



White Paper

**Insights Not Numbers:
The Appropriate Use of Economic Models**

By

Janet Peace and John Weyant

April 2008

Insights Not Numbers: The Appropriate Use of Economic Models¹

by

Janet Peace and John Weyant

April 2008

Executive Summary

Economic modeling has played a prominent role in the climate-change policy debate as stakeholders have sought to understand the impacts and assess the costs of different strategies for reducing greenhouse gas (GHG) emissions. Models are an invaluable tool for exploring alternative policy choices and for generating insights about how the economy might respond to different types and forms of regulation. They cannot, however, predict future events, nor can they produce precise projections of the consequences of specific policy.

Every model uses its own set of assumptions, definitions, structure and data – its results ultimately depend on these attributes and choices. A proper understanding of economic models, their uses and limitations, is therefore critical in furthering a constructive debate about options for climate policy. As a starting point we highlight three general observations about the use of economic models:

- While economic models have become increasingly sophisticated, forecasting the future remains inherently uncertain. The longer the time horizon of the analysis, the larger the uncertainties involved.
- Model results are strongly dependent on input assumptions and on the structure of the model itself. Critical assumptions and structural biases are not always readily apparent to the outside observer.
- What is left out of a model can be as important as what goes in. Whether a model accounts for the benefits (or avoided costs) of climate mitigation, technological change

¹ The maxim “insights, not numbers” has a long and illustrious history starting with Hamming (1962) who argued that “insights not numbers” constitute the purpose of computing. The same maxim was subsequently applied by Geffrion (1976) in the context of mathematical programming and by Huntington, et al. (1982) in the context of mathematical modeling. We are also indebted to William Hogan who made the link to the Geoffrion piece and Richard Richels for occasionally reminding us what our objectives in modeling ought to be. These ideas probably all build on the work of W. Edwards Demming in the 1950s who, without ever explicitly using the phrase, surely implied that insights, not numbers are the purpose of statistical quality control.

spurred (or “induced”) by climate policy, or the “recycling” of revenues generated through certain policies can have large effects on the results.

Many of the cost analyses published over the last decade rely on general equilibrium models that use complex systems of mathematical equations and large amounts of data to simulate the workings of the economy. Comparisons across multiple studies suggest that several categories of assumptions are especially important in driving model results:

- (1) specific features of the policy or policies being analyzed (including the degree of flexibility allowed in meeting the emissions constraints);
- (2) reference case (or baseline assumptions) about how the economy and environment will perform in the absence of the policy;
- (3) flexibility in the economy—that is, the ease with which consumers/producers can adapt to emissions limits;
- (4) pace and magnitude of technological change/innovation; and
- (5) treatment of benefits (or avoided costs) from climate-change mitigation—what benefits are included and how.

A detailed comparison of results from two modeling initiatives sponsored by the Pew Center reveals that cost estimates can differ widely as a result of structural characteristics and assumptions embedded in the model, even where other key parameters (such as the policy being analyzed and base-case projections of future emissions) are the same. For example, the responsiveness (or elasticity) of various components of the economy—including assumptions not only about how readily low-carbon alternatives will be substituted for carbon-intensive goods and services, but also about how readily individuals make trade-offs between consumption and leisure are critical assumptions. A model which assumes a highly responsive relationship between consumption and leisure will find larger economy-wide impacts than one that assumes a less responsive relationship. This type of variable is a key component of most economic models and often there is no single, accepted value that all models or modelers use, so the choice of a particular number remains inescapably subjective.

The fact that modeling requires subjective judgment does not diminish the value of economic modeling but rather reinforces the idea that models are not perfect predictors of the future. In addition the individual characteristics and assumptions used in each model make comparisons of results between models difficult. Notably where modeling analyses differ in critical input assumptions, it is impossible to make an “apples to apples” comparison of their results. Nevertheless, such analyses are valuable for at least three reasons: (a) internal consistency in any one model or model projection provides a good basis for assessing the relative implications of policy alternatives; (b) despite all the complexities and uncertainties involved, some rough bounds on mitigation costs are apparent, and (c) modeling can help to illuminate what types of policy architectures are likely to lead to lower rather than higher costs.

In terms of crucial insights for policy architectures, numerous studies find a strong link between program flexibility and cost. Maximizing the options available to firms and citizens as they respond to GHG constraint, for example, leads to lower mitigation costs across all models. Notably, policy flexibility can be enhanced in a number of dimensions—by allowing emission permits, including both allowances and offsets, to be traded across sectors and between countries and by including greenhouse gases other than carbon dioxide. Modeling studies have also pointed to additional options for reducing cost, such as complementing emissions limits with well-designed technology policies (such as public support for research and development) and announcing policies well in advance of implementation so that firms have time to adjust and invest accordingly. Finally, modeling can be used to explore the distributional impacts of policies and to craft strategies for addressing disparate burdens on different regions, sectors, and segments of the population.

In summary, estimates of the cost of combating climate change are highly contingent on the underlying assumptions and modeling approach used to generate them, as well as on the specific policies and measures being analyzed. As the climate policy debate evolves, it is increasingly important that stakeholders understand the strengths and limitations of economic models and look to them for broad insights, not absolute answers.

Introduction

Many participants in the climate change debate—in government, industry, academia, and non-governmental organizations—have used economic modeling to assess the costs of various policies to address climate change, often with widely diverging results. Some analyses suggest that reducing greenhouse gas (GHG) emissions will produce net economic benefits, while others point to enormous costs. The fundamental reason for this divergence of results is that the underlying economic models are not like crystal balls—they cannot predict the future. Instead, models are complex mathematical representations of the economy, designed to give insight into economic relationships, assess the importance of key variables, and explore the sensitivity of various outcome measures to different policy options. While economic modeling has progressed significantly in the last several years and while the variety of applications for which it can be used has significantly expanded, modeling results still depend—and always will—on the unique set of inputs, embedded assumptions, and model structure itself used to generate them.

Few modelers would claim that their results represent precise predictions of the future; indeed most are quick to point to the assumptions and uncertainties inherent in their analyses. Unfortunately such caveats are often lost when findings are portrayed to the general public and to policy makers. For example, in testimony before the Senate Committee on Commerce, Science and Transportation in 2006, an economist stated unequivocally that the McCain-Lieberman climate bill would cost an average U.S. household \$725 dollars per year in 2010 and result in the loss of 1.3 million U.S. jobs by 2020 (Thorning, 2006).² While these numbers may sound definite, they are not. In that case, the model used specific assumptions about the lack of flexibility of the U.S. economy, the high cost of low-carbon energy alternatives, and very high future “business-as-usual” emission levels—all of which yielded results that suggest curbing GHG emissions will be very expensive. Cost estimates are also highly sensitive to the specific policy being modeled (e.g., a command-and-control type of regulatory approach will tend to produce significantly higher cost estimates than a market-based approach). In short, model results are only as good as the underlying data, assumptions, and model structure allow. And

² The bill referenced here, S. 280, is a prominent GHG cap-and-trade proposal introduced in the 110th Congress by Senators John McCain and Joe Lieberman.

while such results are very useful for analyzing climate policy options, they must be viewed as highly uncertain and ultimately contingent on the design of the analysis that produced them. As Warwick McKibbin, an economist internationally known for his contribution to global economic modeling, has said: “economic models can play a very useful role but they need to be used carefully and form the core of a structured debate not the source of definitive answers” (McKibbin, 1998).

