Incorporating Investment Uncertainty into Greenhouse Policy Models

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Abstract: Greenhouse gas policy decisions require comprehensive undertanding of atmospheric, economic, and social impacts. Many studies have considered the effects of atmospheric uncertainty in global warming, but economic uncertainties have received much less analysis. We consider a key component of economic uncertainty: the return on investments in new technologies. Using a mathematical programming model, we show that ignoring uncertainty in technology investment policy may lead to decreases as great as 2% in overall expected economic activity in the U.S. with even higher losses in possible future scenarios. These results indicate that both federal and private technology investment policies should be based on models explicitly incorporating uncertainty.

1 Introduction

Decisions regarding greenhouse gas emission policies necessarily involve a variety of concerns about the net social impact of the policies in economic and noneconomic costs for climate changes. A critical component in these decisions is the value of uncertainty about the extent of global warming from increased greenhouse gases and about the costs of that warming. Several studies (17,19) indicate that resolving uncertainty about greenhouse impacts has substantial value, but perhaps that early resolution is not critical (17).

One element of these models that may have direct current economic impact is the effect of new technology. This effect has indeed been quite significant in past environmental challenges (1). In specific greenhouse studies, Nordhaus's DICE model (14) implies that geoengineering solutions to climate change may be the best alternative for long-term economic well-being. That and other previous studies do not, however, consider the effects of uncertainty in the development of new technology and the relationship between investment and technology availability.

In our study, we include technology investment uncertainty directly into an

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economic model developed earlier by Manne and Richels (12). As in their model, we use fixed emission targets to achieve given levels of environmental benefits without explicitly evaluating those benefits. We show that ignoring investment uncertainty in policy decisions can have a significant economic impact and that near term decisions can be affected.

2 The Stochastic Model

We constructed a stochastic dynamic optimization model based on the deterministic model, Global 2100, developed by Manne and Richels (11). In this model, the climatic costs of greenhouse, in particular, carbon, emissions are represented through either an exogenous limit or a tax on carbon emissions. Given these possible policy resolutions of climate uncertainty, the goal of the model is then to determine the world-wide economic response, calculated in terms of reduced GNP from the "business-as-usual" case.

Our stochastic model of the U.S. region builds on the Global 2100 model to investigate how results change when uncertainty is explicitly modeled. We focus on the uncertain relationship that exists between investment initiatives and their payoffs. In particular, we model the uncertainties that exist between present day investment and the future availability of noncarbon based energy technology, the availability of nonrenewable resources through exploration, and the extent to which macroeconomic energy efficiency improvements are made. These areas become critical for dealing with greenhouse gases because the success of these investment initiatives will have a great bearing on the world economy's ability to continue to grow without significantly increasing greenhouse gas emissions.

Figure 1 diagrams our Stochastic Global 2100 model. The dashed lines indicate the additions to the Global 2100 model. Note that we include investment effects in efficiency improvements and resource exploration as well as new technologies.

The overall model can be represented as determining a path of consumption (including electric and non-electric energy production), investment, and capital stock to maximize the expected present value of a discounted utility function of future consumption. These decision variables are represented as a vector, x_t, in each period t. The choice of x_t depends, however, on the outcomes of events, such as efficiency improvements and new technology, that cannot yet be observed. We use ξ_t to denote these random quantities that are observable over time. The set of all outcomes is $\Xi = \{\xi = (\xi_1, \ldots, \xi_T)\}$.

Within the decision vector, x_t, in each period, the key components are the types of technologies for both electric and nonelectric energy production, the production from these technologies, and investments in new capital stock, resources, and efficiencies. Tables 1 and 2 give the names and descriptions of the various technologies taken from the Global 2100 Model.

