

Methods for Developing Emissions Scenarios for Integrated Assessment Models

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1. Introduction

The overall objective of this research was to contribute data and methods to support the future development of new emissions scenarios for integrated assessment of climate change. The most recent set of emissions scenarios produced by the Intergovernmental Panel on Climate Change (IPCC) in their Special Report on Emissions Scenarios (SRES) (Nakicenovic, 2000) has provided a common set of projections for use in assessment models. However, one major shortcoming with the scenarios is the lack of an explicit probabilistic design. In order to support climate change research and decision making, future scenario sets should be designed that explicitly represent uncertainty in future emissions, and that do so efficiently within a relatively small set of scenarios. The U.S. Climate Change Science Program's (CCSP) strategic plan (Mahoney et al., 2003) includes the updating of greenhouse gas emissions scenarios (synthesis and assessment product 2.1¹). While the current effort is focused on concentration stabilization scenarios, future efforts will surely need to revisit the range of uncertainty in scenarios, which will be informed by this research.

¹ <http://www.climatechange.gov/Library/sap/sap-summary.htm>

There are a number of issues that must be resolved for the development of probabilistic emissions projections and the design of scenarios. One of these issues is the estimation of the uncertainty in key economic and technological drivers that determine emissions. While future economic outcomes may not be the same as the past, historical data on the variability can inform expert judgments about future uncertainty and mitigate against cognitive biases. Previous and ongoing work, described below, has analyzed data on historical variability in economic growth and changes in energy efficiency for this purpose. However, this work has identified a second obstacle: that estimates of historical data may not be directly consistent with the representation of parameters in integrated assessment models, which have different structures. Thus, if probability density functions (PDFs) derived from data are used without alteration as input for model parameters, the resulting projections may not be consistent or meaningful. Furthermore, different models have different parameterizations. They aggregate national economies into different groupings, aggregate economic sectors differently, and represent the production within a sector differently. Understanding how national reported data maps into different representations of economies in current

integrated assessment models is crucial to the development of improved emissions scenarios for use in a wide range of models.

Another major issue that has yet to be addressed is the efficient design of multi-gas emissions scenarios. The study of climate change requires an understanding of numerous emissions beyond carbon dioxide: methane, nitrous oxide, and other greenhouse gases, sulfate aerosols, black carbon aerosols, organic carbonaceous aerosols, tropospheric ozone and its precursors, and others. The combined and interactive effects of these species on radiative forcing, both directly and indirectly through effects on cloud processes, are critical to assessing climate impacts. These emissions all are uncertain, and will not be perfectly correlated with each other, nor will they be completely independent. Because the purpose of standard scenarios for climate assessment is to provide common inputs to modeling studies, including full three-dimensional atmosphere-ocean global circulation models (AOGCMs) which have significant computational costs, a set of scenarios needs to span the range of joint uncertainty in emissions efficiently and with a minimal number of scenarios. Work is needed to develop methods for designing such a set of scenarios that isolate the key combinations of emissions and account for the correlation in their

production. This issue was not addressed adequately in the IPCC Third Assessment Report (TAR) (Reilly et al., 2001), and will not be addressed in the ongoing Fourth Assessment (AR4), but future assessments will need to revise scenarios to describe uncertainty, and this issue will be revisited.

Specifically, this research had two main objectives:

1. Use historical data on economic growth and energy efficiency changes, and develop PDFs for the appropriate parameters for two or three commonly used integrated assessment models. From this work across different models, some general rules and methods will be developed to guide other modelers who in the future undertake similar explorations of uncertainty in their models.
 - a. As a part of objective #1, and an important extension of previous work, we will perform similar explorations of estimates of elasticities of substitution based on historical data. The research into historical energy efficiency trends to inform the autonomous energy efficiency improvement (AEEI) parameter in models has shown that the estimated value is dependent on the assumed elasticities of substitution in production. Therefore, significant effort to

estimate elasticities for different countries and different sectors or sectoral aggregations is crucial to be able to represent uncertainty in future technical progress and to map correctly into a given model structure.

- b. With analysis of the uncertainty in substitution possibilities, and data on historical variability in energy efficiency and productivity growth, the project will then develop distributions for model parameters that would give projections consistent with the observed variability for several models. This will produce background information that can be used in expert elicitation exercises, and will also provide guidance to development of consistent scenarios for other models with different structures.
2. Using the parameter distributions developed through the first task and previous work, we will develop methods of designing multi-gas emission scenarios that usefully span the joint uncertainty space in a small number of scenarios. Alternative designs will be explored by propagating uncertainty in emissions through a climate-chemistry model, and testing various criteria for selecting a

small number of emissions scenarios. This task will result in the development of improved scenario design methods and an illustrative set of scenarios.

Section 2 of this report summarizes results on AEEI. Section 3 describes an uncertainty analysis of elasticities of substitution. Section 4 presents the probabilistic emissions scenario approach.

2. Autonomous efficiency improvement or income elasticity of energy demand: Does it matter?

2.1 Introduction

Analysis of climate policy choices requires projections of future emissions of greenhouse gases and other substances, and of the costs of restricting these emissions through a policy constraint. Future emissions and costs depend on projections of economic growth, energy use, and the fuel composition in energy production. Any conclusions drawn about climate policy depend critically upon assumptions that drive projections of energy use, and its responsiveness to policy instruments such as a carbon cap or tax.

One important observation that applies to most developed countries is that over long periods of time they exhibit a decrease in the energy input (measured in physical units) per unit of total output (measured in monetary units) at the aggregate level. This is often referred to as declining energy intensity of GDP.

Declining energy intensity is not easily explained as a purely energy price response because over much of the period where decreasing intensity has been observed, real energy prices declined and if energy price was the main driver of this change one should expect rising rather than declining energy intensity.

Drivers of changes in energy intensity can be grouped into three generic categories: (1) a price response, where higher energy prices lead to substitution of other inputs for energy, toward less energy-intensive goods and services, or spur technical innovation; (2) reduced energy use per unit of output in specific processes and sectors due to technical change unrelated to energy prices (e.g., technical change that saves on materials and labor might also be energy saving); or (3) an income elasticity of less than unity, reflecting preferences for less energy-intensive products and

resulting in less than proportional increase for energy and energy-intensive or energy-using products as income rises. Historical observations are typically underdetermined, making it impossible to definitively ascertain the relative contribution of the latter two causes. Attempts to model the relationship of economic activity to make projections that are consistent with observations about declining energy intensity include a relationship to the scale of economy which often implies an income elasticity of 1.0, and an Autonomous Energy Efficiency (AEEI) parameter that then allows intensity to decline even if energy prices are stable or falling. [Table 1](#) lists assumptions in several integrated assessment models in the literature that directly determine AEEI and energy demand elasticities with respect to income and price. In addition, many of these models have additional structural features that indirectly induce a relationship between income and energy intensity, such as the dependence of AEEI on income in MERGE ([Manne et al., 1995](#)) and a dependence on income of changes in sectoral shares in consumption and elasticities of substitution in consumption in

EPPA (Paltsev et al., 2005).

Does it matter, or for what purposes does it matter, if the energy intensity relationship we observe is either an exogenous technological trend or some endogenous function of income? In this paper, we explore the implications of the choice between representing non-price driven changes in energy efficiency in energy-economic models, using the MIT Emissions Projection and Policy Analysis (EPPA) model (Paltsev et al., 2005). We show that the choice of representing non-price technical change as an income response implies a higher cost for CO₂ reduction policies. As a motivation, we present the historical experience of the U.S. economy from 1970 to 2000 in Section 2. In Section 3, we briefly review the EPPA model, which in the standard version assumes an energy demand elasticity with respect to income equal to 1.0, and we describe an alternative version allowing the income elasticity of energy demand to vary from 1.0. We present results in Section 4, and a discussion of the implications in Section 5.

Table 1 - 1: Parameter values in several integrated assessment models

Model name	AEEI (%/year)	Price elasticity of energy	Income elasticity of energy demand	Source
CETA	0.25	-1.0 (Cobb-Douglas)	1.0 ^a	Peck and Teisberg (1992)
DICE-99	1.0 declining to 0.5 ^b	None	1.0 ^a	Nordhaus and Boyer (2000)
EPPA	1.0	-0.4	1.0 ^a	Paltsev et al. (2005)
ER	1.0	-0.4	0.5 (Developed) > 1.0 (Developing)	Edmonds and Reilly (1985)
MERGE	0.5 ^c	-0.4 (USA, OECD) -0.3 (other regions)	1.0 ^a	Manne et al. (1995)
MiniCAM	0.0-2.6 varies by region, time	-0.7	1.0 (OECD) 1.25 (FSUEE) 1.4 (DEV)	Edmonds et al. (1995)
SGM	Varies by sector and country; e.g. 0.5 for USA, Other Goods; 1.0 for household oil	-0.1	1.0 ^a	Brenkert et al. (2004)

^a CES or Cobb-Douglas functions with constant returns to scale imply doubling output doubles all inputs, absent a price effect.

^b DICE-99 does not represent energy explicitly, and therefore instead of AEEI uses an exogenous rate of declining carbon intensity.

