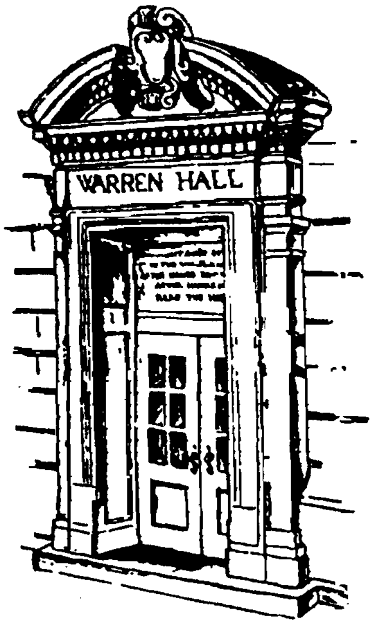

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A Critical Overview of the Economic Structure of Integrated Assessment Models of Climate Change

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A CRITICAL OVERVIEW OF THE ECONOMIC STRUCTURE OF INTEGRATED ASSESSMENT MODELS OF CLIMATE CHANGE

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1. Integrated Assessment Modeling of Climate Change: A New Frontier

The decade of the 1990s witnessed the genesis and growth of a new genre of applied economic modeling in the context of climate change. These models, popularly known as Integrated Assessment Models (IAMs), combine the standard tools of neoclassical economics with climate modeling. The key to their popularity is that they provide a medium for translating the scientific, technological, and economic complexities of the climate change problem into succinct, economically efficient policy prescriptions. In effect, they assist in answering the central questions of climate change policy: *by how much, and by when should greenhouse gas (GHG) emissions be reduced? Which economic instruments are suitable to bring about these reductions and what will be their likely impact on the economy?* These models are a very timely development since there is a renewed international pressure for a commitment to mitigate the effects of anthropogenic global warming (see, for instance, Bureau of National Affairs, 1997). Surprisingly, there are almost no international initiatives for adaptation.

Typically, IAMs comprise four interconnected modules: a macroeconomic module, an atmospheric and ocean chemistry module, a climate module, and an impacts module. The macroeconomic module serves as the engine of the entire framework, determining trajectories for broad economic aggregates such as gross economic output, investment in tangible capital, energy use, and anthropogenic GHG emissions.[1] The atmospheric and ocean chemistry modules determine globally uniform GHG concentrations. The climate module represents the earth's climate system through a series of equations that link GHG concentrations to equilibrium climatic change.[2] These equations are generally reduced-form representations of large climate models known as general circulation models (GCMs) that use a complex set of partial differential equations representing the physical properties of the earth's atmosphere and oceans to predict changes in various climate variables including temperature, precipitation, incoming solar radiation, and wind speed. For the sake of computational tractability, IAMs focus almost exclusively on equilibrium temperature change. The magnitude of temperature change is then used to determine the economic impact of climate change in the impacts module.[3] Generally, this is calculated as the loss in gross economic output through previously estimated empirical relationships. The loss in output feeds back to the macroeconomic module to determine the net economic output of the economy.

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[1] Most models focus on CO_2 emissions, with a very simplistic treatment of other GHGs such as CH_4, N_2O, and SO_2.

[2] Due to the thermal inertia of oceans, there is a long transient period during which the climate system approaches the new equilibrium climate. In addition to slowing down the rate of change, different air-sea thermal contrasts may produce climate patterns that are likely to be very different from the final equilibrium climate. Therefore, it is erroneous to simply scale equilibrium climate change model simulations to predict the transient changes. It is justified on the grounds that it is usually quite expensive to perform transient climate simulations (Schultz 1997a).

[3] Some studies also incorporate the *rate* of temperature change into the assessment. See Tol (1996) and Peck and Teisberg (1994).

This paper presents a detailed overview of the mathematical structure of some of the most popular IAMs of climate change. We focus on the macroeconomic and impacts modules, with an exclusive emphasis on optimization models, as opposed to including the simulation models.[4,5] This focus on optimization models is necessary for the sake of comparability, an issue that cannot be emphasized enough. The climate change literature is awash with reviews that compare models with very different, sometimes theoretically inconsistent, underlying economic structures. Any general conclusions drawn from such comparisons must necessarily be treated with caution.

For example, Sanstad and Greening (1996, p. 4) state that IAMs with a greater regional aggregation result in higher damage mitigation costs and also higher emissions levels. This conclusion is based on model comparisons undertaken by the Energy Modeling Forum 12, where several macroeconomic energy models with widely varying structures were operated under a set of identical economic and technological assumptions (see Gaskins and Weyant 1993). By controlling for these factors, this exercise highlighted the importance of model structure.

In counterpoint to the Sanstad and Greening conclusion, it is instructive to compare the results of the DICE and RICE models developed

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[4] An example of IAMs that are simulation models are the Integrated Climate Assessment Models, ICAMs 1 & 2, developed by Dowlatabadi and Granger (1993) and Dowlatabadi *et al.* (1994).

