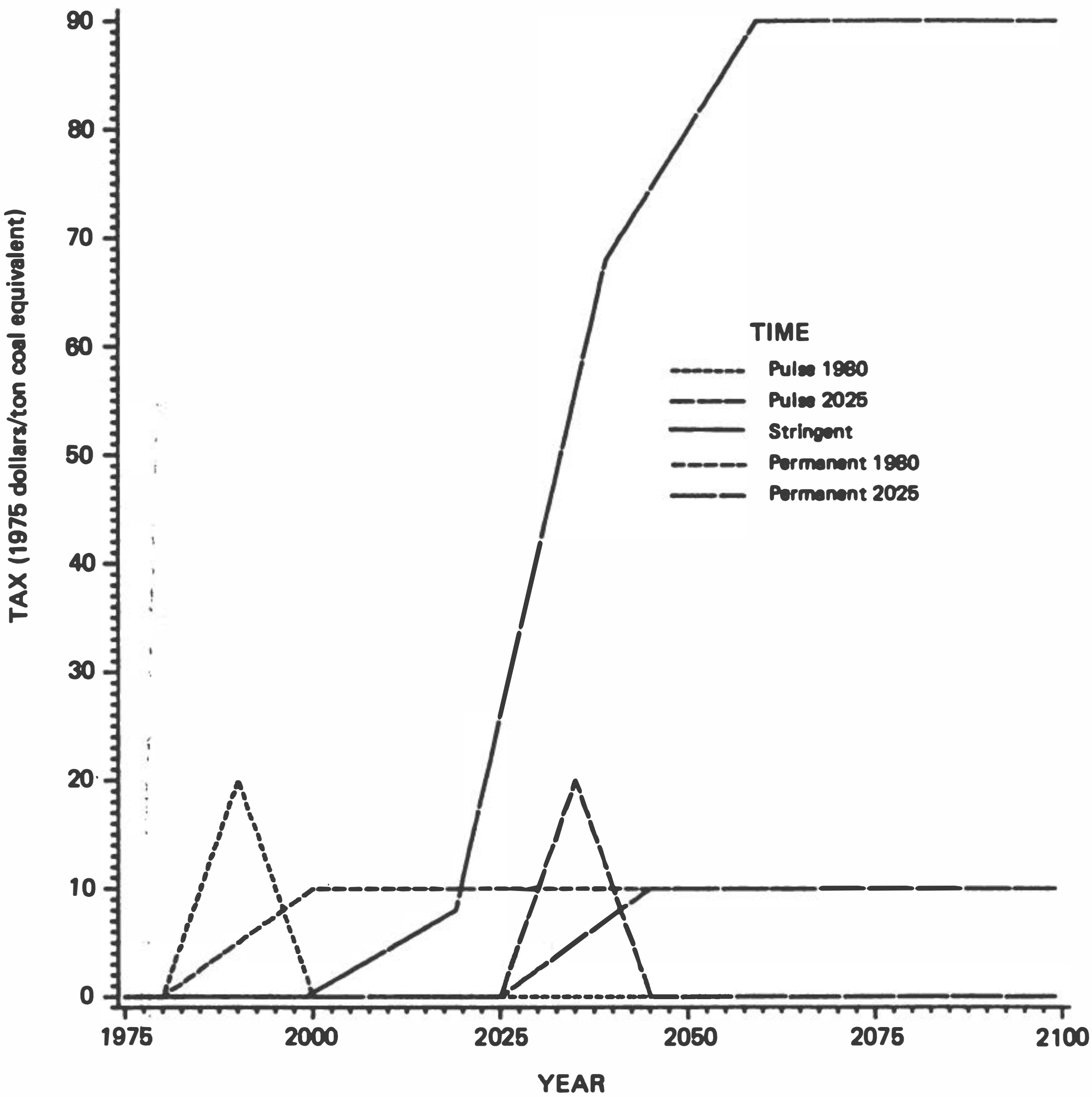


FIGURE 2.19 Taxation on carbon fuel price (1975 dollars per ton coal equivalent). The time tracks of a stringent tax and four alternative $10 per ton of coal equivalent taxes; the temporary taxes peak at $20 to accommodate the model.