^c AEEI is income dependent.

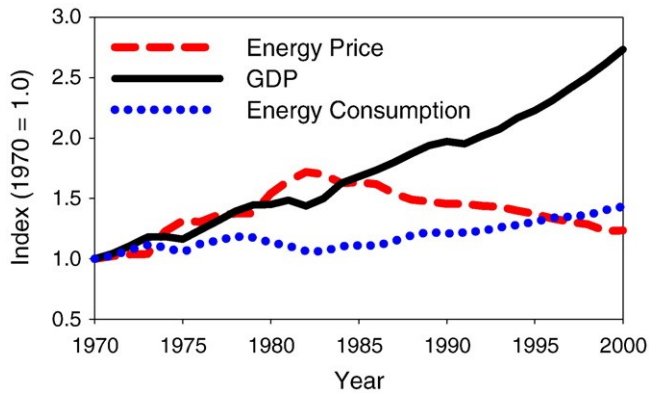


Fig. 1-1. GDP, energy consumption, and energy prices in U.S. 1970–2000.

2.2 Evidence for and use of non-price drivers of energy intensity change

We begin by presenting historical observations from the U.S.

economy from 1970 to 2000, to illustrate the ambiguous nature of energy intensity changes. We use U.S. GDP data from the Penn World Tables (PWT), version 6.1 (Heston et al., 2002), energy consumption data in physical units from the Energy Information Administration (EIA, 2003), and energy price data from the International Energy Agency (IEA, 2004). Energy price data are only available from 1970 onward, limiting our investigation to the period 1970–2000. The data include prices for crude oil, natural gas, coal, and electricity. We combine these series into a divisia price index by weighting each fuel by its value share of total energy.¹ Quantities of each fuel used for non-electric and electric are also obtained from EIA (2003).

Fig. 1 shows the paths of GDP, energy consumption, and energy prices since 1970 (each series is indexed so that 1970 = 1.0). In general, the trends are (1) rising GDP over this period, (2) a steep rise in the aggregate energy price from 1970 to 1982 followed by a gradual fall through 2000, and (3) nearly flat energy consumption until 1985 and then rising but at a rate slower than GDP. A simple

calculation of the long-term average residual from this aggregate data yields an estimate of approximately 2.5% per year for the U.S. decrease in energy/GDP over this period. The focus of this paper is the trend from 1982 to 2000: why during a period of falling energy prices and rising GDP does energy demand grow at a slower rate than GDP?

To further motivate the modeling study presented in later sections, we estimate an aggregate model similar to those widely used in demand modeling (e.g., Schmalensee et al., 1993; Bohi, 1981) where the main explanatory factors are the good's own-price and income and we allow for an additional time trend effect—the residual AEEI:

$$\ln E_t = \alpha + \beta \ln P_{t-1} + \theta \ln GDP_{t-1} + \gamma t + \varepsilon_t$$

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where E_t is aggregate energy use, P_{t-1} is the aggregate energy price, GDP_{t-1} is the Gross Domestic Product, α , β , θ , and γ are estimated parameters, ε is the error term, and "ln" is the natural logarithm. In this logged form parameters are directly

interpretable as elasticities. All price effects (reduced use within a sector and shifts among sectors) should be captured by the price variable eliminating the problem in highly disaggregated models that some of the shift may result from changing prices of the sectoral output resulting from the changing energy input price. If a growing economy exhibits constant returns to scale (no income effect), we would expect $\theta = 1$. To the extent that structural change or some other income response that shifts the economy toward rising or falling energy intensity occurs as a response to growth in GDP, that will be captured by θN or b_1 .

Eq. (1) results in an estimate of the price elasticity of energy demand (β) that is statistically significant and robust across the specifications, ranging from -0.22 to -0.24 (Table 2), which is consistent with estimates of the aggregate economy's short-run price elasticity (see, for example, Table 3-1 in Bohi, 1981). The estimated income elasticity is 0.3 and the AEEI time trend is negligible but slightly increasing. Neither of these terms is statistically significant, suggesting collinearity. Dropping the time

trend (specification 2 in [Table 2](#)) results in a statistically significant income elasticity estimate of 0.34. Restricting the coefficient of the income variable to 1.0 (specification 3), representing the Constant Returns to Scale (CRS) assumptions common in many models, gives an estimated time trend of 2% per year. Restricting the coefficient of the income elasticity to 0.5 (specification 4) as in [Edmonds and Reilly \(1985\)](#) gives an estimated time trend of 0.5% per year.

More complex ways to formulate the data and the econometric problem can reveal interesting relationships that are potentially behind the apparent aggregate response, and there is a variety of literature which attempts to do just that (e.g., [Hogan and Jorgenson, 1991](#); [Kaumann, 2004](#); [Sue Wing and Eckaus, 2007](#)). The point of this example is not to provide econometric estimates, but rather to illustrate that non-price driven energy efficiency improvements can be represented in models either by an autonomous time trend with an AEEI parameter or as a response to rising income levels with an income elasticity

parameter. Because of collinearity (GDP growth is fairly smooth over time and thus collinear with the time trend), the data cannot tell us how much of the change in energy intensity is related to the gradual long-term trend of increasing income or the marching forward of technology. We next turn to a numerical model to explore whether this choice has implications for future projections.

2.3. The MIT emissions prediction and policy analysis model

The Emissions Prediction and Policy Analysis Model (EPPA) is a recursive-dynamic general equilibrium model of the world economy developed by the MIT Joint Program on the Science and Policy of Global Change ([Paltsev et al., 2005](#)). The EPPA model is built on the GTAP dataset ([Hertel, 1997](#); [Dimaranan and McDougall, 2002](#)), which accommodates a consistent representation of energy markets in physical units as well as detailed data on regional production and bilateral trade flows. Besides the GTAP dataset, EPPA uses additional data for greenhouse gases (carbon dioxide, CO₂; methane, CH₄; nitrous oxide, N₂O; hydrofluorocarbons, HFCs; perfluorocarbons, PFCs; and sulphur hexafluoride, SF₆)

and air pollutants (sulphur dioxide, SO₂; nitrogen oxides, NO_x; black carbon, BC; organic carbon, OC; ammonia, NH₃; carbon monoxide, CO; and non-methane volatile organic compounds, VOC) emissions based on United States Environmental Protection Agency inventory data. For use in EPPA, the GTAP dataset is aggregated into 16 regions and 24 sectors with several advanced technology sectors that are not explicitly represented in GTAP (the regions and sectors are shown in [Table 3](#)).

Much of the sectoral detail is focused on energy production to better represent different technological alternatives in electric generation. The base year of the EPPA model is 1997. From 2000 it is solved recursively at 5-year intervals. The EPPA model production and consumption sectors are represented by nested Constant Elasticity of Substitution (CES) production functions (or the Cobb–Douglas and Leontief special cases of the CES). The model is written in the GAMS software system and solved using MPSGE modeling language ([Rutherford, 1995](#)). The EPPA has been used in a wide variety of policy applications (e.g., [Jacoby et al., 1997](#); [Reilly et al., 1999](#); [Babiker, Metcalf, and Reilly, 2003](#); [Reilly](#)

Table 1-2: Energy consumption as function of price, income, and time effects

Specification (Eq. (1))	Estimated parameters (standard errors)				Calculated values	
	α Constant	β Price elasticity	θ Income elasticity	γ Residual time trend	AEEI % per year	R ² % Variance explained
1. All	10.4 (6.1)	-0.23** (0.040)	0.30 (0.21)	0.0013 (0.0066)	-0.13 (0.66)	0.90
2. Const, Pr, GDP	9.2** (0.58)	-0.23** (0.040)	0.34** (0.021)	-	-	0.90
3. ($\theta=1$)	-9.8** (0.21)	-0.24** (0.047)	1	-0.0206** (0.00080)	2.0 (0.08)	-
4. ($\theta=05$)	4.5** (0.18)	-0.23** (0.04)	0.5	-0.005** (0.00068)	0.5 (0.15)	-

**Significant at $p < 0.05$ level.

Table 1-3: Countries, regions, and sectors in the EPPA model

Country or region	Sectors	Factors
<i>Developed</i>	<i>Non-energy</i>	Capital
United States (USA)	Services (SERV)	Labor
Canada (CAN)	Energy-Intensive Products (EINT)	Land
Japan (JPN)	Other Industries Products (OTHR)	Crude Oil Resources
European Union+ ^a (EUR)	Industrial Transportation (TRAN)	Natural Gas Resources
Australia & New Zealand (ANZ)	Household Transportation (HTRN)	Coal Resources
Former Soviet Union ^b (FSU)	Agriculture (AGRI)	Hydro Resources
Eastern Europe (EET)	<i>Energy</i>	Shale Oil Resources
<i>Developing</i>	Coal (COAL)	Nuclear Resources
India (IND)	Crude Oil (OIL)	Wind/Solar Resources
China (CHN)	Refined Oil (ROIL)	
Indonesia (IDZ)	Natural Gas (GAS)	
Higher Income East Asia ^c (ASI)	Electric: Fossil (ELEC)	
Mexico (MEX)	Electric: Hydro (HYDR)	
Central & South America (LAM)	Electric: Nuclear (NUCL)	
Middle East (MES)	Electric: Solar and Wind (SOLW)	
Africa (AFR)	Electric: Biomass (BELE)	
Rest of World ^d (ROW)	Electric: Natural Gas Combined Cycle (NGCC)	
	Electric: NGCC with Carbon Capture and Storage (NGCAP)	
	Electric: Integrated Gasification with Combined Cycle and Carbon Capture and Storage (IGCAP)	
	Oil from Shale (SYNO)	
	Synthetic Gas (SYNG)	
	Liquids from Biomass (BOIL)	
Emission of climate relevant		
Substances	Sources	
CO ₂ , CH ₄ , N ₂ O, HFCs, SF ₆ , PFCs, CFCs, CO, NO _x , SO _x , VOCs, black carbon (BC), organic carbon (OC), NH ₃	Combustion of refined oil, coal, gas, biofuels and biomass burning, manure, soils, paddy rice, cement, land fills, and industrial production.	