This paper builds on earlier Pew Center reports that have sought to improve and demystify economic models in a climate policy context. It begins by providing background and context, including a review of key modeling assumptions;³ next it compares assumptions and model variability in the two reports, Ross et al. 2008 and Jorgenson et al. 2008, released in conjunction with this paper (available at <http://www.pewclimate.org>). Finally, the conclusion identifies key climate policy insights that have emerged from economic modeling efforts to date (including those from the Pew Center’s two most recent reports).

Background and Context

In the past decade a large number of analyses about the economic implications of climate policy—for states, for nations and even globally—have been published. These analyses frequently rely on economic models, which are useful because they integrate economic theory (and sometimes scientific theory) with reams of data using computer programs. The result is a single framework that can be used to tease out insights about the relative merits of alternative policy designs.

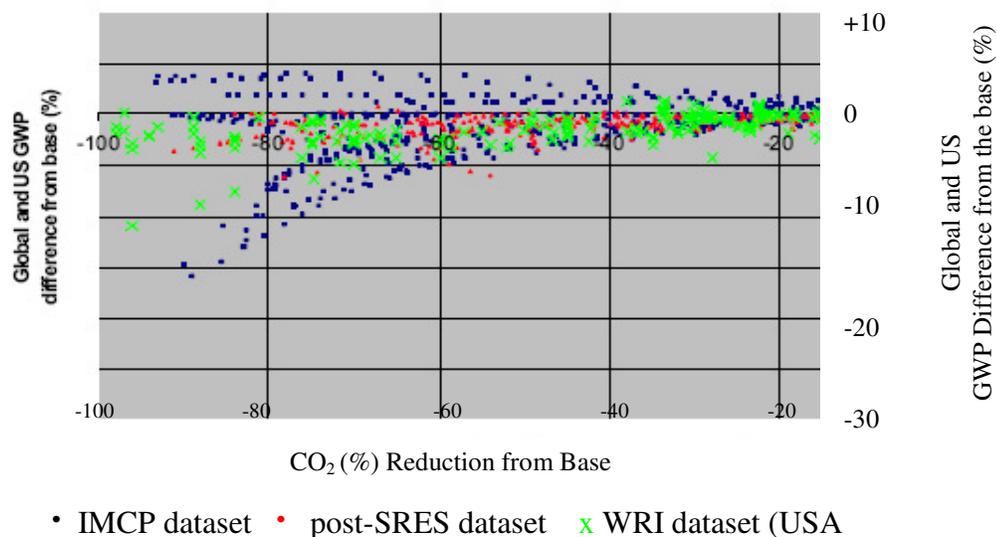
One of the most common tools used to analyze the long-run economic implications of climate policy is called a computable general equilibrium (CGE) model. Constructed of systems of mathematical equations, CGE models can analyze very large amounts of data about the economy as a whole; about production and consumption by industry sector; about investment and taxes, etc.; and about inputs and prices of capital, labor, and energy. In a general sense, CGE models attempt to represent a market economy by simulating the interaction of households and firms as they optimize their economic choices. State-of-the-art CGE models solve multiple equations

³ Readers interested in a more detailed discussion of these issues should consult Weyant, 2000 & 2002; Fischer and Morgenstern, 2005; Barker, 2006; or IPCC, 2007.

simultaneously to capture the interrelated behaviors of different economic agents and thereby illuminate the direct and indirect effects of policy on the broader economy over the long run. Their application to climate policy requires that data about the energy sector (which is responsible for most GHG emissions) and the rest of the economy are incorporated at a significant level of detail so that interactions between the two can be assessed. CGE models can highlight policy sensitivities, identify unintended consequences, provide some rough bounds on potential costs, and generally provide a benchmark for “good” policy.

Looking at the huge range of CGE-generated cost estimates in the literature on climate change mitigation, however, it is hard not to conclude that there is a lot of uncertainty surrounding model projections. A range of cost estimates for the same level of mitigation can vary by nearly two orders of magnitude. A relatively recent meta-analysis of economic modeling results by Barker (2006) illustrates the large disparity between model estimates of mitigation cost (see Figure 1).⁴ This analysis also illustrates that the larger the magnitude of emissions reductions modeled (moving from right to left on the graph), the wider the spread of results and consequently the greater the uncertainty about mitigation costs.

Figure 1. Estimates of Cost in 2030—as Percent Reduction in Gross World Product (GWP)—Compared to Different Levels of CO₂ Reduction



Source: Barker et al., 2006

⁴ A meta-analysis is a statistical research technique designed for cross-model comparisons of methodological or other factors that explain the wide range of cost estimates.

Note: Figure 1 shows estimated 2030 costs of stabilizing CO₂e at 500–550 ppm for three sets of modeling data. IMCP refers to the Innovation Modeling Comparison Project (Grubb et al. 2006); this dataset originates from a nine-model analysis that looked at three stabilization scenarios for CO₂ concentrations by 2100. The post-SRES data (Nakicenovic, et al., 2000) come from results associated with the IPCC Special Report on Emissions Scenarios. The WRI (World Resources Institute) data are for the United States only and reflect modeling results spanning 14 years (1983–1997) from 16 different energy-economy models (Repetto and Austin, 1997).

Table 1 presents mitigation cost estimates generated as part of the recently completed Fourth Assessment Report of the Intergovernmental Panel for Climate Change (IPCC). Costs were estimated for a range of GHG stabilization targets ranging from 445 to 710 parts per million (ppm).⁵ Here again, the wide variability in results indicates a high level of uncertainty. Notably these cost estimates are likely to be optimistic because the IPCC scenarios assume perfect global GHG emissions trading starts immediately (in some cases they assume global trading began in 2000) and continues for the rest of the century. Put another way, the IPCC results assume that mitigation policies are introduced in a globally coordinated fashion such that the marginal cost of GHG abatement measures is equalized across all regions and countries. Any reduction or restriction in the number of participating countries or regions would increase both the carbon permit price and the economic cost (GDP or GWP reduction) associated with achieving a given stabilization target (Weyant and Hill, 1999). Obviously globally coordinated policies were not in place in 2000, nor is this scenario likely to emerge in the short term.

⁵ Stabilization targets represent a goal for limiting GHG concentrations in the atmosphere at a specific level in order to prevent significant alterations to the climate. Common targets that have been proposed in national and international policy debates include 450 ppm and 550 ppm. To put these numbers in context, the atmospheric concentration of CO₂, measured at Mauna Loa in Hawaii in December 2006 was about 382 ppm; in recent years this number has been increasing by about 2.5 ppm per year.

Table 1. IPCC Estimates of Mitigation Cost in 2050 (GDP impacts are expressed as a percentage relative to BAU baseline)

Stabilization levels (ppm CO ₂ eq)	Median GDP impact (%)	Range of GDP impact (%)	Impact on average annual GDP growth rates (percentage points)
590-710	(-0.5)	+1 to (-2)	< (-0.05)
535-590	(-1.3)	Slightly positive to (-4)	<(-0.1)
445-535	Not available	< (-5.5)	<(-0.12)

Source: Adapted from IPCC, 2007, p. 15.