[5] For a review that includes simulation models, see IPCC (1996, chapter 10) and Dowlatabadi (1995). Also see Sanstad and Greening (1996) for an assessment of key design and implementation issues relating to the underlying economic structure of IAMs.

by Nordhaus (Nordhaus 1992, 1994; Nordhaus and Yang 1996). This pair of models provides an excellent platform for assessing the sensitivity of IAM results to the level of geographical aggregation, since the models are otherwise identical in structure.[6] In the DICE-RICE pair, the CO_2 trajectory in the disaggregated version is much higher. By the year 2100, CO_2 emissions in the uncontrolled or market scenario in RICE are 38 billion tons of carbon (BTC) as compared to 21 BTC in the DICE base case scenario (Nordhaus and Yang 1996, p. 749).[7] Another model that facilitates a similar comparative analysis is CETA, developed by Peck and Teisberg (1992, 1995). This model has been operated for a homogenous global economy and also for the case of two mutually exclusive and exhaustive regions. In both versions, the base case aggregate emissions trajectory is virtually identical.

We review five integrated assessment models. These are the Dynamic Integrated Climate Economy or DICE model (Nordhaus 1992, 1994), the Regional Integrated Climate Economy or RICE model (Nordhaus and Yang 1996), the model developed by Khanna and Chapman (1997), the Model for Evaluating Regional and Global Effects of GHG reduction policies or MERGE (Manne *et al.* 1995), and the Carbon Emissions Trajectory Assessment or CETA model (Peck and Teisberg 1992, 1994, 1995). The significant mathematical details of these models

[6] The DICE model is a highly aggregated representative agent model, whereas the RICE model incorporates interactions for 6-10 economic regions.

[7] In RICE, exogenous forcings of non-CO_2 GHGs are lower than in DICE. This explains the lower temperature change in RICE despite the higher CO_2 emissions trajectory (Nordhaus and Yang 1996, p. 761).

are documented in tables 1 through 6. In the following section, we critically discuss some of the broad policy issues that emerge. The paper concludes with a section highlighting major areas for future research.

2. Optimization Models

2.1 Brief Overview of Model Structures

Integrated assessment models of climate change came into their own with the seminal work of William Nordhaus at Yale University. The DICE model was the first to incorporate the core biogeochemical and climate relationships in an optimal economic growth framework, with feedbacks between the various constituent modules. Based on the Ramsey (1928) model of intertemporal choice, the model is designed to calculate the optimal trajectory for capital investment and GHG emissions reductions. One of the strengths of the model is its relatively simple structure that captures the essence of the major economic and climate dynamics, and the interactions between them, in a few equations. This is complemented by a candid discussion of concepts and methodology in the 1994 publication. The result is a transparent framework that set the stage for a range of sensitivity analyses and further developments and extensions. Nordhaus and Yang later developed the RICE model which is a regionally disaggregated version of DICE. This extension enabled the analysis of alternative strategic approaches to international climate policy, including cooperative and nationalistic policies.

The Khanna and Chapman model builds upon the work by Nordhaus to include separately the demands for coal, oil, and natural gas.

These demands depend on own price, prices of substitute fuels, per capita income, and population. An augmented Hotelling model captures the effect of depleting oil resources. A methodological advantage of including price, income, and population sensitive energy demand functions is that it allows substitution possibilities in the "production" of emissions. Furthermore, it allows the analysis of energy tax regimes in an environment of growing world population and income, and declining petroleum availability.

CETA is closely related to the Global 2100 model developed by Manne and Richels (1992). It consists of broad economic aggregates, such as gross output, investment, and consumption in an optimization framework, along with a menu of energy technologies that determine the level of CO_2 emissions and the costs of reducing them. CETA closes the loop by including a GHG dependent time path for temperature change, and a damage function representing the corresponding economic costs. In this way, the model determines the optimal path for GHG emissions by balancing warming costs against the cost of control.

The core economic structure of MERGE is defined by the Global 2200, an advanced version of Global 2100. Instead of a set of parallel calculations for each region, Global 2200 is a fully integrated computable general equilibrium model. Each region is a an independent price taker subject to an intertemporal budget constraint. Demand-supply equilibrium is reached through the prices of the internationally traded commodities: oil, natural gas, coal, carbon emission rights, and a numeraire good that represents the output of all sectors excluding the energy sector. Explicit modeling of non-market damage valuation is a distinguishing feature of MERGE, one that sets it apart from other integrated assessment models of climate change. It is assumed that the willingness-to-pay to avoid climate change related ecological damage depends on temperature change and per capita GDP.

2.2 Macroeconomics

2.2.1 *Maximized Variable*

Agents maximize the discounted sum of either (i) the log of per capita consumption multiplied by population (RICE, DICE, CETA, and Khanna and Chapman), or (ii) the log of aggregate consumption (MERGE). (See table 1 and also table 4) While these two maximands have very similar mathematical forms, they embody very different welfare implications.[8]

[8] The authors thank Vivek Suri for bringing this point to their attention. Also see Suri (1997).