^a The European Union (EU-15) plus countries of the European Free Trade Area (Norway, Switzerland, Iceland).

^b Russia and Ukraine, Latvia, Lithuania and Estonia, Azerbaijan, Armenia, Belarus, Georgia, Kyrgyzstan, Kazakhstan, Moldova, Tajikistan, Turkmenistan, and Uzbekistan.

^c South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand.

^d All countries not included elsewhere: Turkey, and mostly Asian countries.

and Paltsev, 2006; Clarke et al., 2007; Paltsev et al., 2007).

Because of the focus on climate and energy policy, the model further disaggregates the GTAP data for transportation and

existing energy supply technologies and includes a number of alternative energy supply technologies that were not in widespread use in 1997 but could take market share in the future under changed energy price or climate policy conditions.

Bottom-up engineering details are incorporated in EPPA in the representation of these alternative energy supply technologies.

Advanced technologies endogenously enter only when they become economically competitive with existing technologies.

Competitiveness of different technologies depends on the endogenously determined prices for all inputs, as those prices depend on depletion of resources, economic policy, and other forces driving economic growth such as savings, investment, energy efficiency improvements, and productivity of labor.

Additional information on the model's structure can be found in [Paltsev et al. \(2005\)](#).

2.3.1. AEEI in EPPA

In EPPA, we implement the conventional approach for taking non-price induced technological change into account as it affects energy efficiency in long-term energy projections by using an

exogenous factor referred to as the Autonomous Energy Efficiency Improvement (AEEI). The AEEI reduces the energy required in each sector to produce the same amount of output, assuming other variables such as energy prices are unchanged. In an actual forward simulation of the model, other variables such as energy prices change endogenously, and these changes also affect energy efficiency. The actual energy efficiency of production of each sector in forward simulations is thus a combination of the exogenous AEEI factor, and endogenous effects through changes in fuel and other prices. The AEEI can thus be seen as a reduced-form parameterization of the evolution of non-price induced changes in energy demand. Often it is assumed that AEEI represents technical change, but it should be seen as broadly representing other processes such as changes in the structure of production within the relatively highly aggregated sectors (Paltsev et al., 2005).

The EPPA4 model differentiates the rate of AEEI among regions and between non-energy and energy sectors of the economy. The EPPA assumptions for AEEI among the Annex B countries are based

on Edmonds and Reilly (1985) and Azar and Dowlatabadi (1999). They imply an energy efficiency improvement in the electric sector of 0.40% to 0.45% per year while non-electric sectors increase in energy efficiency by 1.2% to 1.3% per year. This pattern is different for developing countries, which have shown little reduction in energy intensity or even increases. To follow the historic pattern for developing economies we assume a gradual decrease in AEEI - i.e. worsening rather than improving energy efficiency - through the next few decades and energy efficiency improvement later in the century. The evolution of the AEEI for the non-energy sectors of the economy by region is shown in Fig. 2. We assume no AEEI trend in coal, gas, crude oil, and refined oil production sectors.

2.3.2. Income elasticity of energy demand

The reference version of EPPA does not represent an income elasticity of energy demand that can be easily adjusted. A value of 1.0 is implied by the use of constant-return-to-scale CES productions functions throughout the model. For the purposes of this study, we have constructed an alternative version of EPPA which makes energy intensity explicitly depend on income, a

relationship consistent with economic theory. There are several ways in which income elasticity could be implemented. Both GDP and GDP per capita are possible measures of income. We use GDP per capita because using GDP would imply a decrease in energy intensity from an increase in population with all else constant. Alternative measures such as consumption or investment would only capture part of the income, and would be less consistent with theory. The elasticity could be represented with in the consumer's utility function, but this would only

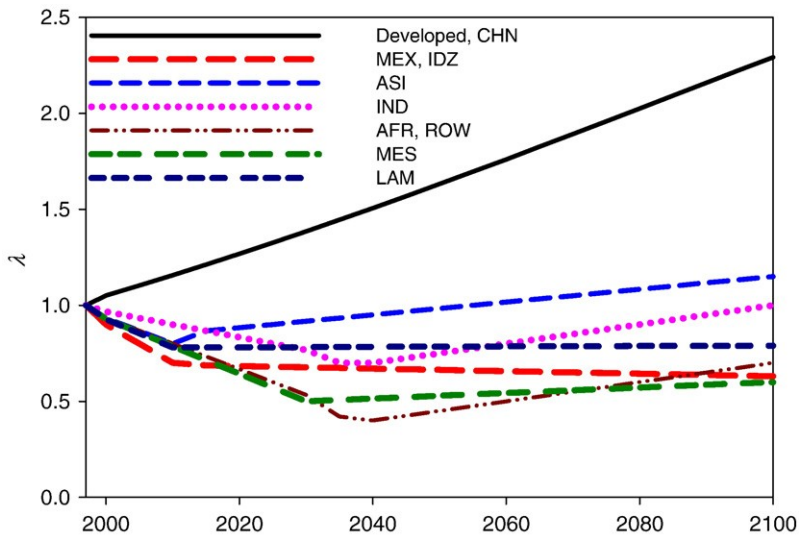


Fig. 1-2. Exogenous AEEI trends in EPPA4.

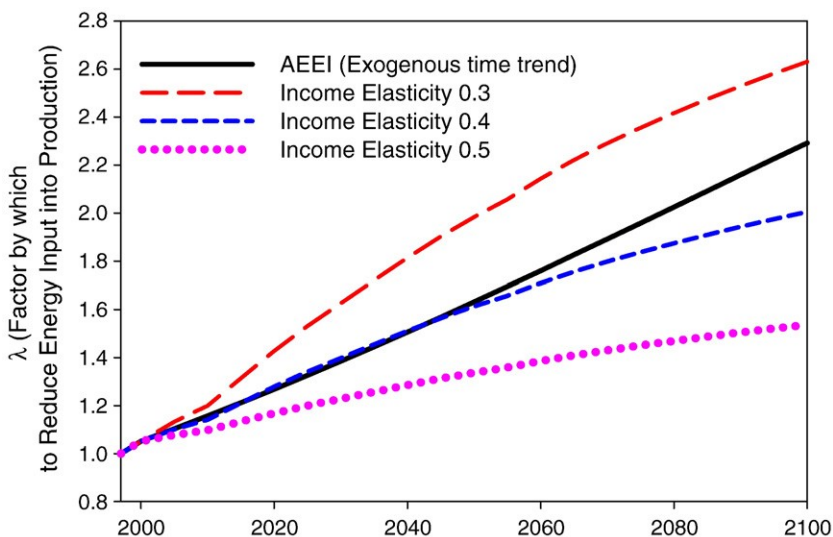


Fig. 1-3. Scaling factor for energy input into production (λ) for standard EPPA with AEEI and several alternative values for the income elasticity of demand.

affect the final household demand for energy, and not the broader changes in energy intensity that occur where energy is an intermediate input to production. Thus, our representation of the income elasticity will scale the energy inputs into production as a function of the change in GDP per capita.

To implement this, we employ the same AEEI demand reduction factors that scale production sectors' use of

energy per unit of output that are normally an exogenous time trend but here the AEEI is an endogenous function of the realized GDP per capita growth from one period to the next. Thus the energy demand reduction factor λ_t is determined as:

$$\lambda_{t+1} = \lambda_t + \alpha \cdot \% \Delta \text{GDP}_{\text{pc}}$$

where α determines the relationship between income growth and the efficiency factor and $\% \Delta \text{GDP}_{\text{pc}}$ is the percentage change in GDP per capita from the previous period. We choose values for the parameter α such that the resulting percent change in energy demand divided by the percentage change in GDP per capita over the period 2005–2030 (i.e., the elasticity of demand with respect to income) is equal to a desired value. As noted above, there are additional feedbacks in EPPA that change the consumption shares and the elasticities of substitution in consumption with income, based on studies of shifting sectoral shares with time/income (e.g., [Kydes, 1999](#);

Howarth et al., 1993; Howarth and Schipper, 1991). These parameters are held constant across the two versions of EPPA in this study, and generally have a weak effect.