Note: These results suggest that for GHG stabilization targets ranging from 445 to 710 ppm CO₂-equivalent in 2050, estimated costs based on the existing models reviewed by IPCC range from a positive GDP gain of 1 percent for the least ambitious target to a negative GDP loss of 5.5 percent for the most ambitious goal (stabilizing global GHG concentrations below 535 ppm).

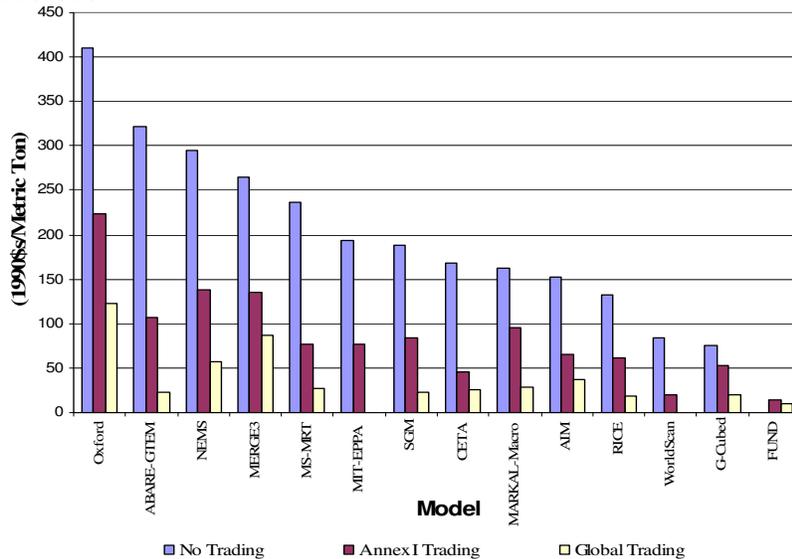
Given the wide variety of options that exist for reducing GHG emissions and the magnitude of the policy challenge in terms of the shift that will need to occur in global emissions trends, it is not surprising that a large amount of uncertainty exists with regard to future mitigation costs. To estimate these costs, changes in the world economy and future energy systems need to be projected over many decades using numerous assumptions about productivity growth, fuel prices, and technology development and deployment. Resulting cost estimates are also highly sensitive to the interest rate/discount rate used, with higher discount rates leading to lower values for future costs and benefits.⁶ Finally, modelers must also make critical assumptions concerning future government policies. What type of post-2012 global climate policy will be developed? What countries will adopt binding emissions targets? Will a global trading program be established? What incentives will exist for developing alternative forms of energy and will these incentives tend to increase or reduce GHG emissions? For example, policies to reduce

⁶ A discount rate attempts to account for the time value of money, recognizing that—for example—a \$1000 cost experienced 50 years in the future is not equivalent to a \$1000 cost experienced today. Rather, a cost of \$1000 incurred 50 years in the future would be worth \$608 today at a 1 percent per year discount rate or \$228 at a 6 percent per year discount rate. The issue of which discount rate to use when evaluating the social benefits of long-lived environmental goods is fairly contentious—as was demonstrated in the critical debate over the Stern Review. Willam Nordhaus, for example, has pointed out that if the discount rate used by the Review were changed (along with the consumption elasticity) from 0.1 percent to 1.5 percent, the social cost of carbon would change from the \$350-per-ton figure estimated in the Review to \$35 per ton—an order of magnitude difference (Nordhaus, 2007).

dependence on conventional oil could increase emissions (if, for example, they promote oil shale development) or reduce emissions (if they promote sustainable biofuels development).⁷

An earlier Pew Center report (Weyant, 2000) further illustrates the large uncertainties associated with projecting mitigation costs while also highlighting the importance of policy flexibility as a driver of likely cost. The findings of this report, which was largely based on an assessment by Stanford’s Energy Modeling Forum (EMF) of the costs of compliance with the Kyoto Protocol (Weyant and Hill, 1999),⁸ are shown in Figure 2. The figure shows projections of the carbon price that would be required for the United States to achieve its Kyoto target in 2010.⁹

Figure 2. Estimated Year 2010 Carbon Price Needed to Achieve U.S. Target under Kyoto Protocol



Source: Weyant, 2000 (based on EMF-16 results)

The first thing to note about the results is that they range widely: from about \$10 per ton of carbon to about \$400 per ton. This huge range again underscores the uncertainty surrounding these projections. Furthermore, this uncertainty about future costs may be even larger than the figure implies, simply because model inputs and parameters are often held within unrealistically narrow ranges—that is, they reflect mean projections with little or no uncertainty analyses.

⁷ Of course, even policies to promote biofuels could produce mixed results from a climate perspective, particularly if they result in land-use changes that transform carbon sinks to carbon sources (e.g., induced deforestation).

⁸ Stanford’s EMF has produced a series of assessments or studies; the one referenced in Weyant, 2000 and Figure 2 is EMF Study #16.

⁹The United States ultimately chose not to commit to achieving this target.

Predicting future trends and developments is never easy and it becomes more difficult the further out in time one attempts to project. The current debate on climate policy involves time spans of at least 50 years and often 100 years into the future. To put the modeling challenge in perspective, one need only think of the likelihood that anyone in 1957 could have foreseen the technological developments that have shaped our current economy (e.g., cell phones, computers, the internet, etc), let alone the likelihood that someone in 1907, when horses and buggies still dominated the roadway and the patent for a flying machine had only recently been approved,¹⁰ could have made accurate predictions about the state of the world a century later.

The Importance of Model Assumptions

That climate change is a long-term issue and that there is significant uncertainty inherent in economic models does not make the models irrelevant for examining climate policy—just the reverse. Economic models, and CGE models in particular, provide a framework for assessing the many complicated issues and interactions important in our economy and allow us to test how the economy may respond to various policy scenarios under differing assumptions. The importance of input assumptions and model structure, however, cannot be overstated, both in terms of understanding and interpreting model results and in terms of the insights that these results provide for policy design.

Weyant's earlier report for the Pew Center (2000) identified five key categories of assumptions that explain the majority of differences in modeled cost estimates:

- (1) type of specific policy or policies included (including the degree of flexibility allowed in meeting the emissions constraints);
- (2) reference case (or baseline assumptions) about how the economy/environment will perform in the absence of climate policy;
- (3) flexibility in the economy (ease with which consumers/producers can adapt);
- (4) pace and magnitude of technological change/innovation; and
- (5) characterization of the GHG-reduction benefits, particularly how and what benefits are included.