TABLE 2.18 Concentrations and Emissions along the Likelihood Path under Various Taxes on Carbon-Based Fuels

	1975	2000	2025	2050	2075	2100
Concentrations						
Base	341	368	428	516	633	780
1980 Permanent[a]	341	367	423	506	617	759
1980 Peaked[b]	341	367	423	513	633	778
2025 Permanent[c]	341	368	428	513	632	763
2025 Peaked[d]	341	368	428	521	638	783
Stringent Taxes[e]	341	368	425	487	561	661
Emissions						
Base	4.61	5.54	10.3	13.3	17.5	20.0
1980 Permanent[a]	4.61	5.06	9.5	12.5	16.7	19.5
1980 Peaked[b]	4.61	5.31	10.3	14.0	17.6	19.4
2025 Permanent[c]	4.61	5.54	10.3	12.3	16.5	19.3
2025 Peaked[d]	4.61	5.54	10.3	13.1	17.3	19.9
Stringent Taxes[e]	4.61	5.54	8.4	7.9	10.7	13.9

[a]A permanent tax of $10 per ton imposed linearly beginning in 1980 and reaching its full value by the year 2000.
[b]A pulse tax of 20 years' duration beginning in 1980, climbing linearly to $20 per ton by 1990 and then falling to zero by the year 2000; it averages $10 per ton.
[c]A permanent tax of $10 per ton imposed linearly beginning in 2025 and reaching its full value by the year 2045.
[d]A pulse tax of 20 years' duration beginning in 2025, climbing linearly to $20 per ton by 2035 and then falling to zero by the year 2045; it averages $10 per ton.
[e]A gradually increasing tax rising linearly from zero to $8 per ton between 2000 and 2020, from $8 to $68 per ton between 2020 and 2040, from $68 to $90 per ton between 2040 and 2060, and remaining at $90 per ton thereafter. This tax was drawn from Nordhaus (1979, Chapter 8).

taxes, which would place 60% surcharges on the prices of fossil fuels, did not prevent doubling before 2100 in our most likely case.*

*Nordhaus (1979) presented an earlier estimate of the taxes needed to curtail the carbon dioxide buildup in an optimizing linear programming framework. In that calculation the potency of carbon taxes was very close to the estimates here. The estimate here is 0.46% reduction in 2100 carbon dioxide concentration per $1 of carbon tax, while in the earlier work the estimate was 0.36% reduction per $1. Note that comparison is not completely appropriate because these reactions are likely to be nonlinear.