Given the sets of decisions, we assume a probability function P on the out-

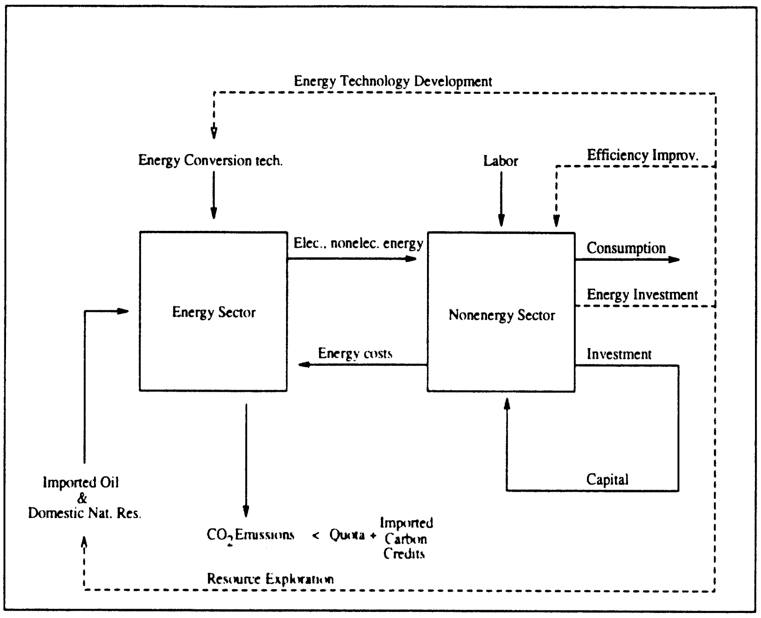

Figure 1: The Stochastic Global 2100 Model. The solid lines show the interactions in Global 2100. The dashed lines indicate the additions in the stochastic model. This diagram shows a constraint (quota) on carbon emissions. An alternative is to include carbon taxes.

come set, Ξ. The goal of the model is then to choose $x = (x_0, \ldots, x_T)$ in a space X to maximize the expectation of the discounted utility function:

$$\int_{\Xi} \sum_{t=1}^{T} f_t(x_{t-1}(\xi_0, \ldots, \xi_{t-1}), x_t(\xi_0, \ldots, \xi_t), \xi_0, \ldots, \xi_t) P(d\xi), \tag{1}$$

where T is the horizon length, f_t represents both the utility objective and any constraints, such as production capacities and resource limits, by imposing infinite penalties whenever a constraint is violated. The formulation in (1) explicitly forces the decision variables x_t to depend only on outcomes, $\xi_0, \ldots, \xi_t$, that have occurred up until period t. This restriction, called ***nonanticipativity*** (21), may also be placed as an explicit constraint on x.

In our example, each period corresponds to ten years of activity. We have eleven (T in the utility function (1)) total periods ranging from the decade ending in 2000 to the decade ending in 2100. At the end of each period, we observe a new set of outcomes, ξ_t, and determine the next set of decisions, x_t.

Completely characterizing the set of possibile future outcomes, Ξ, and describing a probability function, P, requires some form of simplification to obtain a tractable model. These simplifications produce bounds on the range of potential values for (1) (see Birge and Wets (7)) by picking certain outcomes that reflect both pessimistic and optimistic views. Using this process, we limit the set of outcomes to four distinct future scenarios. These scenarios reflect the potential returns on investment with uncertainty resolution beginning in the year 2020. Further resolution occurs in 2030. The result is a tree of scenarios given in Figure 2.

To determine the values on investment returns we took the effective Global 2100 values as mean values. We then constructed scenarios with the same mean (each scenario weighted equally) but with returns reflecting degrees of uncertainty. The returns on investment used for the model, along with the ranges from our most pessimistic scenario (#1) to our most optimistic scenario (#4), are shown in Table 3[1].

In this case, proven technologies, with uncertainty only in resource discovery, receive a much lower range than the new technologies. The term "efficiency" refers to improvements in efficiency that are not modeled explicitly. We use the Global 2100 model mean with a modest range based on Manne and Richels' observations (12). Other ranges from those in Table 3 could of course be considered but would not substantially alter the results below.