2.4. Results: AEEI vs. income elasticity of energy demand

For this study, we focus exclusively on the behavior of the USA region in EPPA under the alternative assumptions. The impacts on other regions are qualitatively the same; only the numbers differ. We begin by showing the effects of different assumed values of the income elasticity parameter. Then we show that although an income elasticity of 0.4 produces equivalent behavior for projections over 2005–2050 as the standard AEEI version, the projections diverge over longer time horizons. We also show that the uncertainty in future emissions and policy costs have less variability under an income elasticity than under an exogenous time trend, because of the GDP feedbacks to energy intensity.

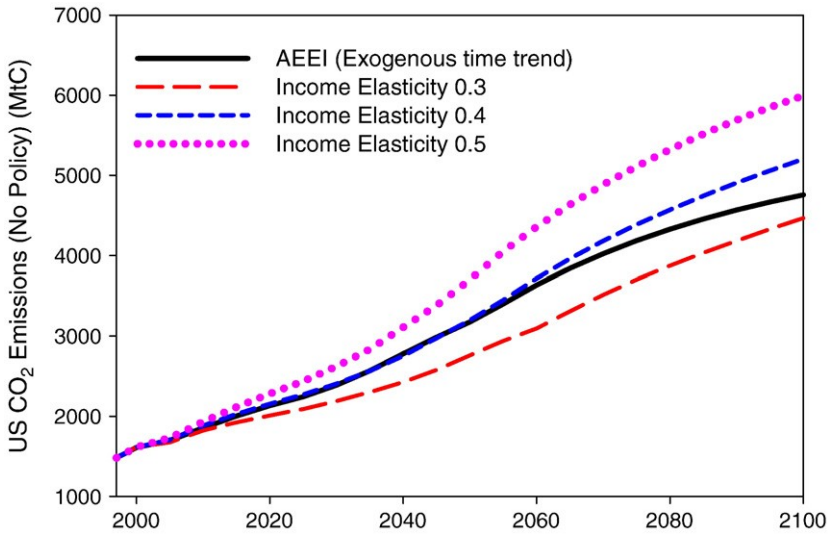


Fig. 1-4. Projected CO₂ emissions from US to 2100 (in the absence of any climate policy) under AEEI and three alternative values for income elasticity.

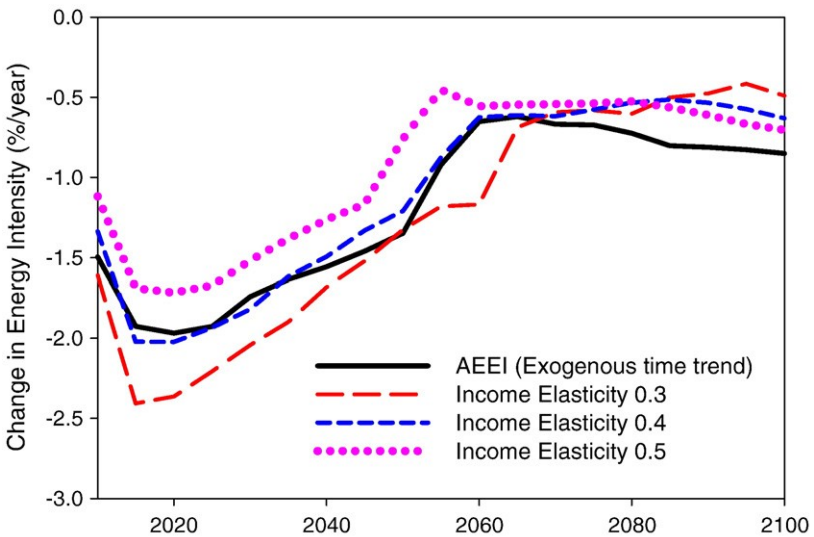


Fig. 1-5. Change in energy intensity of the US, calculated in annual percentage terms.

2.4.1. Calibration and near-term projections

In both versions of the EPPA model, the AEEI version and the income elasticity version, the same parameter k is set as exogenously dependent on time or endogenously dependent on income, respectively. This parameter is used to scale the physical energy inputs required for production; the energy demand for production is divided by λ to determine the physical quantity of energy units needed in production processes and in final consumption. [Fig. 3](#) shows the trend for the scaling factor k for the USA under the standard AEEI approach and three different values for income elasticity, ranging from 0.3 to 0.5. An income elasticity of 0.4 produces a trend for k that is nearly indistinguishable from the AEEI version up to 2050, after which they diverge. This highlights the fact that just as one can explain historical data essentially equally well as either driven by income or as an exogenous process, so too can one generate a very similar projection assuming this parameter is either exogenous or income driven. The two

diverge in the long-run EPPA forecast because eventually GDP growth slows in the forecast, but the march of time is unaltered.

The resulting projections of CO₂ emissions (Fig. 4) and rates of energy intensity reductions (Fig. 5) under AEEI and under an income elasticity of 0.4 also match closely up to 2060, because the underlying trend in k is the same. The CO₂ emissions from the version with an income elasticity of 0.4 are similar to those from the version with AEEI up until 2060. From 2060 to 2100, the emissions diverge between these two cases (Fig. 4), with the income elasticity version projecting higher emissions. The cause of this divergence is the decrease towards the end of the century in productivity and GDP growth rates. In EPPA, we assume that by the year 2100 the labor productivity growth rates fall to 0.8%/yr for developed countries (e.g., USA) and 1.4%/yr for developing countries (e.g., China). This assumption of decelerating growth is common among models used for emissions projections (e.g., Nordhaus and

Boyer, 2000), and if anything the EPPA model has growth falling off less than other models (Clarke et al., 2007).

2.4.2. Sensitivity to uncertainty in GDP growth

Given the many large uncertainties in future economic and energy projections, treatment of these uncertainties is critical in any analysis of climate policies. One of the most influential of these uncertainties is in future economic growth, and its underlying drivers (Webster et al., 2002; Scott et al., 1999). One important difference between modeling non-price technical change as an autonomous time trend and as an income response is the resulting interaction between GDP growth and energy intensity.

To demonstrate this interaction, we simulate two sensitivity cases, one with 50% higher labor productivity growth rates and one with 50% lower labor productivity growth rates, using both versions of EPPA, the AEEI version and the version with an income elasticity of 0.4.

Fig. 6 shows the resulting GDP growth rates for the US for the reference, low, and high growth cases. For the sensitivity

analyses in this section, we calibrate the AEEI (exogenous time-dependent) version of EPPA by imposing the identical time series for k over time as in the income dependent version under reference GDP growth rates. In this way, the two versions are identical under the reference growth assumption, but will differ in important ways under the high and low growth assumptions.

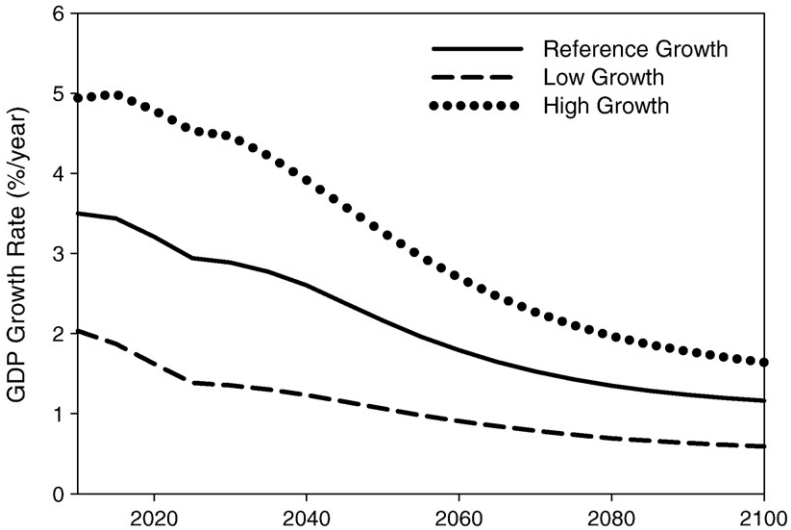


Fig. 1-6. Reference, low, and high GDP growth rates for USA used in sensitivity testing.

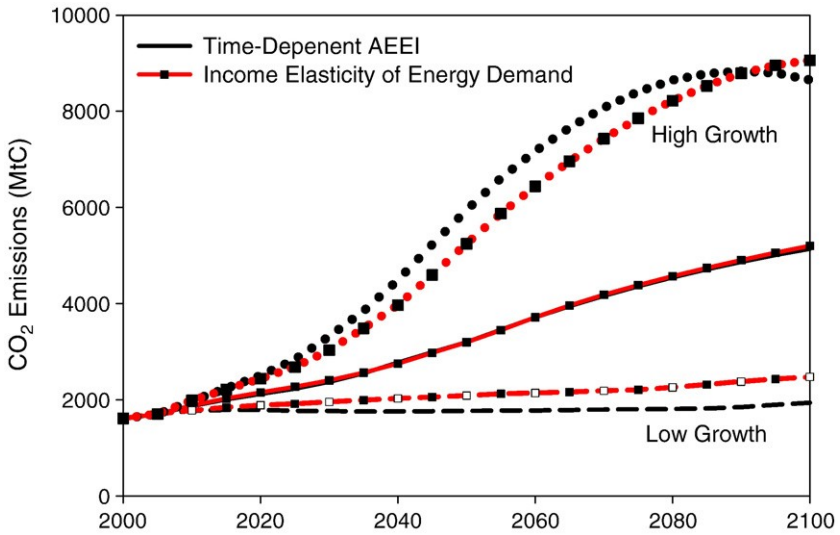


Fig. 1-7. USA no policy CO₂ emissions. Solid lines show emissions for reference GDP growth rates, dashed lines for low growth, and dotted lines for high growth rates.