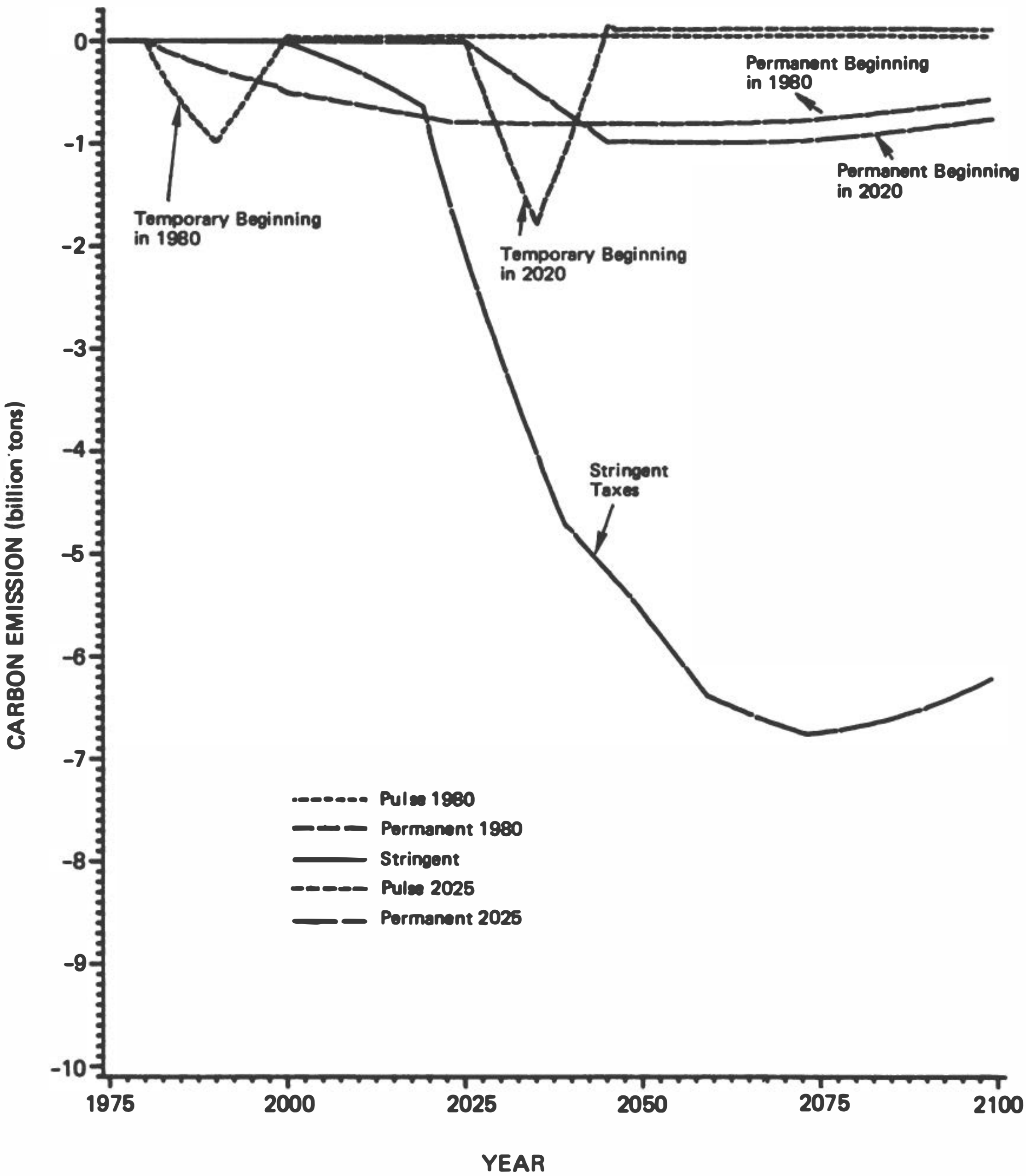


FIGURE 2.20 Plot of carbon emission versus time for taxed runs. Deviation in emissions from the base run for various taxes.

It should be emphasized that this conclusion about the potency of CO_2 taxes (or their regulatory equivalents) is extremely tentative. It is based on a model for which many of the parameters are known imperfectly. On the other hand, the model's conclusions appear to confirm results of a completely independent model, as reported in the last footnote and those of Edmonds and Reilly (1983).