Table 1
Optimizing Models

Model/Authors	Maximized Variable	Control Variable
RICE (Nordhaus & Yang 1996)	*Non-cooperative scenario*: each region maximizes its utility function defined as the sum of the discounted value the log of its per capita consumption times its population *Cooperative scenario*: global welfare defined as the weighted combination of the regional utility functions (defined above)	Regional investment levels; regional control rate for carbon emissions;
DICE (Nordhaus 1994)	Sum of discounted value of the log of global per capita consumption times global population	Global investment level; global control rate for carbon emissions;
Khanna & Chapman (1997)	Same as DICE	Same as DICE
MERGE (Manne, Mendelsohn, & Richels 1995)	Sum of discounted value of log of aggregate consumption for each region	Regional investment levels
CETA (Peck & Teisberg 1992, 1995)	Sum of discounted value of the log of global per capita consumption times global population	Global investment level; energy use level;

Consider the example where a fixed amount of consumption has to be optimally divided between two generations. In the case of the first utility function, the optimal distribution occurs such that the per capita consumption is equal for both generations. In the second case, it occurs at the point where the aggregate consumption is equal between the two generations. In this latter case, the generation with a larger population must, therefore, be allocated a lower level of per capita consumption. Thus, maximising the discounted value of the log of aggregate consumption inherently discriminates against more numerous future generations.

At the same time, it is important to note that the quantitative policy results are independent of the choice between these two maximized variables. The present authors' simulations run with the DICE model using both (i) and (ii) found that the trajectories for capital stock and the control rate for CO_2 emissions are virtually identical in both cases.

Another interesting feature of the maximized variable is that all the models reviewed use an identical pure rate of time preference of 3% per year, despite the controversy raging around the numerical value of this parameter (IPCC 1996 chapter 4, Khanna and Chapman 1996, Schelling 1995, Cline 1992, Parfit 1983). In effect, the authors of these IAMs implicitly favour the descriptive rather than the prescriptive role of discounting.[9] Perhaps what is most surprising is that none of the authors, except Nordhaus (1994, pp. 122-135), include a sensitivity analysis with

[9] See IPCC (1996, chapter 4) for the distinction between the descriptive and prescriptive approaches to discounting.

respect to alternative values of the discount rate. This is an important exercise since the discount rate has emerged as one of the most contentious issues in the integrated assessment arena. Using a simplified version of the Nordhaus DICE model, Chapman *et al.* (1995, pp. 6-7) have shown that the optimal control rate is highly sensitive to the value of the discount rate, affecting both the timing and the extent of CO_2 abatement.

2.2.2 *Determinants of Energy Use*

The models differ widely in terms of the determinants of energy use (table 2). In the Nordhaus models energy use is not modeled explicitly. Instead, it is implicit in the CO_2 emissions trajectory. Changes in the fuel mix over time are captured entirely by the time path of the CO_2-GDP ratio. In addition to economic output, the only other factors that directly affect energy use are the growth in total factor productivity and the decarbonization rate, both of which are exogenously determined. Thus, this pair of models ignores the behavioral and structural complexities of energy markets and long-term energy use.