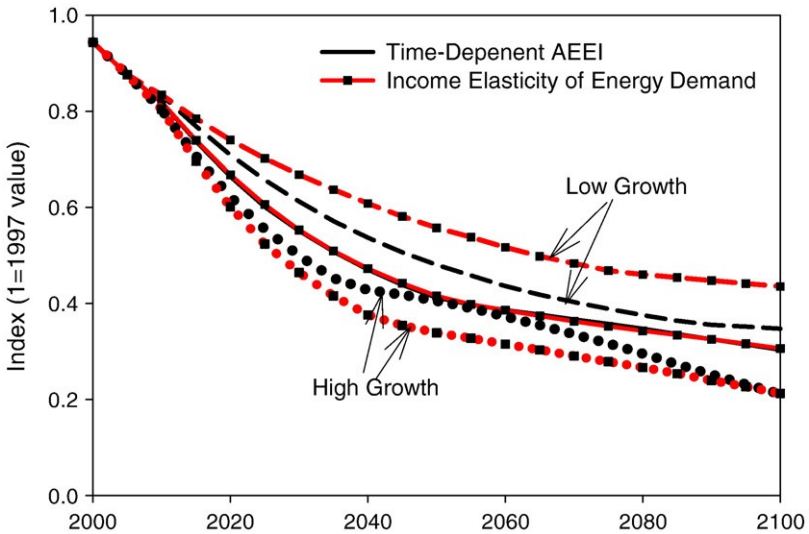


Fig. 1-8. Energy intensity in USA relative to 1997 level. Solid lines show emissions for reference GDP growth rates, dashed lines for low growth, and dotted lines for high growth rates.

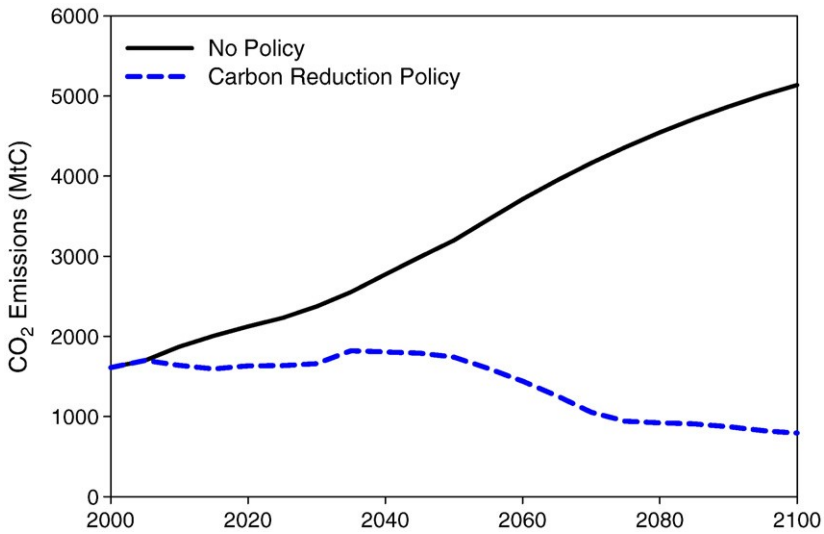


Fig. 1-9. USA CO₂ emissions under no policy and under hypothetical carbon constraint.

The resulting CO₂ emissions from the AEEI version are higher (lower) than the income elasticity version assuming higher (lower) productivity growth rates (Fig. 7). In other words, the variance in emissions as a result of GDP growth is greater in the exogenous AEEI version than it is in the endogenous income elasticity version. The reason for this is that the change over time in energy intensity, and therefore in emissions, is endogenous and dependent on GDP growth. Thus the resulting energy intensity decreases faster (slower) when GDP grows

faster (slower) than in the AEEI version (Fig. 8). The effect of the endogeneity assumption in the income elasticity version is that the energy impacts of faster or slower economic growth are dampened.

An important consequence of the exaggerated effect of growth on energy intensity in the exogenous AEEI version is that the uncertainty in costs of an emissions reduction policy will also have lower variance in the presence of economic growth uncertainty. We demonstrate this effect with a sample emissions cap, imposed in the USA without international emissions trading (Fig. 9). As with emissions in the absence of policy, the costs of the emissions cap, as measured by welfare loss and by carbon prices, are virtually identical under a reference GDP growth assumption. However, the welfare losses under the high growth assumption (dotted lines in Fig. 10) are significantly different between the two versions, with the exogenous AEEI version exhibiting much greater welfare losses. The costs under a low growth assumption

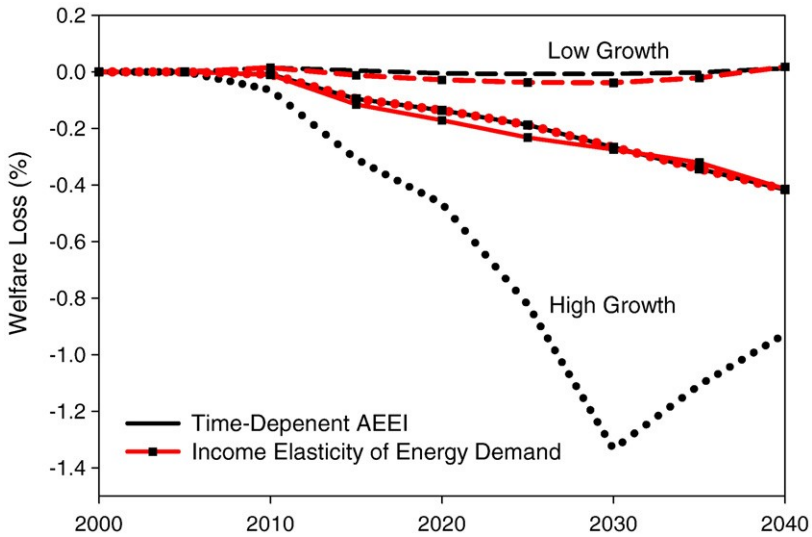


Fig. 1-10. Welfare losses to USA under carbon constraint. Solid lines show emissions for reference GDP growth rates, dashed lines for low growth, and dotted lines for high growth rates.

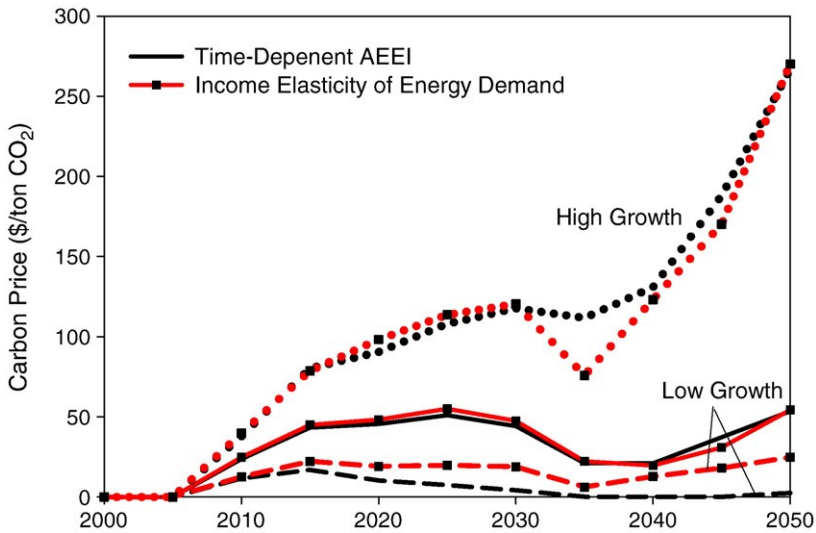


Fig. 1-11. Carbon prices in USA under carbon constraint. Solid lines show emissions for reference GDP growth rates, dashed for low, and dotted for high growth.

also differ, but the effect on welfare loss (Fig. 10) is much smaller than the effect on carbon prices (Fig. 11), because the magnitudes of the welfare losses under low growth are so small.

The differences in costs under high GDP growth assumptions are even more apparent under a more stringent global policy with international emissions trading. We simulate two additional policy cases, the 550 ppm and 750 ppm stabilization cases from the U.S. Climate Change Science Program Synthesis and Assessment product 2.1a (Clarke et al., 2007). The welfare losses under high GDP growth differ significantly between the AEEI and the income elasticity version for both the 550 ppm (dashed lines in Fig. 12) and the 750 ppm case (solid lines in Fig. 12). The same is true for carbon prices (Fig. 13).