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[1]Nonelectrical technologies: EXAJ/10^{12} \$. Electrical technologies: TKWH/10^{12} \$. Efficiency: (Percentage reduction in energy intensity)/10^{12} \$.

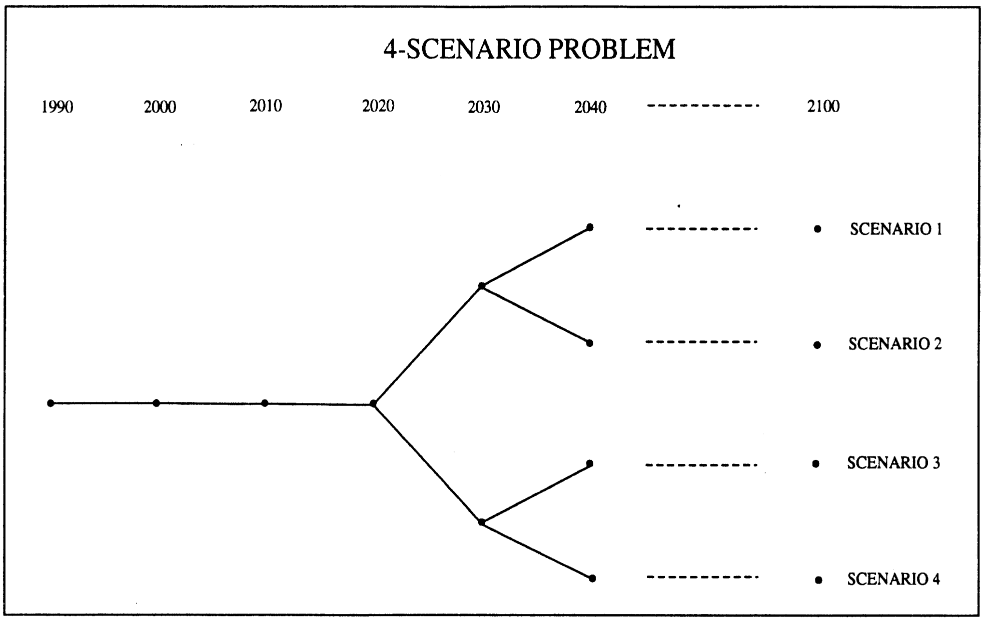

Figure 2: The Scenario Tree.

3 Solution and Results

The model in (1) is a stochastic nonlinear program with a total of almost 3000 variables and 7000 constraints, of which, over 175 constraints involve nonlinear functions with 500 variables. To solve problems of this size (and a larger version involving as many as 32 scenarios), we developed a method that decomposes the optimization problem into subproblems that can be solved in parallel. The implementation scheme is described in (6). The method is based on earlier work by Dantzig and Madansky (9), Benders (2), Van Slyke and Wets (20), O'Neill (16), Louveaux (10), Birge (4), and Noël and Smeers (13).

Our main interest in analyzing the results of solving (1) was to determine the advantages of introducing random parameters into a deterministic model with mean estimates. We measured the stochastic model advantages in terms of the gain in expected objective value (discounted utility) over the deterministic model policy value. This quantity, called the *value of the stochastic solution* (VSS) (3), is related to the *expected value of perfect information* (EVPI) (see, for example, (18)), which measures the value that could be obtained if perfect information about the future were available. To contrast these two quantities, EVPI measures the reward for resolving uncertainty, while VSS measures the value of incorporating uncertainty into a model.

To determine the VSS for (1), we compared the stochastic model with Manne and Richels' Global 2100 model under a single carbon dioxide restriction in which the developed countries are required to reduce their CO_2 emissions by 20% over a twenty year period. We consider only the US region (out of five regions) in Global 2100. We consider two alternatives for trade in carbon rights. In the first alternative, the US is allowed to purchase carbon rights from developing countries, while, in the second alternative, no trade is allowed.