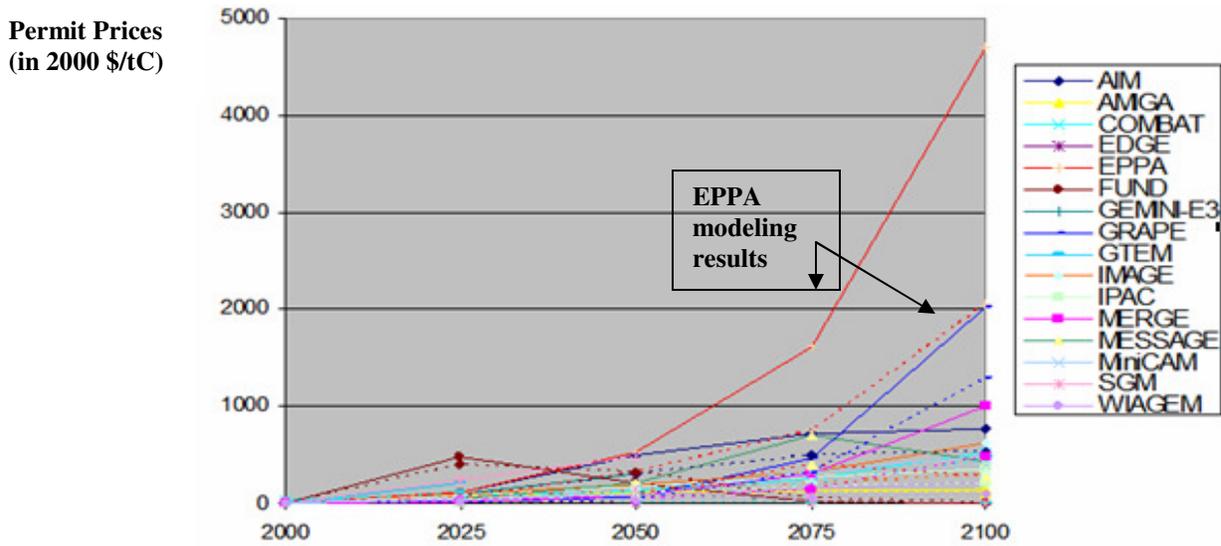
¹⁰ In 1906, the U.S. Patent Office granted the Wright brothers patent No. 821,393, for a flying machine. <http://www.uspto.gov/web/offices/ac/ido/oeip/cc/2003/cc20.pdf>

The Stanford EMF analysis that generated the cost estimates shown in Figure 2 (EMF Study #16) examined the importance of key policy assumptions—including, specifically, the importance of policy flexibility. It found that the additional flexibility afforded by international emissions trading could produce significant cost reductions. Specifically, if trading among developed (Annex 1) countries was assumed, the modeled price of carbon was reduced by about a factor of two or more compared to a no-trading scenario. Estimated costs were further reduced—by another factor of two or more—if full international emissions trading (including developing as well as developed countries) was assumed. A broader scope for emissions trading allows the model to take full advantage of the potential for low-cost reduction opportunities in different regions around the world. Fewer such opportunities exist, and costs are higher as a result, when trading is restricted to a smaller area (as would be the case in a U.S.-only program). Early experience with the European Union’s Emissions Trading Scheme (EU ETS) suggests that implementing a large-scale international trading system will not be cheap or easy, but the economic benefits of such a system seem well worth pursuing despite the difficulties.

The importance—from a cost perspective—of assumptions about the types of GHGs covered by the policy was also identified by Reilly et al. (2003) and EMF Study #21 (Weyant et al., 2006). Specifically, both of these studies analyzed the relative impact of including or not including GHGs other than carbon dioxide (CO₂). Reilly found that both carbon prices and welfare losses were 33 percent lower when all GHGs were covered.¹¹ The EMF study (as illustrated by Figure 3) demonstrated that the impact of including non-CO₂ gases might be even larger.. Cost estimates obtained using the Emissions Prediction and Policy Analysis (EPPA) model developed by the Massachusetts Institute of Technology (MIT), for example, suggest that including all gases could reduce the costs of a trading program more than 150 percent by 2100 (the MIT EPPA results are represented by the red dashed line in Figure 3).

¹¹ Welfare is a measure of well-being often used to refer to changes in national income or household income.

Figure 3. Comparison of Modeled Permit Prices for CO₂-Only vs. Multi-Gas Policies



Source: Weyant, et al., 2006

Note: The dotted lines represent multi-gas scenarios whereas the solid lines represent the CO₂-only scenarios. Notice that the dotted lines are consistently much lower than the solid lines.

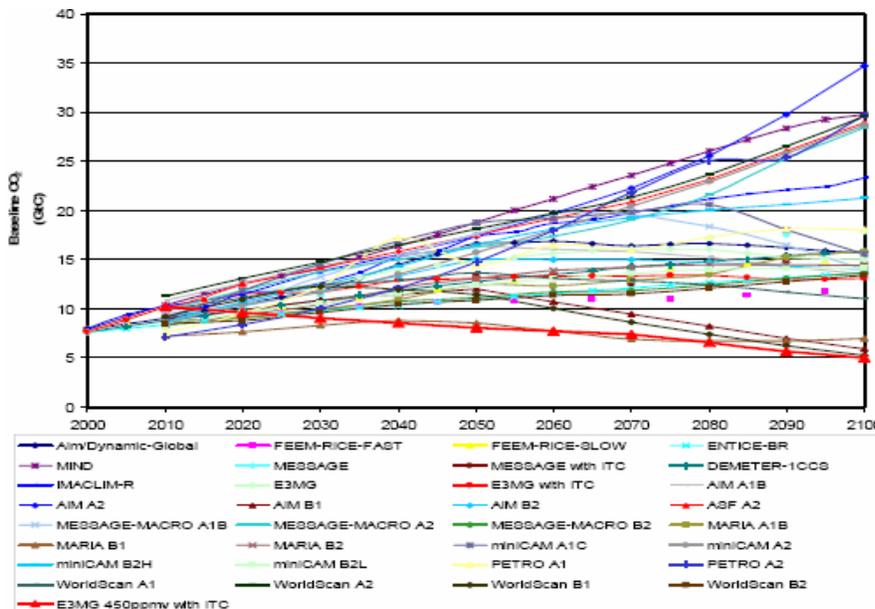
The logical consequence of these findings is that analysts cannot make very accurate cost projections without knowing what basic policy regime will be used to limit future GHG emissions and how stringent that regime will be (in terms of the emissions mitigation target it is designed to achieve). As a result, cost estimates are meaningless if they are presented without reference to the specific set of policies and measures assumed in the modeling analysis. For example, an analysis that assumes only CO₂ emissions will be covered under a future policy regime will project higher economy-wide costs for achieving a given GHG-mitigation target than an analysis that assumes both CO₂ and non-CO₂ gases are included. Assumptions about program scope and coverage, as well as other important aspects of policy design, must therefore be clearly communicated when presenting the results of any cost analysis.

Another key set of assumptions in any modeling analysis concerns the choice of a “base case.” The base case, also known as the baseline, reference, or “business-as-usual” (BAU) case, reflects modelers’ best guess about what will happen in the future without policy intervention to limit GHG emissions. Embedded in the base-case projection are assumptions about population,

economic growth, emissions growth, resource availability/resource prices, and technology availabilities/costs—all variables that can strongly affect model results. The higher expected BAU growth in economic activity and emissions, the more emissions must be reduced and the higher the cost to achieve a particular environmental target. Base-case projections for key economic parameters, such as GDP or employment, are also important because they constitute the baseline against which the costs of a climate policy are typically measured.

Fischer and Morgenstern (2005) and more recently Barker et al. (2006) have also noted the importance of base-case assumptions. Figure 4 from Barker’s 2006 meta-analysis compares base-case emissions projections from different modeling analyses. Not surprisingly, the divergence between forecast emissions (and hence the uncertainty associated with any given projection) increases over time. In Figure 4, the highest base-case emissions projection for 2100 is six times greater than the lowest base-case projection.