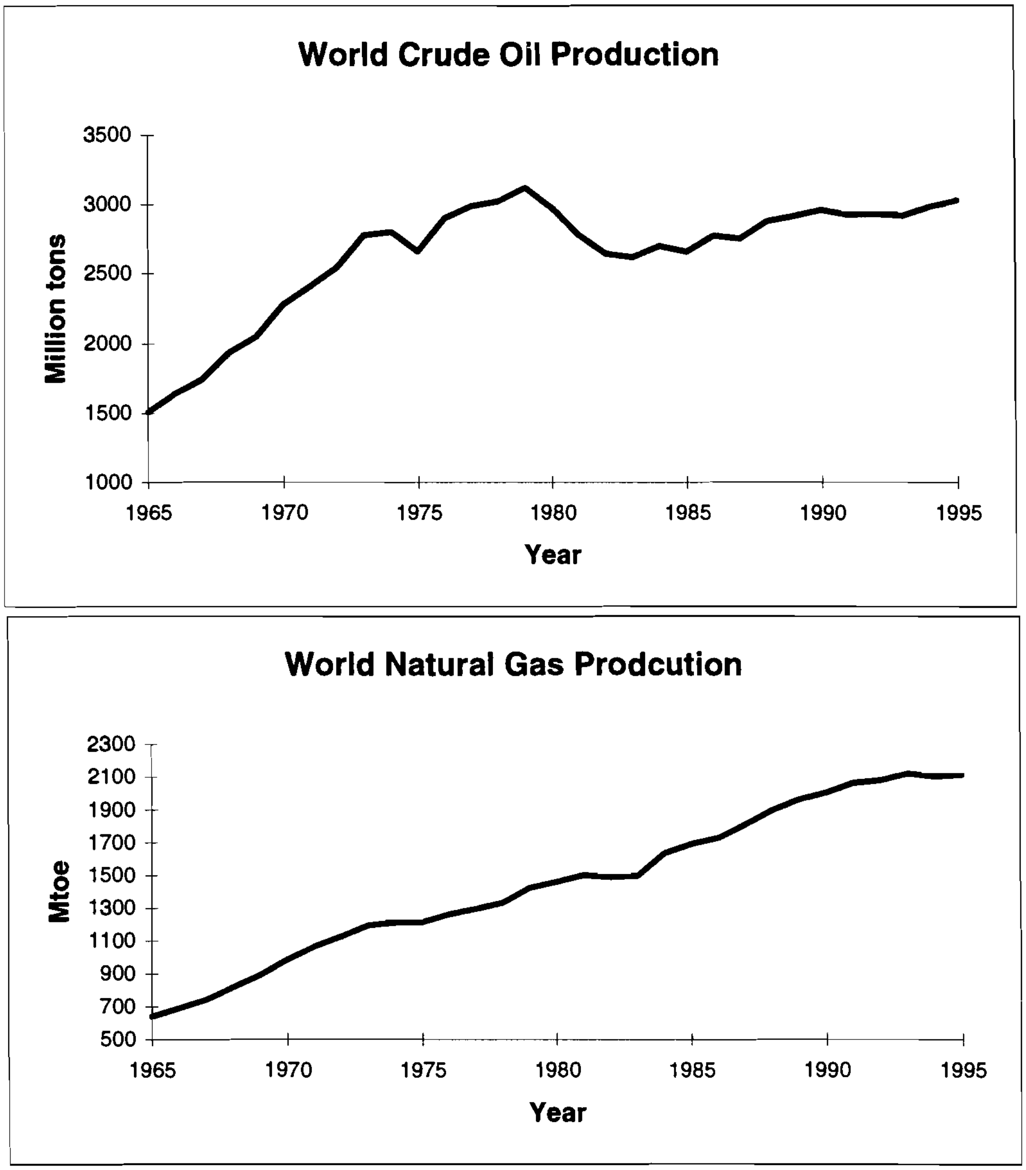
Table 2

Determinants of Energy Use

Model/Authors	**Definition of Energy**	**Factors Directly Affecting Energy Use**
RICE (Nordhaus & Yang 1996)	Not explicitly modeled Implicit in regional CO_2-GNP ratios.	Prices not explicit; finite fossil resources not explicit; regional output; growth in total factor productivity and decarbonization rate.
DICE (Nordhaus 1994)	Not explicitly modeled. Implicit in CO_2-GNP ratio.	Same as RICE. Output and productivity growth aggregated to global level.
Khanna & Chapman (1997)	Coal, gas, & synfuel (backstop) modeled as Cobb-Douglas demand functions. Oil production increases near term according to Hotelling-type resource depletion model.	*Coal, gas, & synfuel demands* are a function of energy prices, population, and per capita income. *Oil production* depends on global per capita income & population; remaining oil resources; extraction cost; cost of backstop.
MERGE (Manne, Mendelsohn, & Richels 1995)	Energy is a factor of production in a nested CES production function. Energy defined as a Cobb-Douglas function of electric & non-electric energy.	Oil prices dependent on inelastic supply; regional output and population; supply cost; technology expansion & decay factors; remaining coal, oil, and gas resources; oil use path exogenously fixed & monotonically declining; AEEI; ESUB.
CETA (Peck & Teisberg 1992, 1995)	Same as MERGE	Same as MERGE. Output & population are aggregated to global level.

MERGE and CETA have an identical, fairly detailed representation of the energy sector.[10] Both models distinguish between several energy supply technologies that are used to meet the optimally determined energy demand. These technologies differ in terms of their cost and carbon emission coefficients, and also the capacity restrictions. These factors are crucial in determining the technology mix over time. The models also take account of the exhaustion of oil and gas resources, using a forward-looking framework that is loosely based on the Hotelling model for exhaustible resources. However, the optimal production trajectories for both fuels are forced to be monotonically declining. This is inconsistent with the actual production data over the last three decades (see figure 1).

[10] This framework is essentially the Global 2100 model developed by Manne and Richels (1992).



Source: Brown et al., 1996

Figure 1
Trends in World Production of Crude Oil and Natural Gas (1965-1995)

Khanna and Chapman have made an attempt to reconcile historically observed oil production data with model predictions. They employ an augmented Hotelling model in which optimal crude oil production depends not only on remaining stocks and future price and cost expectations, but also on a growing per capita income and population.[11] The predicted oil production trajectory rises in the near term, peaks, and eventually declines to exhaustion.

For the other fossil fuels, Khanna and Chapman use demand functions that allow for own- and cross-price effects, income effects and population effects. Among the models reviewed, this is surprisingly the only one that includes cross-price effects. From a policy standpoint, this omission could be a potentially grave error since the policy instrument for CO_2 abatement in these models is a carbon tax based on the differential carbon content of fuels. As fuel prices are raised by the tax, there are cross-substitution effects, thereby lowering the effectiveness of the carbon tax in attaining any given emissions trajectory. Khanna and Chapman (1997, pp. 25-27) show that in the presence of cross-price effects, unrealistically high tax rates are required to lower the emissions trajectory to the optimal level.

2.2.3 *Production Structure*

All five of the models employ a constant elasticity of substitution

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[11] This methodology can be easily extended to incorporate more than one exhaustible fuel, and also to include cross price effects within the Hotelling framework. See Barron *et al.* (1996, pp. 6-14).

aggregate production function (table 3). The DICE, RICE, and Khanna and Chapman models use the special case of a unitary substitution elasticity, so that the production function reduces to the familiar Cobb-Douglas form. Furthermore, this subset of models have capital and labour as the only inputs in aggregate production. The other two models, CETA and MERGE, use a nested production function in electric and non-electric energy, in addition to capital and labour. An advantage of using a nested production function instead of a production function with all four inputs entering directly is that it allows for differential elasticities of substitution between the factors of production (Layard and Walters 1987, pp. 275-276). In the particular form used in CETA and MERGE, the substitution elasticities between factors within a nest is one. For factors across nests, the elasticity of substitution is also constant and depends on the optimal value shares for the factors, and the substitution elasticity between the value-added and energy aggregates. See appendix 1.