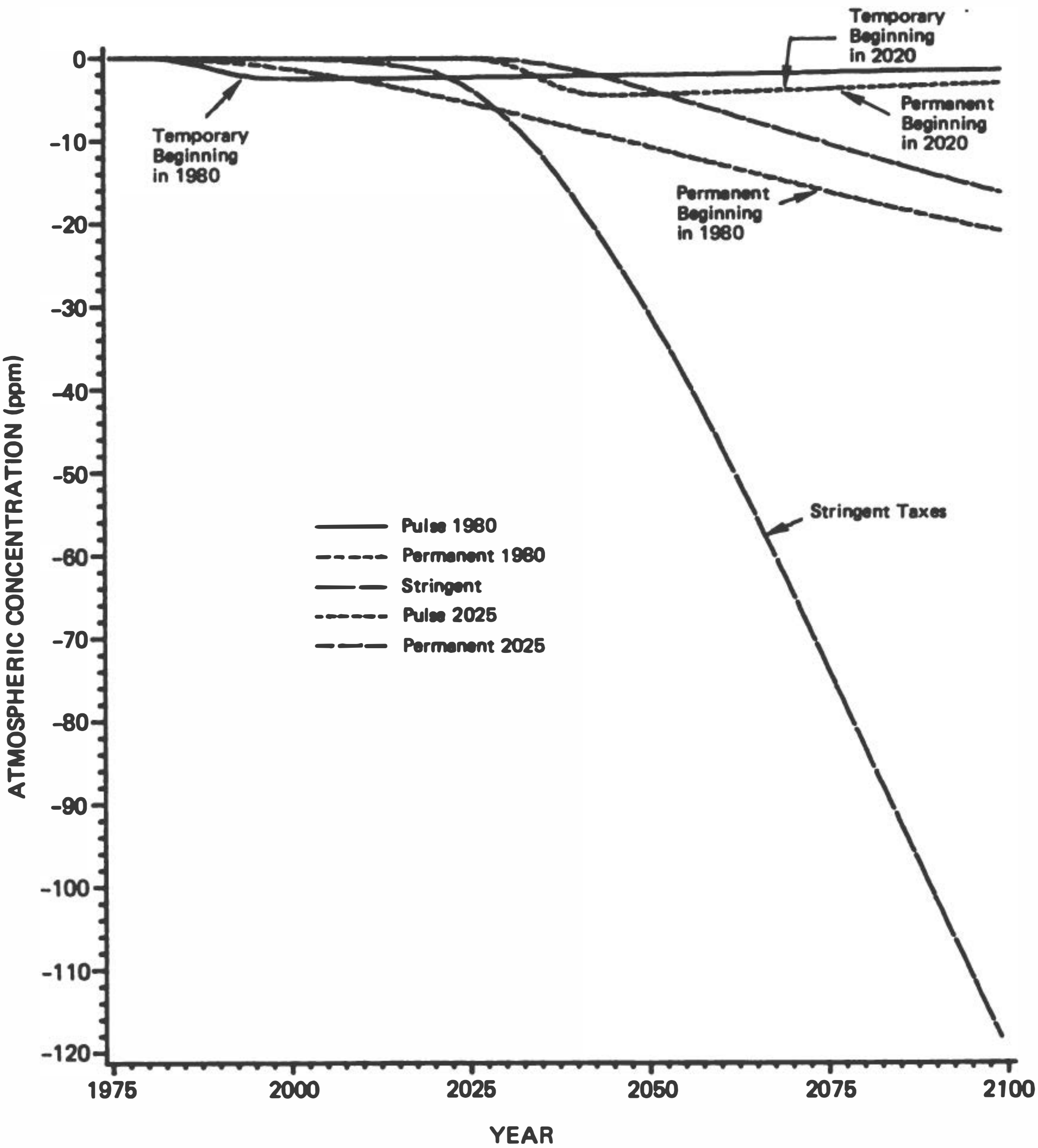


FIGURE 2.21 Effect of carbon taxes on atmospheric concentration (parts per million per year). Deviation of run from base run without carbon taxes.

Nevertheless, the conclusions about the potency of policy are sobering. They suggest that a significant reduction in the concentration of CO_2 will require very stringent policies, such as hefty taxes on fossil fuels. Global taxes of around $60 per ton of coal equivalent (approximately $10 per barrel of oil equivalent) reduce the concentrations of CO_2 at the end of our period by only 15% from the base run. Moreover, these taxes must be global; it is presumed that a tax imposed by only a fraction of the countries would have an effect roughly proportional to those countries' share of carbon emissions.

To the extent that such an approach can offer guidance, therefore, it suggests that there are unlikely to be easy ways to prevent the buildup of atmospheric CO_2. The strategies suggested later by Schelling (Chapter 9)--climate modification or simply adaptation to a high CO_2 and high temperature world--are likely to be more economical ways of adjusting to the potential for a large buildup of CO_2 and other greenhouse gases. Whether the imponderable side effects on society--on coastlines and agriculture, on life in high latitudes, on human health, and simply the unforeseen--will in the end prove more costly than a stringent abatement of greenhouse gases, we do not now know.

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2.2 A REVIEW OF ESTIMATES OF FUTURE CARBON DIOXIDE EMISSIONS

Jesse H. Ausubel and William D. Nordhaus

2.2.1 Introduction

In analyzing prospects and policies concerning future carbon dioxide buildup, it is necessary to begin with projections of levels of CO_2 emissions. Because of the long residence time in the atmosphere of CO_2 emissions, along with the potential for large and durable societal impacts of higher CO_2 concentrations, there is great interest in long-term projections--those extending a half-century or more. While it is clearly necessary to make global long-term projections in this area, the projections are intrinsically uncertain, and the uncertainty compounds over time.

This section reviews methods involved in making projections of carbon dioxide emissions, describes the major projections, and offers some comparisons and comments. It is intended to serve three purposes. First, it should help to acquaint the reader with the state of the art in CO_2 forecasting and the range of previous forecasts. Second, this review may help to identify shortcomings of current efforts and point to directions for new research. Third, it should establish the context of the forecasts developed by Nordhaus and Yohe (Section 2.1) for this report.

Projections of future trajectories of CO_2 emissions can be roughly divided into three categories: (A) projections that are no more than extrapolations and that are primarily intended to be used to initiate studies of the carbon cycle or the climate system; (B) those based on relatively detailed examination of global energy supply and demand in which CO_2 emissions are largely incidental; (C) projections deriving from analysis of the energy system in which changing levels of CO_2 are themselves taken into account. Leading examples of category A, in which CO_2 emissions are projected with little more than passing reference to energy modeling, are Keeling and Bacastow (1977) and Siegenthaler and Oeschger (1978). These papers extrapolate emissions