Figure 4. Model Variation between EMF-Forecasted Baseline CO₂ Emissions



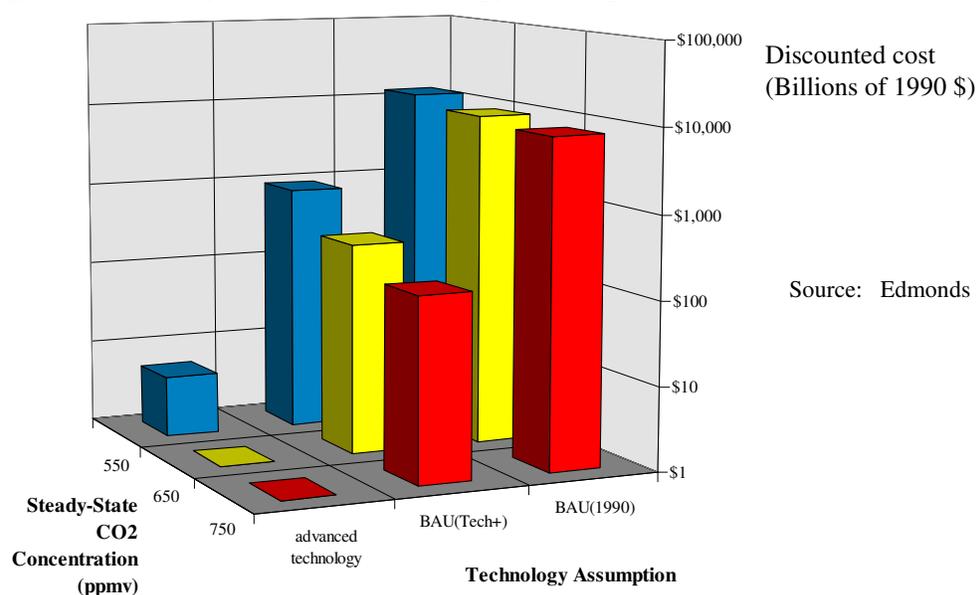
Note the greater than six-fold difference between assumed baseline emission levels in 2100

Source: Barker, 2006

The technology assumptions embedded in models are also critically important to the base-case projections and mitigation cost estimates generated by a given analysis. Optimistic assumptions about technological change—how quickly it will occur, how broad its scope will be, and how quickly costs for new technology are likely to decline—will produce lower cost estimates for

achieving a given GHG stabilization target. Figure 5 presents results from Edmonds et al. (2000) that underscore the important relationship between technology assumptions and cost projections.

Figure 5. The Importance of Technology Assumptions



Source: Edmonds et al. (2000)

While assumptions about basic policy structure, baseline, and technological change are critical in driving final model results, other modeling assumptions and parameters are also important. For example, Stern (2007) has identified several additional factors that account for the wide divergence of cost estimates found in the Barker (2006) meta-analysis:

- different assumptions about how revenues generated by a GHG mitigation policy would be used or “recycled”¹²
- ability of different models to account for induced technological change¹³
- inclusion (or not) of climate and other benefits of GHG mitigation measures
- type of economic model used to generate cost estimates

¹² A carbon tax would generate revenues for the government, as would a GHG trading program in which some or all emissions permits (or allowances) are sold by the government rather than distributed for free. The net economic impacts of any policy that generates revenue will depend in part on how those revenues are used—and in particular, whether the revenues collected by government are returned to the economy in a way that maximizes economy-wide benefits. For example, most economic models find that economy-wide benefits are higher from a carbon tax or trading program if the collected revenues are used to reduce taxes on income or capital investment.

¹³ Induced technological change refers to the additional change that would occur—above and beyond whatever rate of technology advancement is assumed in the base case—in response to price signals or other incentives generated by the policy being modeled.

Table 2 shows the impact of different model assumptions on estimates of future gross world product (GWP) in the cost studies reviewed as part of Barker’s meta-analysis. With assumptions that would tend to reduce mitigation costs (e.g., active revenue recycling, induced technological change, accounting for non-climate benefits, etc.), modeled estimates of future GWP were, on average, 3.9 percent higher than the base case. In analyses that did not include or “turned off” these assumptions, projected GWP was, on average, 3.4 percent lower than the base case.¹⁴

Table 2. Average Impact of Model Assumptions on World GWP¹⁵

	Percentage point GWP (% difference from the base case)
Worst case assumptions	-3.4
Best case assumptions	+3.9
Key assumptions	
Active revenue recycling	1.9
Induced technology	1.3
Non-climate benefit	1.0
Climate benefit	0.2
International mechanism	0.7
Backstop technology	0.6
CGE model	1.5

Source: Sterns 2007 (based on Barker et al, 2006)

Economic models only estimate how the economy will perform given very specific assumptions and only as allowed by the structure of the model. Different assumptions and different model structures yield very different results. This general point is reinforced by results from two recent modeling studies commissioned by the Pew Center to explore different design options for a market-based climate policy.

¹⁴ Best and worst case impacts are not the sum of impacts from all assumptions because not all assumptions were included in any one model.

¹⁵ Meta-analyses survey multiple studies, using statistics to compare model assumptions to model results, as a way to assess the relative importance of different model inputs. Their findings thus depend on the underlying models and the degree to which these models agree. By their very nature, meta-analyses are no more or less accurate than the individual analyses they examine.

A Comparison of Results from Two Pew Center Modeling Analyses

The Pew Center has always maintained that well-designed climate policies are critical to ensure that GHG emissions are reduced as cost effectively as possible. To facilitate policy discussions and explore the implications of alternative policy designs and instruments, the Center has been engaged for a number of years with two major modeling efforts. The first, led by Professors Dale Jorgenson and Richard Goettle of Harvard University and Northeastern University, respectively, uses IGEM (the Intertemporal General Equilibrium Model). The second effort is led by Dr. Martin Ross and colleagues at an independent research institute, RTI International, and uses the ADAGE (Applied Dynamic Analysis of the Global Economy) model.

IGEM and ADAGE are general equilibrium models that can simulate the effects of a policy on all sectors of the economy. For both of the modeling studies discussed here, analysts (1) assumed a modest climate policy that stabilizes emissions at 2000 levels by 2010; (2) allowed for inter-temporal optimization (that is, the models assume that economic agents have perfect knowledge about what will happen in the future and incorporate this knowledge into “current” decisions); (3) utilized the same emissions projections from the Energy Information Administration’s 2004 Annual Energy Outlook (AEO 2004); (4) included non-CO₂ GHGs in the cap-and-trade program being modeled; and (5) allowed for the use of emissions offsets (essentially, credits for GHG reductions from sources not covered under the cap).¹⁶ Superficially, the IGEM and ADAGE models are quite similar—yet their results vary significantly because of differences in the structural characteristics and assumptions embedded in each model.

Table 3 summarizes policy assumptions and modeling results from the two analyses. In terms of the projected price of emissions permits in 2020, the IGEM estimate is about 20 percent lower than the ADAGE estimate: \$10.50 per metric ton of CO₂-equivalent emissions compared to \$13.60 per metric ton. Despite lower expected permit prices, however, projected GDP losses under IGEM are nearly two times higher than indicated by the ADAGE results.

¹⁶ For further information on the details of the modeling analysis, see companion reports by Jorgenson (2007) and Ross (2007).