Table 3

Typical Functional Forms Employed for Three Major Variables

1. *Maximized variable*

$$U(\cdot) = \sum_{t=0}^{T} \frac{1}{(1+r)^t} \ln(C_t) \qquad \textbf{(1)}$$

U(•) = level of utility
r = discount rate
C_t = the aggregate consumption level, or the level of per capita consumption

Note that CETA and MERGE use the function shown above. In the case of RICE, DICE, and the Khanna & Chapman analysis where per capita consumption is used, the log term is multiplied by the population level.

2. *Damage characterization*

$$\frac{D_t}{Q_t} = \alpha(\Delta T)^{\beta}$$

D_t/Q_t = fractional loss in gross output due to climate change (world or region)
ΔT = temperature rise relative to a pre-industrial level
β = 2 or 3 in all models surveyed
α = calibration constant

3. *Aggregate output*

$$Q = [A(K^{\alpha} \cdot L^{(1-\alpha)})^{\rho} + B(AEEI \cdot E^{\beta} \cdot N^{(1-\beta)})^{\rho}]^{1/\rho}$$

Q = output excluding energy sector
K = capital input
L = labour input
E = electric energy input
N = non-electric energy input
A, B = scale factors
AEEI = autonomous energy efficiency improvements
α = optimal value share of capital in the capital-labour aggregate
β = optimal value share of electric energy in the energy aggregate
ρ = (ESUB - 1)/ESUB
ESUB = elasticity of substitution

Note that this is the precise functional form used in CETA and MERGE. The Cobb-Douglas functional form used in RICE, DICE, and Khanna & Chapman is a special case of the above form obtained when $\rho \to 0$, and $B = 0$.

2.2.4 *Tax Policies*

As mentioned previously, all the models use a carbon tax to achieve the optimal CO_2 abatement. However, the definition of the carbon tax varies tremendously across the models (table 4). In the DICE and RICE models the carbon tax is the shadow price of carbon per unit of consumption. While this is a theoretically neat approach, it is difficult to translate it into policy relevant terms such as dollars per barrel of oil. The CETA and MERGE models follow Manne and Richels (1992) in defining the carbon tax as the price of carbon that is just sufficient to induce a technology shift from a high carbon intensity to a lower carbon intensity technology. Once again, the same criticism applies. Khanna and Chapman have made an attempt to bridge this gap by determining tax rates for each of the fossil fuels separately. However, they have simulated only one out of the many possible combinations of taxes that would achieve the desired amount of CO_2 abatement. Future research should attempt to determine the unique set of optimal taxes that would correspond to the optimally determined emissions control rate.

Table 4

The Carbon Tax Metaphors: C Tax Definitions in Selected Models

1. *DICE and RICE: Nordhaus (1994, 1996)*

The carbon tax is defined as the shadow price of carbon per unit of consumption. It is calculated as the negative of the ratio of two costate variables: the costate variable corresponding to the capital formation constraint, and the costate variable corresponding to the emissions constraint. Suppose that,

$$\lambda_t^K := \frac{\partial U(\cdot)}{\partial K_t} \quad ; \qquad \lambda_t^E := \frac{\partial U(\cdot)}{\partial E_t} \quad ;$$

Then,

$$-\frac{\lambda_t^E}{\lambda_t^K} \equiv -\frac{\partial U(\cdot)/\partial E_t}{\partial U(\cdot)/\partial K_t} = \frac{\partial K_t}{\partial E_t} \ : \ \frac{\$}{Tons\ of\ carbon}$$

U(.) = utility function
K_t = capital stock in period t
E_t = CO_2 emissions in period t

2. *Global 2100: Manne and Richels (1992) ; CETA: Peck and Teisberg (1992, 1995); MERGE: Manne et al. (1995)*

Both models employ an identical definition of the carbon tax as the price of carbon that is just sufficient to induce a technology shift from a high carbon intensity to a lower carbon intensity technology. Therefore, in the long run, when there is positive production of both the synfuel and the carbon-free non-electric backstop, the carbon tax is such that the consumer is just indifferent between the two technologies. The appropriate tax in this case is the ratio of the difference in their per unit costs and the difference in their per unit carbon emission levels. In other words, the long run equilibrium carbon tax is:

$$carbon\ tax = \frac{cost\ differential\ (\$/GJ)}{carbon\ emission\ differential\ (tons\ of\ C/GJ)}$$

2.3 Impacts Assessment

The impacts assessment module translates changes in climate variables into quantitative impacts on the economy. This determines damages from climate change. Viewed differently, it is the benefit of avoiding climate change.

This module probably constitutes the weakest economic link in IAMs. This is mostly because even outside of the integrated assessment forum, damage assessment issues are largely unresolved and open to debate and criticism (see IPCC 1996, chapter 6). Yet this link is crucial if IAMs are to balance the costs and benefits of climate mitigation in an economically efficient manner.