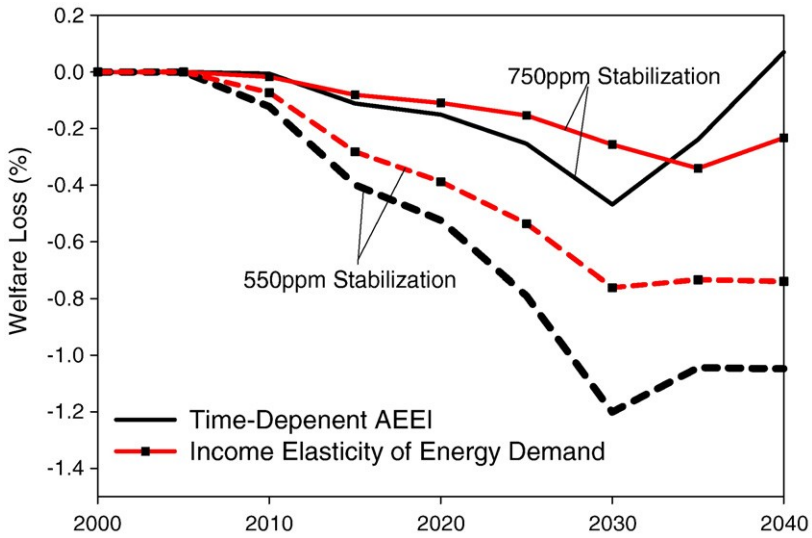


Fig. 1-12. Welfare losses in USA under CCSP 550 ppm and 750 ppm stabilization policies in high GDP growth cases. Solid lines show welfare losses under 750 ppm stabilization and dashed under 550 ppm.

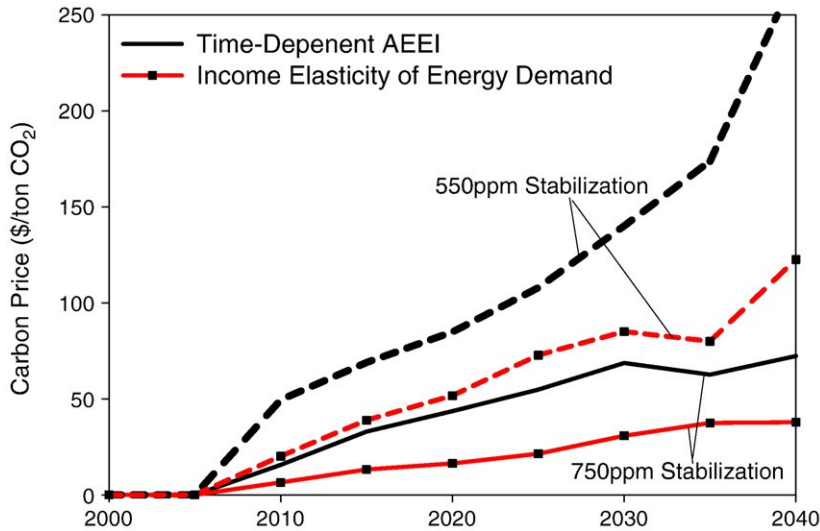


Fig. 1-13. Carbon prices in USA under CCSP 550 ppm and 750 ppm stabilization policies in high GDP growth cases. Solid lines show carbon prices under 750 ppm stabilization and dashed lines under 550 ppm stabilization.

3. Relative Importance of Uncertainties in Elasticities of Substitution

3.1 Introduction

Recent legislative proposals in the U.S. Congress have sought to limit emissions of greenhouse gases (GHGs) through an economy-wide emission target which would take effect in the coming decade.² The macroeconomic costs of such policies are fundamentally uncertain. This is due on one hand to the unavoidable imprecision in forecasts of the economy's baseline no-policy emissions in the future period in which quantitative limits or taxes on emissions are expected to bind, and on the other to our imperfect understanding of the ease with which producers and consumers are able to adjust to such policies. In this paper we study the

² The McCain-Lieberman Climate Stewardship and Innovation Act of 2007 would set caps on GHG emissions at year-2004 levels by 2012 and 1990 levels by 2020. The Bingaman-Domenici Climate and Economy Insurance Act (an amendment to H.R.6, the Energy Policy Act of 2005) seeks to set annual emission limits sufficient to reduce the U.S. economy's emission intensity of GDP by 2.4 percent per year from 2010-2019, with a "safety-valve" provision whereby the government would issue emission permits to keep the marginal cost of abatement below \$7/ton of carbon-dioxide equivalents.

implications of both kinds of uncertainty for the costs of climate change policies within the context of a simulation model of the U.S. economy.

As a first step it is instructive to consider the precursors of uncertainty in baseline emissions. Future growth of the economy exerts a first-order influence on the demand for energy in general and fossil fuels in particular, whose combustion generates atmospheric emissions of carbon dioxide (CO₂), the chief greenhouse gas. Mitigating this increase is a second set of factors, principally shifts in the sectoral composition of the economy toward less energy-intensive services and increases in the efficiency of energy use within industries, which in the past have led to declines in the intensity of energy use per unit of economic output (see, e.g. Sue Wing and Eckaus, 2004). Both of these forces tend to be represented in economic simulations using secular trends—the first as an expansion in the quantities of primary factors with which the economy is endowed, and the second as decline in the coefficients on inputs of energy commodities in firms' cost functions and households' expenditure functions.

Uncertainty in the economy's response to an emission reduction policy may be conceptualized differently depending on the instrument by which it is implemented. A quantity instrument (i.e., a mandate to cut emissions by a given amount relative to the economy's no-policy baseline) results in uncertain marginal abatement cost (MAC), while the consequences of a price instrument (i.e., an emission tax, which increases the marginal costs of fossil fuel commodities by different amounts, depending on their carbon contents) is uncertainty in the levels of emissions and abatement.

Substitution is the key driving force behind these uncertainties (Jorgenson et al., 2000). Both instruments increase the costs of production in polluting firms, reducing their demands for labor and capital, which in turn depresses income and welfare as the prices of labor and capital

fall to clear primary factor markets. The ease with which producers are able to switch from carbon rich fuels such as coal to low-carbon fuels such as natural gas, or replace fossil fuels with non-energy inputs, determines the abundance of cheap abatement opportunities which can mitigate the rise in their production costs. Symmetrically, as increases in the production costs of fossil fuels and their derivative commodities are passed on to downstream users, consumers' ability to shift their expenditure to relatively lower-priced substitutes moderates the erosion of their consumption in real terms. The elasticity of substitution is the economic parameter which determines these possibilities. Indeed, in simulation models, their efficacy in moderating primary abatement costs is governed by the values of the substitution elasticities in firms' cost functions and households' expenditure functions.

Over the last decade, the uphill battle faced by proposals to regulate CO₂ emissions is indicative of concern among policy makers that the continued growth of the economy, pervasiveness of energy as an input to economic activity and scarcity of substitutes for fossil fuels will amount to such regulations having unacceptably high economic costs.

Our approach to investigating these phenomena is to construct a computable general equilibrium (CGE) model which simulates the U.S. economy in the year 2015, which we use as a test bed to analyze the impact of baseline and adjustment uncertainty on the costs of emission reduction policies. We survey the empirical economic literature to develop a range of estimates of the elasticities of substitution among various commodities and inputs to production. We use these to construct probability distributions of the various elasticity parameters within the model.

3.2 The CGE model

The test-bed for our investigation is a static CGE model of the U.S. The model treats households as an aggregate representative agent with constant elasticity of substitution (CES) preferences. Industries are consolidated into the 11 sectoral groupings shown in Table 3, and are treated as representative firms with nested CES production technology. For this purpose we adapt Bovenberg and Goulder's (1996) KLEM production technology and parameterization, as shown in Figure 1 and Table 4.

The model's algebraic structure is numerically calibrated using U.S. data on inter-industry economic flows, primary factor demands, commodity uses and emissions in the year 2000. We simulate prices, economic quantities, and emissions of CO₂ in the year 2015 by scaling both the economy's aggregate factor endowment and the coefficients on energy within industries' cost functions and the representative agent's expenditure function. The probability distributions of these scaling factors, when propagated through the model, give rise to probability distributions for the future value of baseline national income, energy use and emissions.