Table 3. Comparison of IGEM and ADAGE Model Results

Policy Assumptions	IGEM	ADAGE
Constraint GHG basis (2000 levels by 2010)	Yes	Yes
Non-CO2 abatement possibility at economic cost	Yes	Yes
Offsets (15% limit at economic cost)	Yes	Yes
Domestic sequestration	Yes	No
International Permit trading	Yes	Yes
Banking	Yes	Yes
Policy Outcomes 2020		
Permit Price \$(2000) MT CO ₂ e	\$10.50	\$13.60
Real GDP % change ¹⁷	-.69%	-.24%
Real Consumption % change	-.26%	-.12%
Real Investment % change	-1.34%	-.95%
Coal Price % change	39.5%	100%
Coal Quantity % change	-23.2%	-49.6%
Electricity Price % change	3.9%	11.3%
Electricity Quantity % change	-3.8%	-6.6%

Source: Jorgenson (2008) and Ross (2008)

Note: Results shown in Table 3 are relative to the base-case projection for 2020. For example, if GDP growth to 2020 is projected to average 4 percent per year in the base case, a reduction of 0.24 percent implies that GDP growth will instead average 3.76 percent per year.

These differences arise because the models have differing assumptions embedded within their structures. One assumption about the relationship between leisure and consumption, in particular, is quite different.¹⁸ In the IGEM model, Jorgenson and Goettle assume a fairly

¹⁷ Percentage change reflects a change from the base case assumption. For example, if GDP is assumed to grow 4 percent annually, a reduction of 0.24 percent implies that growth would be 3.76 percent.

¹⁸ Economic theory holds that as the prices of goods and services rise, people will substitute leisure for consumption—in other words, people will work less and buy less. Under a mandatory climate policy, prices would be expected to rise for all goods and services with embedded GHG content, including all goods and services whose production or delivery involves the use of fossil fuels. Because the IGEM model assumes a highly responsive relationship between consumption and leisure, a relatively small increase in prices will produce a relatively large loss of consumption and a commensurate increase in the demand for leisure. The result is a larger impact on most measures of economic impact—whether couched in terms of lost GDP or consumption or labor demand, costs look higher. Conversely, the ADAGE model assumes a less responsive relationship between consumption and leisure, higher prices for goods and services will have a smaller effect on consumption. In this case, the model assumes that consumers will, in effect, simply absorb higher prices without changing their work or consumption habits very much. As a result, costs will appear—by most measures of economic impact—to be lower.

responsive relationship between leisure and consumption and apply an elasticity of 0.8 to represent this relationship. In contrast, Ross et al. assume a less responsive relationship and apply an elasticity of 0.4 in the ADAGE model.

Jorgenson and Goettle demonstrate the importance of this assumption for estimating the costs of climate policy in an internally consistent way by running their model with two different elasticities, one implying a more responsive relationship between consumption and leisure and one implying a less responsive relationship. Results in Table 4 show that impacts on the economy are, by all the measures listed in the table, smaller if the model assumes a less responsive relationship. The magnitude of this difference also expands the farther out into the future the model attempts to forecast (once again underscoring the earlier point that model results become even less certain the farther they are projected into the future).

Table 4. The Impact of Alternative Assumptions about the Elasticity of Substitution between Consumption and Leisure within the IGEM model

Domestic Only with 15% Limit on Offsets		
	More Responsive	Less Responsive
Real consumption impacts		
2010-2025	-.19%	-.02%
2025-2040	-.40%	-.12%
Capital Stock impacts		
2010-2025	-.67%	-.47%
2025-2040	-1.15%	-.90%
Labor Demand impacts		
2010-2025	-.46%	-.30%
2025-2040	-.67%	-.35%
Leisure Demand impacts		
2010-2025	.15%	-.09%
2025-2040	.22%	.11%

Source: Jorgenson and Goettle, 2007

While economic theory can provide a foundation for the equations in a model, this example underscores the point that modelers must make many subjective determinations. The relationship between consumption and leisure represents only one of these determinations—critical judgments must also be made about the functional form of the model, what to assume about time delay, how to treat expectations, and how to include technological change, among many others.

The sensitivity of modeling results to a single assumption—in this case, the elasticity of substitution between consumption and leisure—also serves to illustrate that important differences between models are not always obvious. Most casual users would never dive deep enough into model documentation to ascertain that IGEM and ADAGE utilize a different assumption about the tradeoff between consumption and leisure. For this reason, it is very important that model developers (a) make transparent their assumptions and inputs (as Jorgenson, Goettle, and Ross do) and (b) to the extent possible, characterize principal sources of uncertainty in the model design and identify limitations that influence model results.

All models have such limitations, and IGEM and ADAGE are no exception. Neither of these models includes the benefits of avoided climate damage or the co-benefits associated with some GHG-mitigation measures (such as measures that simultaneously reduce emissions of other pollutants).¹⁹ Neither model incorporates a detailed representation of the process of technology innovation, nor does either model explicitly account for promising technologies that are currently on the drawing board, like carbon capture and storage or plug-in hybrid vehicles.²⁰ Furthermore, neither model includes the administrative costs of implementing a policy (including costs for monitoring, enforcement, and verifying offset credits in an emissions trading program). These limitations are important and must be acknowledged, but they do not mean the modeling results are not useful. On the contrary, the models can provide valuable insights concerning the implications of different policy choices. To apply these insights, policymakers must understand that modeling results do not represent exact predictions about what will happen in the future under a given policy regime. Rather, these results, like all modeling results, are closely tied to

¹⁹ Criteria pollutants like SO₂, NO_x and mercury will be reduced as fossil fuel consumption is reduced.

²⁰ At the relatively low carbon prices estimated in the Pew Center scenario, neither carbon capture and storage nor plug-in hybrids would enter the market (as such this is not truly a binding limitation for the scenario considered).

assumptions—they represent what *might* happen in response to a plausible range of input conditions.

Model Insights

While models (including IGEM and ADAGE) cannot predict the future, they can shed light on important economic relationships and test the robustness of alternative policy architectures, and in this way help inform the design of a market-based climate change policy. Likely one of the most significant and robust insights to have emerged from modeling efforts to date is that increased program flexibility reduces cost. Maximizing the options available to individual firms and citizens as they respond to GHG constraints helps to reduce both private and societal costs and leads to lower mitigation costs across all models (see Figure 2).