IAMs typically evaluate the economic impact of climate change using a non-linear damage function that relates the loss in economic output to temperature rise. Based on the results of a number of independent impact assessment studies, this function is calibrated so that a doubling of CO_2 concentrations from the pre-industrial levels leads to some predetermined loss in output. (See, for instance, Nordhaus 1994, pp. 49-59.) Geographical variability in damages, if any, is captured by a region specific scale factor (see tables 3 before and 5 below).

Table 5
Global Damage Characterization

Model/Authors	Functional Form	Geographical Specification
RICE (Nordhaus & Yang 1996)	Quadratic in temperature rise	6 or 10 regions. Exponent same across regions. Regionally calibrated scale factor varies.
DICE (Nordhaus 1994)	Quadratic in temperature rise	Global
Khanna & Chapman (1997)	Same as DICE	Same as DICE
MERGE (Manne, Mendelsohn, & Richels 1995)	*Market damage:* quadratic in temperature rise *Non-market damage:* depends on willingness to pay to avoid ecological damages. WTP depends on per capita income & temperature rise according to an S-shaped function.	*Market damage:* Fraction of GDP lost due to 2.5°C warming is twice as high in developing countries *Non-market damage:* WTP is higher for developed countries. WTP independent of regional location of damage.
CETA (Peck & Teisberg 1992 & 1995)	Cubic in temperature rise relative to pre-industrial levels. 1992 version included linear specification. 1995 version scales damage function by time dependent index of population levels.	Exponent is the same for all regions. Scale factor calibrated such that a 3°C rise in temperature causes a 2% loss in regional gross outputs.

Note: *All models surveyed characterize climate change related damage as a single equation in two variables: loss in GDP, and temperature rise. The only exception is MERGE which distinguishes between market and non-market damages. Details are included in the table above.*

There are several issues that need to be considered here. First, the numerical value of the exponent in the damage function varies from model to model. This makes a comparison of model results somewhat tenuous. Peck and Teisberg (1992, 1994) have shown that the optimal emissions trajectory is highly sensitive to the degree of non-linearity of the damage function. Second, this formulation of the damage function focusses on changes in average temperature and fails to take cognisance of the impact of changes in climate variability and extremes. Yet, these might be much more important in determining the economic impact of climate change (IPCC 1996, chapter 6). Third, the fixation of current IAMs on temperature rise as the exclusive indicator of climate change might be a grave error. Other climate related variables, for example, precipitation and cloud cover, may have equal, if not more important, socio-economic impacts (Toth 1995, p. 254). Fourth, all models except MERGE ignore the explicit valuation of non-market impacts, including those on natural ecosystems. According to Toth (1995, p. 254) this might explain why IAMs tend to produce very conservative results with a very modest emissions reduction. These impacts constitute an important missing piece in the damage/benefit assessment incorporated in these models. Fifth, in regional models the scale parameter acts as the catch-all term for the variation in impacts across regions that differ not only in terms of their geography, but also in their stage of development. Obviously, this is a gross aggregation of the many economic, political and natural factors that determine the economic value of the impacts of a changed climate.

Each of the five issues mentioned above are areas for significant future research in order for IAMs are to have a credible impact on future climate policy. Without these uncertain and missing parameters and variables, there remains an unacceptably large amount of "noise" in the results obtained from these models.

2.4 Some Other Issues

Table 6 compares the global, base case CO_2 emissions predicted by the 5 models for the year 2100. The results are clustered in the range of 20-40 BTC, despite the different structural and numerical assumptions embodied in the models. The outlier in this set is the model developed by Khanna and Chapman. Several factors explain the high value predicted for CO_2 emissions in this model. First, Khanna and Chapman allow for cross-price effects in the demand for fossil fuels. Second, they assume zero autonomous energy efficiency improvements. Chapman *et al.* (1996, pp. 6-7) have shown that the emissions trajectory is highly sensitive to the numerical value assumed for this parameter. Third, the backstop fuel for oil incorporated in the Khanna and Chapman model is a highly carbon intensive coal-based synthetic fuel. While both CETA and MERGE also incorporate the same backstop, it is quickly replaced by an assumed carbon-free technology that results in a sharp decline in the emissions trajectory.

Table 6

Global CO_2 Emissions and Concentrations in 2100 (base case)

Model/Authors	Concentrations (ppmv)	Emissions (BTC per year)
RICE (Nordhaus & Yang 1996)	1700 (BTC)	38
DICE (Nordhaus 1994)	1500 (BTC)	25
Khanna & Chapman (1997)	2650 (BTC)	68
MERGE (Manne, Mendelsohn, & Richels 1995)	800	28
CETA (Peck & Teisberg 1992, 1995)	Not reported	40

Note: *The DICE, RICE, and Khanna & Chapman models do not report the concentration levels in terms of ppmv. Instead, the cumulative atmospheric levels of GHG emissions, after taking account of the natural decay processes and transfer to the deep ocean, are reported.*

The similarity in the results obtained from these models raises an important question of the impact of funding sources on research output. Funding may be an indirect influence on the nature and outcomes of research. In the U.S., almost all of the integrated climate assessment research groups have received some support from the Electric Power Research Institute (EPRI) in Palo Alto, CA (Dowlatabadi 1995, p. 290. Also see table 7). In present context, there is a potential conflict of interest since EPRI has close affiliations with electric utilities, the major customers of the domestic coal industry. This could be a problem, since there might be an interest in downplaying the economic significance of climate change and its impacts, so as to override any arguments for reducing coal use.