3.1 The Case with Trade

In this case, the United States faces a required reduction in carbon dioxide production, but also has the option to purchase rights from other countries to produce carbon emissions. To obtain the VSS and EVPI, we calculated three values called :

- *wait-and-see (WS)*, the value of (1) assuming perfect information, i.e., that all uncertainty is resolved before a decision is made;
- *here-and-now (HN)*, the value of (1), assuming that we cannot resolve the uncertainties before acting;
- *expectation of mean value (EMV)*, the value of (1) using a policy from the model that replaces random investment returns with their expectations.

The three quantities, WS, HN, and EMV, appear in Table 4 with the EVPI and VSS. Note that the VSS is actually much larger than the EVPI. At 1.4% of total discounted domestic product, it represents almost one trillion dollars of lost consumption due to following a policy that does not consider randomness in investment returns. The small value for EVPI on investment uncertainty states that resolving uncertainty here is not as important as accounting for it in the model.

Reasons for the results in Table 4 concentrate on the need for hedging in situations where outcomes are uncertain. When models are simplified by removing uncertainty, the model tends to favor policies that involve a single investment that appears best in an average case. This solution is often poor in practice. In resource planning models, it is generally impossible for an optimal policy in the deterministic model to include more than one different new technology investment (5). In these cases, the VSS again may appear high while the EVPI is generally low (8). In other words, it is not so important to know which new technology will succeed eventually as long as policies favor a variety of investments that cover a broad range of possibilities. EVPI values may be higher, as noted in (17), when additional random parameters (such as emission effects in place of strict limits) are considered and when suboptimal policies (such as from a deterministic model) are followed.

The consumption loss effect of following a policy from the deterministic model can be quite severe in certain instances when the new technology with highest expectation is not realized as predicted. Figure 3 shows the graph of

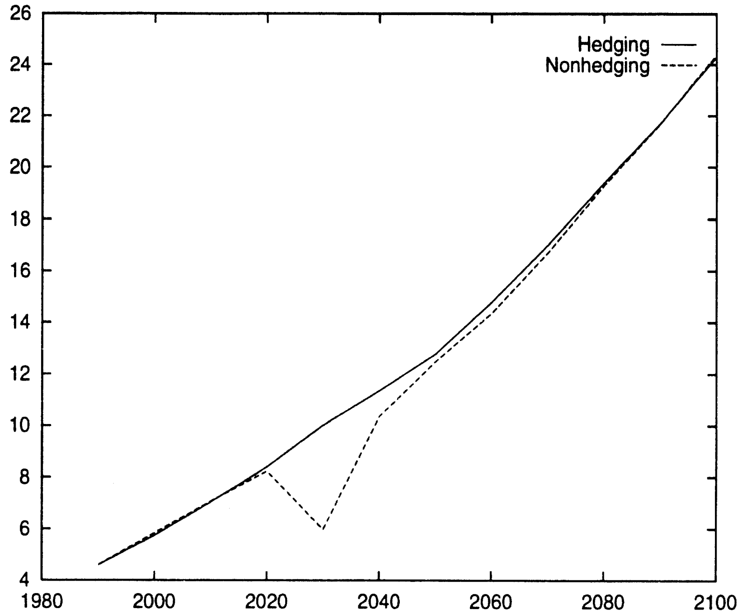

Figure 3: Consumption over time for the hedging policy (stochastic model) and the nonhedging policy (deterministic model). The lack of hedging leads to large economic losses in the 2020s.

consumption over time in the case of the most pessimistic technology scenario (Number 1) under the stochastic model policy (*Hedging*) and the deterministic model policy (*Nonhedging*). In this case, the US economy suffers an annual \$2 trillion loss in the third decade of the 21st century because insufficient capital investment was made into existing technologies.