The parameters which govern the malleability of production are the elasticities of substitution between composites of primary factors (KL) and intermediate inputs (EM), which we denote σ_{KLEM} ; between inputs of capital (K) and labor (L), denoted by σ_{KL} ; between energy (E) and materials (M), indicated by σ_{EM} ; and among different intermediate energy and material commodities (e and m), denoted by σ_E and σ_M , respectively. In natural resource-dependent sectors (e.g., production of primary fuels such as coal) the resource is modeled as a fixed factor which enters at the top of the production hierarchy, governed by the elasticity σ_R . The electric power sector encompasses two nested production structures, one for primary electricity generated from fixed factors (e.g., nuclear, hydro and wind) which exhibits features of resource-dependent

Figure 3-1. The Structure of Production in the CGE Model

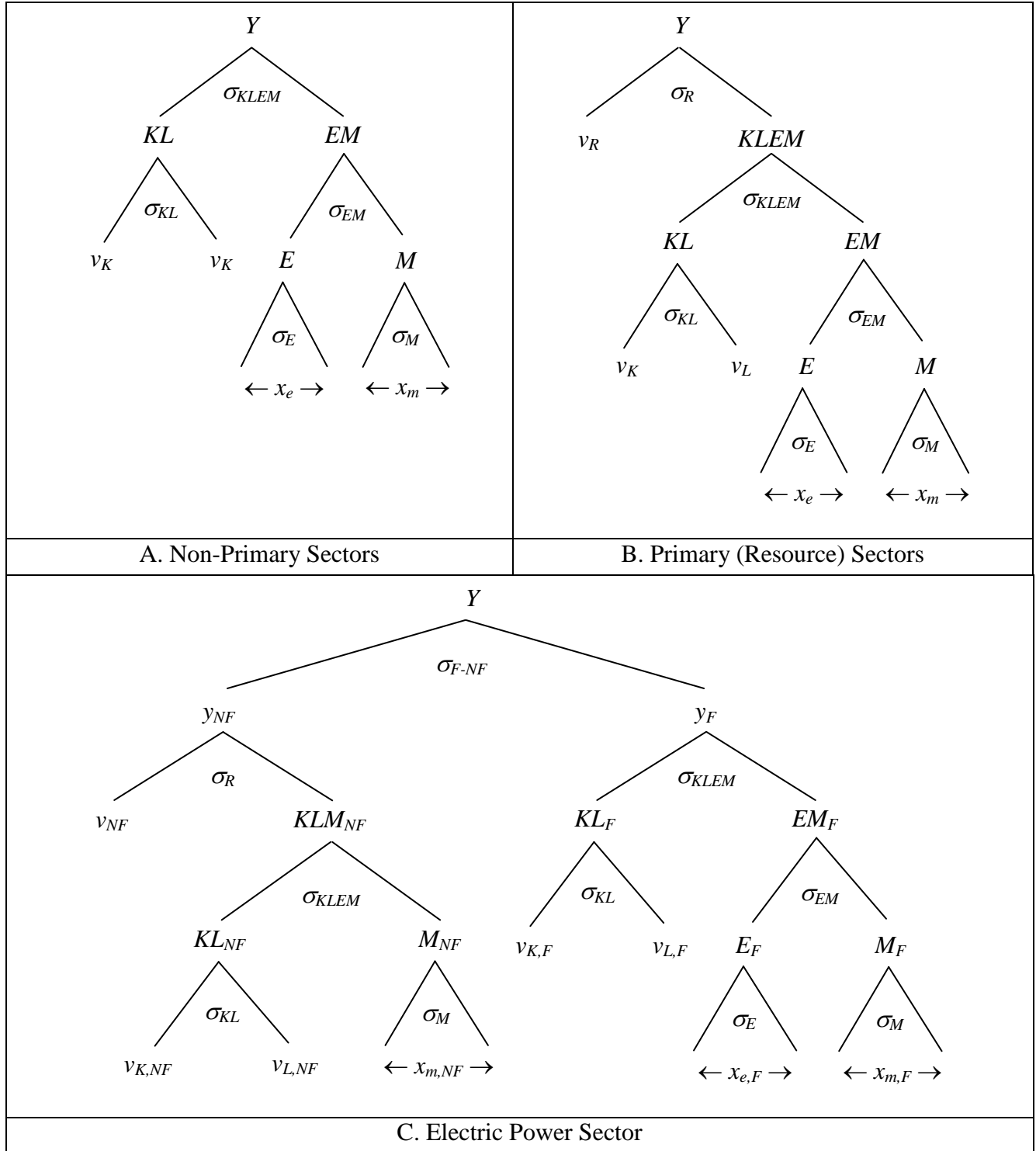


Table 3-1. Sectors in the CGE Model

CGE model sectors	Constituent industries (approximate 2-digit SIC)
Agriculture	Agriculture
Coal	Coal mining
Crude oil & gas	Crude oil & gas
Natural gas	Natural gas
Petroleum	Petroleum
Electricity	Electricity
Energy-intensive industries	Paper and allied; Chemicals; Rubber & plastics; Stone, clay & Glass; Primary metals
Manufacturing	Food & allied; Tobacco; Textile mill products; Apparel; Lumber & wood; Furniture & fixtures; Printing, publishing & allied; Leather; Fabricated metal; Non-electrical machinery; Electrical machinery; Motor vehicles; Transportation equipment & ordnance; Instruments; Misc. manufacturing
Transportation	Transportation
Services	Communications; Trade; Finance, insurance & real estate; Government enterprises
Rest of economy	Metal mining; Non-metal mining; Construction

sectors, and another representing fossil fuel generation which exhibits features of non-resource sectors. The ability for the outputs of these subsectors to substitute for each other is governed by the elasticity σ_{F-NF} . Probability distributions for these eight parameters, when propagated through the model, generate probability distributions for the changes in income and emissions from their baseline levels in response to climate policy.

3.2.1 Model Structure

The model is a simplified version of that developed by Sue Wing (2006a,b). It represents the U.S. in the small open economy format of Harrison et al (1997). Imports and exports are linked by a balance-of-payments constraint, commodity inputs to production or final uses are modeled as Armington (1969) CES composites of imported and domestically-produced varieties, and industries' production for export and the domestic market are modeled according to constant elasticity of transformation (CET) functions of their output.

Commodities (indexed by i) are of two types, energy goods (coal, oil, natural gas and electricity, denoted $e \subset i$) and non-energy goods (denoted $m \subset i$). Each good is produced by a

single industry (indexed by j), which is modeled as a representative firm that generates output (Y) from inputs of primary factors (v) and intermediate uses of Armington commodities (x).

Households are modeled as a representative agent who is endowed with three factors of production, labor (L), capital (K) and industry-specific natural resources (R), indexed by $f = \{L, K, R\}$. The supply of capital is assumed to be perfectly inelastic. The endowments of the different natural resources increase with the prices of domestic output in the industries to which these resources correspond, according to sector-specific supply elasticities, η_R . Income from the agent's rental of these factors to the firms finances her consumption of commodities, consumption of a government good, and savings.

The representative agent's preferences are modeled according to a CES expenditure function. The agent is assumed to exhibit constant marginal propensity to save, so that savings make up a constant fraction of aggregate expenditure. The government sector is modeled as a passive entity which demands commodities and transforms them into a government good, which in turn serves as an input to both consumption and investment. Aggregate investment and government output are produced according to CES transformation functions of the goods produced by the industries in the economy. The demand for investment goods is specified according to a balanced growth path rule:

Production in industries is represented by the multi-level CES cost functions shown schematically in Figure 1, which are adaptations of Bovenberg and Goulder's (1996) structure. Each node of the tree in the diagram represents the output of an individual CES function, and the branches denote its inputs. Thus, in the non-resource based production sectors shown in panel A, output (Y_j) is a CES function of a composite of labor and capital inputs (KL_j) and a composite of energy and material inputs (EM_j). KL_j represents the value added by primary factors'

contribution to production, and is a CES function of inputs of labor, v_{Lj} , and capital, v_{Kj} . EM_j represents the value of intermediate inputs' contribution to production, and is a CES function of two further composites: E_j , which is itself a CES function of energy inputs, x_{ej} , and M_j , which is a CES function of non-energy material inputs, x_{mj} .

The production structure of resource-based industries is shown in panel B. In line with its importance to production in these industries, the natural resource is modeled as a sector-specific fixed factor whose input enters at the top level of the hierarchical production function. Output is thus a CES function of the resource input, v_{Rj} , and the composite of the inputs of capital, labor, energy and materials ($KLEM_j$) to that sector. In both resource-based and non-resource-based industries, input substitutability at the various levels of the nesting structure is controlled by the values of the corresponding elasticities: σ_{KLEM} , σ_{KL} , σ_{EM} , σ_E , σ_M and σ_R .

The production function for electric power embodies characteristics of both primary and non-primary sectors described above. The top-down model therefore represents the electricity sector as an amalgam of the production functions in panels A and B. Conventional fossil electricity production combines labor, capital and materials with inputs of coal, oil and natural gas according to the production structure in panel A. Nuclear and renewable electricity are generated by combining labor, capital and intermediate materials with a composite of non-fossil fixed-factor energy resources such as uranium deposits, wind energy and hydrostatic head using a production function similar to that in panel B, but without the fossil fuel composite, E . The resulting production structure is shown in panel C, where total output is a CES function of the outputs of the fossil (F) and non-fossil (NF) electricity production sub-sectors. The elasticity of substitution between y_F and y_{NF} is $\sigma_{F-NF} \gg 1$, reflecting the fact that they are near-perfect substitutes.

3.2.2 *Model Formulation, Numerical Calibration and Solution*

The economy is formulated in the complementarity format of general equilibrium (Scarf 1973; Mathiesen 1985a, b). Profit maximization by industries and utility maximization by the representative agent give rise to vectors of demands for commodities and factors. These demands are functions of goods and factor prices, industries' activity levels and the income level of the representative agent. Combining the demands with the general equilibrium conditions of market clearance, zero-profit and income balance yields a square system of nonlinear inequalities that forms the aggregate excess demand correspondence of the economy (Sue Wing 2004). The CGE model solves this system as a mixed complementarity problem (MCP) using numerical techniques.