Table 7
Affiliation of Authors With Energy Industry, Agencies

Author	Affiliation	Funding Sources
Chapman	Cornell University	Cornell University
Dowlatabadi	Carnegie Mellon University	NSF, EPRI
Khanna	Cornell University	Cornell University
Manne	Stanford University	EPRI
Mendelsohn	Yale University	EPRI
Nordhaus	Yale University, Cowles Foundation	NSF, Yale, Cowles Foundation, EPA
Peck	EPRI	EPRI
Richels	EPRI	EPRI, DoE
Teisberg	Teisberg Associates	same as Peck?
Wigley	NCAR	NSF, DoE, EPRI

Note:

EPRI	Electric Power Research Institute
DoE	Department of Energy
NSF	National Science Foundation
EPA	Environmental Protection Agency
NCAR	National Center for Atmospheric Research, managed by the University Corporation for Atmospheric Research, under contract with NSF

3. Conclusions

Integrated assessment modeling of climate change is an exciting new field. Despite the weaknesses in the present models, this approach has a tremendous potential to bridge the gap between theoretically sophisticated modeling and the policy relevance of the results obtained.

The pioneering work in integrated assessment modeling has usually represented geology, climatology, and impact assessment in a stylized form: a set of basic climatological and damage equations provide the basis for more detailed economic analyses within a cost-benefit framework. Barron *et al.* (1996) have proposed a comprehensive framework that builds upon the present body of climate change literature in an attempt to improve upon the many weaknesses in existing IAMs.[12] In particular, this model incorporates transient climate change, has a better representation of energy markets compared to the models reviewed here, includes climate variables in addition to temperature rise, and includes non-fossil fuel based anthropogenic GHG emissions. See appendix 2 for a more detailed overview.

The extensions proposed by Barron *et al.* are impressive. However, there are several key economic issues that remain elusive to the IAM arena. Future climate change research should, therefore, focus on the following:

- detailed impact valuation at the level of individual economic sectors
- non-market ecosystem impacts

[12] Funding for this research is awaited.

- better representation of the dynamics of energy markets so as to include the possibility of detailed technological choice in the presence of declining energy resources
- more comprehensive coverage of non-CO_2 GHGs
- greatly improved modeling of technological development over time
- inclusion of climate extremes and the related socio-economic impacts

At the same time, it is imperative for researchers in the field not to lose sight of the ultimate goal of applied modeling: to provide policy prescriptions that are robust, transparent and easy to understand. As these models incorporate greater details drawn from disciplines that differ vastly in their philosophies and techniques, there is a real danger that each of these criteria might get compromised. Complex non-linear models of the type proposed by Barron *et al.* tend to be extremely sensitive to exogenous parameter values. Perhaps what is even more troublesome to the present authors is that the initial or starting values specified by researchers are crucial in obtaining results from these models. Often more research time is spent in obtaining convergence and "sensible" results than in analyzing the underlying model assumptions and the policy implications of the results obtained. Therefore, while major strides are required in individual disciplines, the biggest step forward lies in integrated modelers being able to capture these developments in relatively pithy, yet theoretically appealing, formulations.

Appendix 1

Elasticity of Substitution Between Factors of Production in the Nested CES Production Function Used in CETA and MERGE[13]

The production function is:

$$Q = [A(K^{\alpha}\cdot L^{1-\alpha})^{\rho} + B(AEEI\cdot E^{\beta}\cdot N^{1-\beta})^{\rho}]^{1/\rho} \tag{1}$$

The elasticity of substitution between capital and energy is defined as:

$$\sigma_{KE} = \frac{\partial \log(K/E)}{\partial \log(Q_E/Q_K)} = \frac{\partial (K/E)}{\partial (Q_E/Q_K)} \frac{Q_E/Q_K}{K/E} \tag{2}$$

Taking the ratio of derivatives of Q with respect to E and K, we get the following expression for the marginal rate of technical substitution between the two factors:

$$\frac{Q_E}{Q_K} = \frac{B}{A}\frac{\beta}{\alpha}AEEI^{\rho}\frac{N^{(1-\beta)\rho}}{L^{(1-\alpha)\rho}}\frac{E^{\beta\rho-1}}{K^{\alpha\rho-1}} \tag{3}$$

For algebraic ease, let

$$\varepsilon = \frac{Q_E}{Q_K} \qquad \eta = \frac{K}{E} \tag{4}$$

[13] The authors gratefully acknowledge the assistance of Weifeng Weng in cranking through some of the algebra in this appendix.