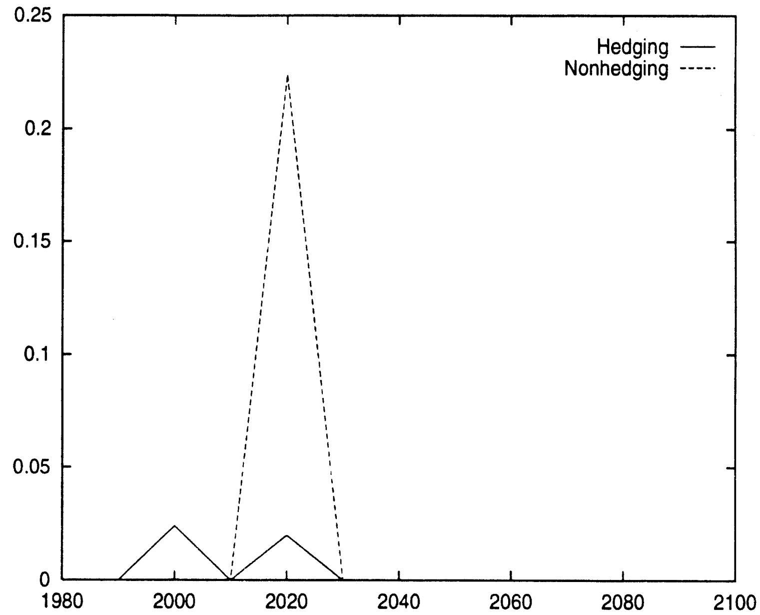

Figure 4: Synthetic fuel investment over time for the hedging policy from the stochastic model and the nonhedging policy result from the deterministic model. The hedging policy smooths out investments to protect against failures.

Instead of relying on building existing technologies, as shown in Figure 4, the nonhedging, deterministic policy relies on synthetic fuel technology and low cost oil (Figure 5). Figure 4 also shows that the hedging policy invests earlier in synthetic fuels than the nonhedging policy and then again later when the technology is more certain. The hedging policy also preserves the low cost oil resource longer (see Figure 5).

Overall, these results show that policies formed without explicitly incorporating uncertainties, in terms of the distribution of outcomes, can have serious consequences. Given that much of the analysis in economic effects of emission policies have considered only deterministic models, the observations here indicate that caution should be taken in following policies that do not promote a wide variety of technologies and that do not favor early investment in new technologies.

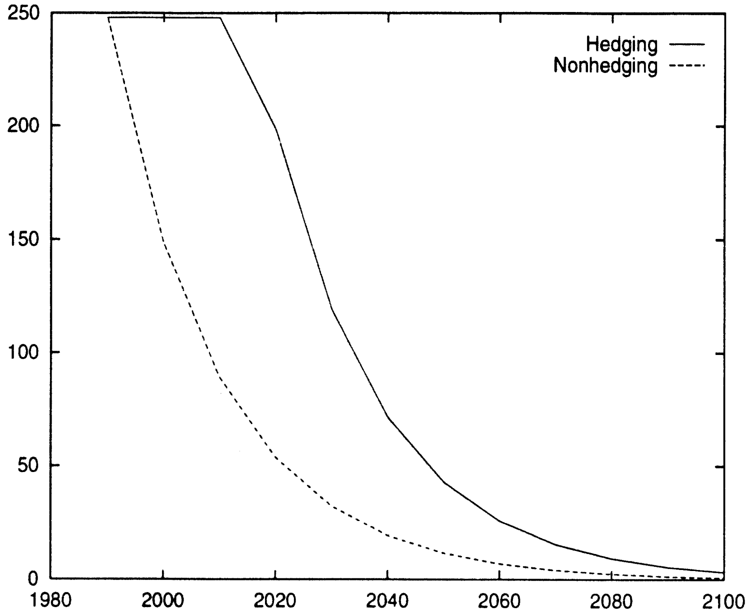

Figure 5: Remaining low cost oil over time for the hedging policy from the stochastic model and the nonhedging policy result from the deterministic model. The hedging policy depletes oil at a significantly reduced rate.