Notably, policy flexibility can be enhanced in a number of dimensions. For example, maximum flexibility to take advantage of the lowest cost mitigation opportunities wherever they exist can be achieved by allowing GHG emission rights and emission offsets to be traded between individuals, sectors, and countries. Results from the IGEM model, for example, suggest that increasing program limits on the use of offsets from 15 percent to 50 percent reduced overall program costs by 30 percent over the 2010–2025 timeframe and by 50 percent over the 2025–2040 time period. Similarly, modeled GHG permit prices were 50 percent lower in 2040 when international emission reductions were allowed into a U.S.-based emissions trading program (see Table 2, of Jorgenson and Goettle). In other words, allowing offsetting emission reductions from sources and countries outside the capped sectors to count toward program compliance dramatically reduces the costs of the policy.²¹

These insights regarding the benefits of trading and of creating a broader market for emission reductions (including offset credits for reductions achieved at sources that are not directly regulated under a cap-and-trade program) were confirmed in the EMF study of Kyoto compliance costs (Figure 1). More recent analysis of S. 280, a prominent GHG cap-and-trade proposal introduced in the 110th Congress by Senators McCain and Lieberman, reaches similar

²¹ Administration costs may somewhat reduce these benefits but models today do not capture this result.

conclusions (EPA, 2007).²² In modeling the costs of the McCain-Lieberman legislation, the U.S. Environmental Protection Agency found that including offset credits without restriction reduced allowance prices by 35 percent each year relative to a scenario in which—as proposed in S. 280—the use of such credits was limited to 30 percent of the overall compliance obligation in a given year. Similarly, modeled effects on GDP and consumption in the years 2030 and 2050 were about 33 percent lower with no limit on the use of offsets. Notably, when offsets were completely excluded (as opposed to being included subject to a 30 percent limit), modeled allowance prices increased by over 150 percent.

Flexibility was also increased (and costs reduced) under a program design that included all major GHGs and not just CO₂ (Figure 2). Intuitively, including non-CO₂ gases (such as methane, nitrous oxide, sulfur hexafluoride, and certain hydrofluorocarbons and perfluorocarbons) expands the universe of available low-cost options for reducing GHG emissions, especially because many of these gases have high warming potential and because, absent a price signal, firms have historically lacked incentives to pursue related mitigation opportunities (Reilly, 2003).

As complements to a market-based mechanism for reducing emissions, additional measures to promote advanced technology have also been shown by models to reduce costs. For example, modeling by Larry Goulder of Stanford University suggests that meeting any specific GHG reduction target will be significantly cheaper if R&D subsidies are implemented along with a carbon price, rather than applying either of these policies (subsidies or carbon price) alone (Goulder, 2004). Goulder also finds that announcing a policy ahead of time, so that firms have time to adjust, significantly reduces program costs. While most current proposals for a mandatory U.S. program to reduce GHG emissions include these elements—in the sense that they build in lead-time for firms to adjust and provide for complementary technology incentives—related modeling efforts do not always capture the benefits of these provisions. When they do, estimated costs are reduced accordingly. As policy makers try to craft a sound, least-cost strategy for reducing GHG emissions, economic models clearly have a critical role to

²² The EPA analysis of S. 280 also used the IGEM and ADAGE models.

play in exploring the implications of alternative program designs and assessing the impact of complementary policies.

Models can also provide important insights concerning the distribution of cost impacts across different industry sectors, households, regions, and even nations. Knowing which sectors or regions are likely to be hardest hit by a cap-and-trade program gives policy makers the knowledge necessary to adjust the policy or structure compensation so as to address equity concerns. Allocating free allowances under a cap-and-trade program is one potential avenue for directing compensation to certain sectors or even states. Because the ADAGE model has significant state-level detail it has been used to demonstrate that alternative allowance allocation options can have important implications for households in different states. An important insight from this is that allocation design can be used to reduce or equalize policy-related cost burdens—on states or across different segments of the U.S. population.

Last but not least, economic models (including the ADAGE and IGEM models) can be used to gauge the magnitude of overall costs that could be expected from the implementation of a cap-and-trade type climate policy. Under a plausible range of assumptions about the U.S. economy and assuming a policy architecture that imposes a modest cap on GHG emissions but allows trading and is implemented gradually, with advance announcement, the likely impact on the U.S. economy in a near- to medium-term timeframe is quite small: a less than 1 percent reduction in the expected growth of U.S. GDP by 2020. Looking at a broader range of modeling results (e.g., EMF, 1999, 2004, 2006; Edenhofer et al., 2006; IPCC, 2007), it is reasonable to conclude that stabilizing GHG concentrations in the atmosphere at 500–550 ppm CO₂-equivalent will cost—depending on how the policies used to reduce emissions are structured—somewhere between 0.1 percent and 10 percent of the world’s total economic output (GWP) per year (Figure 1). That this range is quite large (spanning at least two orders of magnitude) is not surprising, given the large uncertainties involved. It might be possible to narrow the range of cost estimates by half, if the basic elements of the policy regime likely to be adopted in various countries could be identified. Cost uncertainties could be further reduced if it was clear that governments would choose the least-cost policy options in most cases. Generally speaking, this would mean

broadening the scope and maximizing the flexibility of GHG-reduction policies to the extent feasible and consistent with maintaining program integrity.

By bounding the range of likely costs associated with stabilizing atmospheric GHG concentrations, economic models provide some sense of the magnitude of the policy challenge and provide context for weighing climate concerns relative to other broad societal objectives (for example, in the realms of national security, health, education, and welfare). Finally, modeling results can help to highlight the costs and trade-offs associated with accommodating certain political, environmental, or other considerations—whether those argue for postponing near-term mitigation efforts, limiting program flexibility, or imposing more drastic emissions reduction requirements.

Conclusions

More sophisticated economic models and vastly increased computing power have made it possible to simulate the complex workings of the economy and process enormous amounts of data to estimate the likely consequences of different GHG-mitigation policies. Nevertheless, the results obtained using such models represent—at best—approximations. Moreover these approximations are highly dependent on the underlying assumptions and model structure used to derive them. In many cases these drivers are readily apparent; in other cases they are difficult to tease out because they are embedded in detailed aspects of the model’s structure.

Given the wide variation that exists between models and the significant uncertainties inherent in projecting future economic and technological conditions, as well as likely policy outcomes, the question arises: is there any value to projecting mitigation costs? The answer, we believe, remains ‘yes.’ In spite of the substantial variability that characterizes different model results, cost estimates are valuable for at least three reasons: (1) internal consistency²³ in any one model or model projection provides a good basis for assessing the relative implications of policy alternatives; (2) despite all the complexities and uncertainties involved, some rough bounds on

²³ Internal consistency in any one model is important because this allows for an “apples to apples” rather than “apples to oranges” comparison. Comparing results across models with often widely divergent assumptions is without question an “apples to oranges” exercise.

mitigation costs are apparent, and (3) modeling can help to illuminate what types of policy architectures are likely to lead to lower rather than higher costs.

Notably a policy architecture that provides more flexibility in terms of the GHG mitigation options available to producers and consumers—such as a trading program—will yield lower program costs than one that is less flexible. Flexibility can be enhanced by including multiple GHGs (not just CO₂), by allowing offset credits for mitigation measures that address sources or types of emissions not covered by the cap (both domestic and international), and by including well-designed technology policies—such as subsidies for R&D—as a complement. In addition, two further conclusions can be drawn from modeling results to date. The first is that announcing a policy well in advance of implementation will reduce overall costs; the second is that allowance allocation provides the opportunity and the means to reduce net cost impacts on specific states, industrial sectors, and individuals or households.

When model inputs and methodologies are clearly presented and reflect plausible and generally accepted and/or peer reviewed assumptions, the resulting estimates of future mitigation cost can provide valuable insights for policy makers and stakeholders in the climate policy debate. Even a rough bounding of potential costs can be quite useful for policy makers who often hear extremely pessimistic or, alternatively, highly optimistic estimates from analyses designed to support a particular policy agenda.