Then, equation (3) can be rewritten as follows:

$$\varepsilon = cE^{(\beta-\alpha)\rho}\eta^{-\alpha\rho+1} \tag{5}$$

where c is a constant representing exogenous parameters and the labour and non-energy inputs. See equation (6).

$$c = \frac{B}{A}\frac{\beta}{\alpha}AEEI^{\rho}\frac{N^{(1-\beta)\rho}}{L^{(1-\alpha)\rho}} \tag{6}$$

Note that

$$\sigma_{KE} = \frac{1}{\dfrac{\partial\varepsilon}{\partial\eta}\dfrac{\eta}{\varepsilon}} \tag{7}$$

Taking the derivative of ε with respect to η in equation (5) we get following expression:

$$\frac{\partial\varepsilon}{\partial\eta} = c[(1-\alpha\rho)E^{(\beta-\alpha)\rho}\eta^{-\alpha\rho} + (\beta-\alpha)\rho\eta^{-\alpha\rho+1}E^{(\beta-\alpha)\rho-1}\frac{\partial E}{\partial\eta} \tag{8}$$

From equation (4), we get

$$\frac{\partial E}{\partial\eta} = -\frac{K}{\eta^2} \tag{9}$$

Substituting equation (9) in equation (8) we get:

$$\frac{\partial\varepsilon}{\partial\eta} = c[(1-\alpha\rho)E^{(\beta-\alpha)\rho}\eta^{-\alpha\rho} + (\beta-\alpha)\rho E^{(\beta-\alpha)\rho-1}\eta^{-\alpha\rho-1}K] \tag{10}$$

Substituting equations (10) and (4) in equation (7) we get:

$$\sigma_{KE} = \frac{1}{1 - \beta\rho} \tag{11}$$

Note that the elasticity of substitution between energy and capital is independent of the optimal value share for capital in the capital-labour aggregate, i.e., α.

Similarly, the elasticity of substitution between L and N is given by:

$$\begin{aligned} \sigma_{LN} &= \frac{\partial(L/N)}{\partial(Q_N/Q_L)} \frac{Q_N/Q_L}{L/N} \\ &= \frac{1}{1 - \rho(1 - \beta)} \end{aligned} \tag{12}$$

Appendix 2

The Proposed Penn State - Cornell Integrated Assessment Model

The proposed model utilizes a two-tiered structure. In the detailed model tier, the equilibrium costs of emission reductions and climate change damages and adaptations are estimated using energy macroeconomics, GHG and aerosol dynamics, climate change impacts, and policy analyses of adaptation and mitigation, coupled through a network of linkages and feedbacks. A range of optimal atmospheric GHG concentration targets are approximated by the intersection of the long-term equilibrium marginal cost and marginal benefit (avoided damage) functions. The second PCIA model tier comprises of a reduced form version of the detailed model. It is used to explore optimal trajectories towards the previously determined targets under a variety of policy assumptions.

The full model consists of five dynamically coupled, internally-consistent modules. Presented below are some of the basic steps and interlinkages in the model:

1. Optimal control theory is used in the *Macroeconomic Module* to determine economic variables at the global and regional levels, taking account of the interaction between growing populations, rising per capita incomes, and depletion of energy resources. The economic processes define gross economic output, aggregate demand-supply equilibria for fuel types, energy prices, and CO_2 and other GHGs. There are feedbacks from the *Policy Analysis Module*

relating to changing space heating and cooling requirements, and mortality valuation and constraints.

2. GHG and aerosol emissions are inputs into the *GHG/Aerosol Concentration Module*. In addition, non-fossil fuel based emissions of GHGs dependant on anthropogenic activities such as land use changes feed into this module from the *Impact Assessment Module*. Using ocean, terrestrial biosphere, and atmospheric chemistry sub-models, this module determines the concentrations of each atmospheric constituent.

3. The concentration levels determined in the *GHG/Aerosol Concentration Module* feed into the *Climate Change Module*. Here, both transient and equilibrium climate change are determined using a series of coupled ocean-atmosphere and atmosphere general circulation models (GCMs), respectively. These climate change predictions are down-scaled to a 1° x 1° global grid using a neural-network based procedure.[14] The climate variables predicted by this module include temperature, specific humidity, precipitation, incoming solar radiation, and wind speed.

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[14] The neural network procedure finds an optimal form of the equation that will most accurately allow a set of input data to be used to predict a set of output data. In the case at hand, the input data are the climate variables predicted by the GCM, while the output data are the climatic predictions at a 1°x1° resolution. The neural net is trained using observed climate variables at the resolution of the GCM to predict observed climate variables at the 1°x1° resolution (Schultz 1997b). For a good introduction to neural networks, see Hewitson and Crane (1994).

4. Predicted climate change from the *Climate Change Module*, and regional economic output levels from the *Macroeconomic Module* feed into the *Impact Assessment Module*. In the present version, the PCIA focuses on climate-dependent impacts on space heating and cooling energy consumption, and on mortality rates. Both market and non-market impacts are considered, such as energy demand changes and deaths from climate change. These impacts are aggregated to the regional level and fed back into the *Macroeconomic Module*.

5. The *Policy Analysis Module* examines trade-offs between energy use, climate change, and human mortality. Alternative objectives (e.g., maximizing net benefits) and constraints (e.g., "acceptable" levels of mortality risk) are specified. Remedial policies are examined with respect to mitigation and adaptation as well as international and intergenerational equity. Policy instruments include efficient energy pricing, taxation, and marketable permits. The module draws inputs from the *Macroeconomic Module* and the *Impact Assessments Module* and its output feeds back into the *Macroeconomic Module*.

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