3.2 The Case without Trade

The case without trade presents even greater values for perfect information and the stochastic solution. The results appear in Table 5. In this case, the VSS is fully 2% of the discounted consumption utility and represents over a $1 trillion output loss. The same types of observations in terms of consumption and investments apply in this case. The results are magnified because the margin for error is larger when trade is not possible. The general result is that it is important from an economic viewpoint to allow trade in the carbon emission market.

4 Conclusions

Models of economic effects from greenhouse gas emissions and greenhouse gas controls can play an important part in preparing national policy to respond to potential long-term challenges. Some form of government intervention may be needed to achieve optimal investments in new technologies due to the long lead-times in new technology developments and the difficulties in returning climatic gains to an individual firm. While the resolution of uncertainty may not affect the form of these optimal policies in the near term, this study indicates that it may be costly to form policy based on a simplified model that ignores uncertainty in investment returns

Our conclusions are similar to those of Peck and Teisberg (17) who consider the value of information in resolving atmospheric warming and damage function uncertainty. Our results give low order of magnitude values for early information resolution about investment returns as in Peck and Teisberg's early information values for atmospheric uncertainties (which we model exogenously through our carbon limits). Our studies are also similar in showing that suboptimal policies (such as those based on expected parameter values) lead to much greater losses than the expected value of perfect information. Nordhaus's DICE model (15) yields greater values for early resolution of atmospheric and mitigation cost information than Peck and Teisberg's CETA model but these values are still less than our values of the stochastic solution over ignoring uncertainty in investment returns. Overall, our results indicate that modeling technology investment uncertainty may be as valuable as considering atmospheric uncertainties.

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Table 1: Electrical technologies.

Technology	Description
Existing:	
HYDRO	Hydroelectric, geothermal, other renewables
GAS-R	Remaining initial gas-fired
OIL-R	Remaining initial oil-fired
COAL-R	Remaining intial coal-fired
NUC-R	Remaining initial nuclear
New:	
GAS-N	Advanced combined cycle, gas-fired
COAL-N	New coal fired
ADV-HC	High-cost carbon free
ADV-LC	Low-cost carbon free

Table 2: Nonelectrical technologies.

Technology	Description
OIL-MX	Oil imports minus exports
CLDU	Direct uses of coal
OIL-LC	Low-cost oil
GAS-LC	Low-cost gas
OIL-HC	High-cost oil
GAS-HC	High-cost gas
RNEW	Renewables
SYNF	Synthetic fuels
NE-BAK	Nonelectrical backstop

Technology	Scen 1	Scen 2	Scen 3	Scen 4	Relative range
ADV-HC	0.094	0.33	3.3	10.328	109.87
ADV-LC	0.115	0.4	4.0	12.6492	110.00
OIL-LC	7	10	25	48	6.86
GAS-LC	7	10	25	48	6.86
OIL-HC	7	10	25	48	6.86
GAS-HC	7	10	25	48	6.86
RNEW	0.89	3.1	30.9	97.98	110.09
SYNF	2.36	8.17	81.7	258.2	109.41
NE-BAK	0.632	2.2	21.9	69.3	109.65
EFFICIENCY	0.06	0.12	0.15	0.17	2.83

Table 3: Returns on Investment

Table 4: The values of perfect information and the stochastic solution with trade.

WS	HN	EVPI Total	EVPI (% of WS)	EMV	VSS Total	VSS (% of HN)
58848	58746	102	0.17	57953	793	1.4

Table 5: The values of perfect information and the stochastic solution without trade.

WS	HN	EVPI Total	EVPI (% of WS)	EMV	VSS Total	VSS (% of HN)
58589	58470	112	0.20	57290	1180	2.0