In sum, cost estimates are highly contingent on the underlying assumptions and modeling approach used to generate them, as well as on the specific policies and measures being analyzed. To put modeling results in perspective and draw appropriate conclusions, it is critical that all parties have a clear understanding of the assumptions and limitations that underlie the analysis. Such assumptions and limitations must be clearly identified and prominently stated in any report or presentation on the costs of climate change policy. Few if any of the experts who work closely with models believe that whatever estimate they generate for future energy costs or GDP impact will actually materialize under a given policy. Rather, these results are interesting for the broader insights they reveal. In the effort to craft and implement cost-effective, well-designed strategies for addressing the problem of climate change, it is critical that all who seek to

understand and use modeling results share a realistic view of their proper role in the climate policy debate.

References

Barker, Terry, Mahvash Saeed Qureshi and Jonathoan Kohler. 2006. The Costs of Greenhouse Gas Mitigation with Induced Technological Change: A Meta-Analysis of Estimates in the Literature. Cambridge Center for Climate Change Mitigation Research Department of Land Economy, University of Cambridge. July.

Edenhofer, O., K. Lessman, C. Kemfert, M. Grubb. And J. Kohler. 2006. "Induced Technological Change: Exploring its Implications for the Economics of Atmospheric Stabilization. Synthesis Report from the Innovation Modeling Comparison Project". *Energy Journal*, 27, 1-51.

Edmonds, J.A., T. Wilson, and R. Rosenzweig. 2000. A Global Energy Technology Strategy Project Addressing Climate Change: An Initial Report an International Public-Private Collaboration. Joint Global Change Research Institute, College Park, MD.

Edmonds, J.A., T. Wilson, and R. Rosenzweig. 2000. *A Global Energy Technology Strategy Project Addressing Climate Change: An Initial Report an International Public-Private Collaboration*. Joint Global Change Research Institute, College Park, MD.

EPA. 2007. EPA Analysis of the Climate Stewardship and Innovation Act of 2007. July 16. Available on line at <http://www.epa.gov/climatechange/downloads/s280fullbrief.pdf> .

Fischer, Carolyn and Richard Morgenstern. 2005. Carbon Abatement Costs: Why the Wide Range of Estimates? Resources for the Future. Discussion Paper. Nov. Available at <http://www.rff.org/Documents/RFF-DP-03-42-REV.pdf> (Accessed Aug. 6, 2007).

Geoffrion, A.M., "[The Purpose of Mathematical Programming is Insight, Not Numbers](#)," *Interfaces*, 7:1, 81-92 (November 1976).

Goulder, L. 2004. *Induced Technological Change and Climate Policy* Prepared for the Pew Center on Global Climate Change. October. Available at http://www.pewclimate.org/global-warming-in-depth/all_reports/itc Downloaded Aug. 20, 2007.

Grubb, M., C. Carraro, and J. Schellnhuber. 2006. Technological Change for Atmospheric Stabilization: Introductory Overview to the Innovation Modeling Comparison Project. *Energy Journal* 27, 1-16.

Hamming, R.W., 1962. "The purpose of computing is insight, not numbers." *Numerical Methods for Scientists and Engineers*. McGraw-Hill.

Huntington, Hillard G., John P. Weyant, and James L. Sweeney. " Modeling for Insights, Not Numbers: The Experiences of the Energy Modeling Forum." *OMEGA: The International Journal of the Management Sciences*, Vol. 10, No 5, August 1982, pp 449-62.

IPCC 2007. Summary for Policymakers. In: *Climate Change 2007: Mitigation*. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate

Change [B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (eds)] Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jorgenson, Dale W., Richard J. Goettle, Peter J. Wilcoxon and Mun S. Ho 2000. *The role of substitution in understanding the costs of climate change policy*, Pew Center on Global Climate Change, September. Available at http://www.pewclimate.org/global-warming-in-depth/all_reports/role_of_substitution

Jorgenson, Dale W., Richard J. Goettle, Peter J. Wilcoxon, Mun S. Ho. 2008. *The Economic Costs of a Market-based Climate Policy*. Pew Center on Global Climate Change, Forthcoming. Available at [Pewclimate.org](http://www.pewclimate.org)

McKibbin, Warwick. 1998. *Greenhouse gas abatement policy insights from the G-cubed multi-country model*. Journal of Agricultural and Resource Economics. 42 (1) 99-113.

Nakicenovic, N. and A. Gritsevskiy. 2000. "Modeling uncertainty of induced technological change", Laxenburg: International Institute for Applied Systems Analysis.

Nordhaus, William. 2007. The Stern Review on the Economics of Climate Change. May Available at http://www.econ.yale.edu/~nordhaus/homepage/stern_050307.pdf. Accessed June, 2007.

Repetto, Robert, and Duncan Austin. 1997. The Costs of Climate Protection: A Guide for the Perplexed. Washington, D.C.: World Resources Institute. Available at http://www.wri.org/climate/pubs_description.cfm?pid=2475. Accessed Aug. 3, 2007.

Reilly, John, Henry Jacoby, Ronald Prinn. 2003. Multi-gas contributors to global climate change; Climate Impacts and mitigation Costs of Non-CO2 Gases. Prepared for the Pew Center on Global Climate Change. Feb. Available at http://www.pewclimate.org/global-warming-in-depth/all_reports/multi_gas_contributors.

Ross, M.T., B.C. Murray, R.H. Beach and B.M. Depro (2008), "State-level Economic Impacts of Global Climate Change Policies: Analysis of the Climate Stewardship Act (S.A.2028)," Prepared by the Research Triangle Institute International (RTI) for the Pew Center on Global Climate Change, Forthcoming.

Stern, Nicholas. 2007 The Economics of Climate Change, the Stern Review. Cambridge University Press.

Thorning, Margo. 2006. Written Testimony April 5th for the U.S. Senate Committee on Commerce, Science and Transportation Subcommittee on Global Climate Change and Impacts. Available at <http://www.iccfglobal.org/pdf/test-impactVM.pdf> Accessed August 10, 2007.

Weyant, J.P., and J.N. Hill, 1999. "Introduction and Overview." The Energy Journal Special Issue: The Costs of the Kyoto Protocol: A Multi-Model Evaluation, pp. vii-xliv.

Weyant, John. 2000. An Introduction to the Economics of Climate Change. Prepared for the Pew Center on Global Climate Change. Available at http://www.pewclimate.org/global-warming-in-depth/all_reports/economics_of_climate_change . Accessed Aug 5, 2007.

Weyant, John P., 2002 “Review Of Mitigation Cost Studies And Trajectories, And Assumptions That Drive Them,” in U.S. Policy on Climate Change: What Next?, Frank Loy and Bruce Smart, editors, Aspen Institute, 2002.

Weyant, John, Francisco C. de la Chesnaye, and Geoff J. Blanford, 2006 “Overview of EMF-21: Multigas Mitigation and Climate Policy,” in Special Issue of The Energy Journal, Francisco C. de la Chesnaye and John P. Weyant, editors, December, pp. 1-32.

Geoffrion, A.M., 1976 "[The Purpose of Mathematical Programming is Insight, Not Numbers](#)," *Interfaces*, 7:1, 81-92 (November).

Weyant, John. 2007. Presentation at the Haagan-Smit Symposium: Climate Change: Envisioning a Low Carbon Society in 2050 Aptos CA. May 14-17, 2007