The mathematical relations which define the excess demand correspondence are numerically calibrated on a social accounting matrix (SAM) for U.S. economy in the year 2000, using values for the elasticities of substitution (based on Bovenberg and Goulder 1996) and factor supply summarized in Table 2. The basic SAM is constructed using data from BEA for 1999 on input-output transactions and the components of GDP by industry. The resulting benchmark table was then scaled to approximate the U.S. economy in the year 2000 using the growth rate of real GDP, deflated to year 2000 prices, and aggregated according to the industry groupings.

The economic accounts do not record the contributions to the various sectors of the economy of key natural resources that are germane to the climate problem. Sue Wing (2001) employs information from a range of additional sources to approximate these values as shares of the input of capital to the agriculture, oil and gas, mining, coal, and electric power, and rest-of-economy industries. Applying these shares allows the value of natural resource inputs to be

Table 3-2. Substitution and Supply Elasticities

Sector	σ_{KL}^a	σ_E^b	σ_A^c	σ_R^d	η_R^e	χ_E^f	χ_C^g	All Sectors	
Agriculture	0.68	1.45	2.31	0.4	0.5	–	–	σ_{KLEM}^h	0.7
Crude Oil & Gas	0.68	1.45	5.00	0.4	1.0	–	–	σ_{EM}^i	0.7
Coal	0.80	1.08	1.14	0.4	2.0	1.0956	0.0969	σ_M^j	0.6
Refined Oil	0.74	1.04	2.21	–	–	0.2173	0.0131	σ_T^k	1.0
Natural Gas	0.96	1.04	1.00	–	–	0.2355	0.0116		
Electricity	0.81	0.97	1.00	0.4	0.5	0.2381	–	Electricity	
Energy Intensive Mfg.	0.94	1.08	2.74	–	–	–	–	σ_{F-NF}^l	8
Transportation	0.80	1.04	1.00	–	–	–	–		
Manufacturing	0.94	1.08	2.74	–	–	–	–		
Services	0.80	1.81	1.00	–	–	–	–		
Rest of the Economy	0.98	1.07	1.00	0.4	1.0	–	–		

^a Elasticity of substitution between capital and labor; ^b Inter-fuel elasticity of substitution; ^c Armington elasticity of substitution; ^d Elasticity of substitution between KLEM composite and natural resources; ^e Elasticity of natural resource supply with respect to output price; ^f Energy-output factor (GJ/\$); ^g CO₂ emission factor (Tons/\$); ^h Elasticity of substitution between value added and energy-materials composite; ⁱ Elasticity of substitution between energy and material composites; ^j Elasticity of substitution among intermediate materials; ^k Elasticity of output transformation between domestic and exported commodity types; ^l Elasticity of substitution between fossil and non-fossil electric output.

disaggregated from the factor supply matrix, with the value of capital being decremented accordingly.

The electric power sector in the SAM is disaggregated into fossil and non-fossil electricity production (y_F and y_{NF} , respectively) using the share of primary electricity (i.e., nuclear and renewables) in total net generation for the year 2000, given in DOE/EIA (2004). The corresponding share of the electric sector's labor, capital and non-fuel intermediate inputs is allocated to the between non-fossil sub-sector, as is the entire endowment of the electric sector's natural resource. The remainder of the labor, capital and intermediate materials, along with all of the fuel inputs to electricity, are allocated to the fossil sub-sector.

The final SAM, shown in Figure A-2, along with the parameters in Table A-1, specify the numerical calibration point for the static sub-model. The latter is formulated as an MCP and numerically calibrated using the MPSGE subsystem (Rutherford 1999) for GAMS (Brooke et al 1998) before being solved using the PATH solver (Dirkse and Ferris 1995).

3.3.3 *Dynamic Projections and Policy Analysis*

Projections of future output energy use and emissions of CO₂ are constructed by simulating the growth of the economy in 2015. To do this we update the economy's endowments of labor and capital and its supply of net imports, and the growth of energy-saving technical progress.

To keep the analysis simple we assume that the model's base-year endowments of labor, capital and sector-specific natural resources grow at a common, exogenous rate. This is implemented by means of a scaling parameter whose value is specified to increase from unity in the base year at a rate equal to the long-run average annual growth of GDP, about 3.5 percent.

Single-region open-economy simulations require the modeler to make assumptions about the characteristics of international trade and the current account over the simulation horizon. Since trade is not our primary focus, we simply reduce the economy's base-year current account deficit from the benchmark level at the constant rate of one percent per year.

We project energy use and emissions by scaling the exajoules of energy used and megatons of CO₂ emitted in the base year according to the growth in the corresponding quantity indices of Armington energy demand. We do this by constructing energy-output factors (χ_E) and emissions-output factors (χ_C), each of which assumes a fixed relationship between the benchmark values of the coal, refined oil and natural gas use in the SAM and the delivered

energy and the carbon emission content of these goods in the benchmark year.³ The resulting coefficients are applied to the quantities of the corresponding Armington energy goods solved for by the model at each time-step.

3.3 Sensitivity Analyses

Sensitivity analysis of both emissions and equivalent variation outcomes was conducted for a sample policy of a carbon tax of \$50/ton. We investigated the effects on emissions and equivalent variation of halving and doubling each of the eight substitution elasticities in the model while holding all of the remaining parameters at their reference levels. The results are shown in Figures 2 and 3. We also checked the robustness of these results by looking for synergistic interactions in the influence of these parameters. To do this we simultaneously varied

³ Fossil-fuel energy supply and carbon emissions in the base year were divided by commodity use in the SAM, which we calculated as gross output – net exports. In the year 2000, U.S. primary energy demands for coal, petroleum and natural gas and electricity were 23.9, 40.5, 25.2, and 14.8 exajoules, respectively (DOE/EIA 2004). The corresponding benchmark emissions of CO₂ from the first three fossil fuels were 2112, 2439 and 1244 MT, respectively (DOE/EIA 2003). Aggregate uses of these energy commodities in the SAM are 21.8, 185.6, 107.1 and 6.21 billion dollars.

Figure 3-2. Sensitivity of Emissions to a Separate Doubling and Halving of Individual Elasticities of Substitution, $P_{\text{carbon}} = \$50/\text{ton}$.

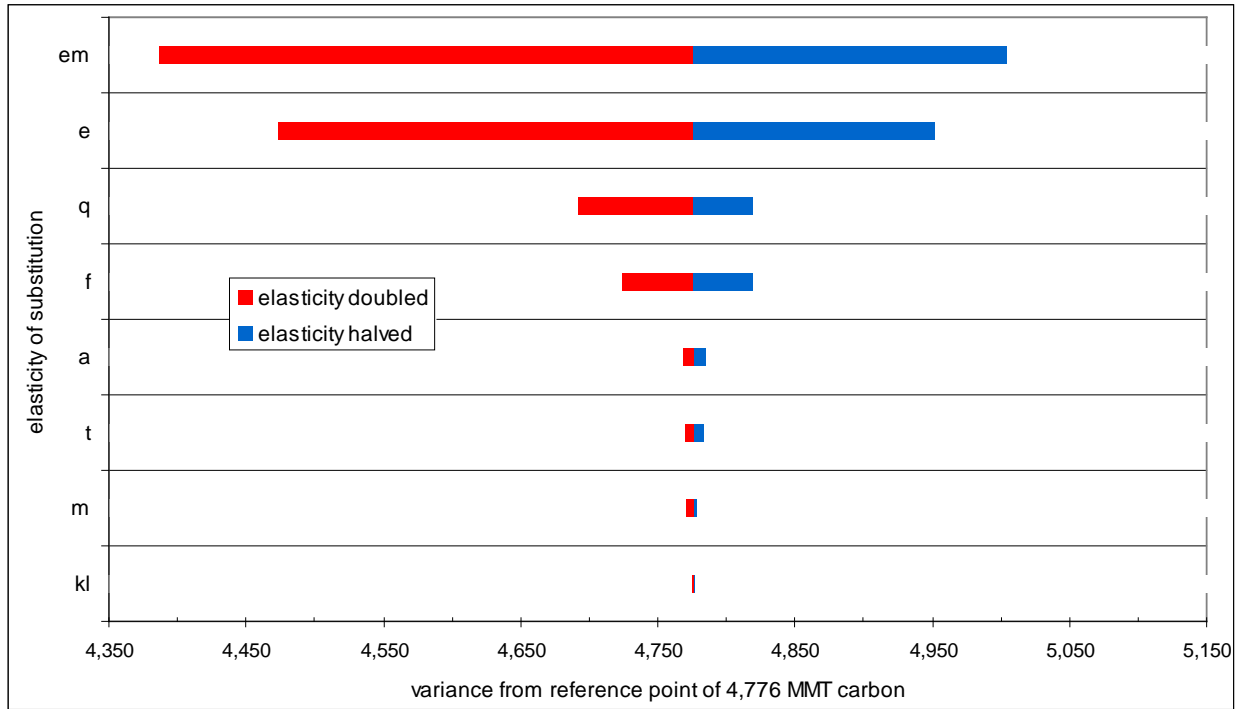
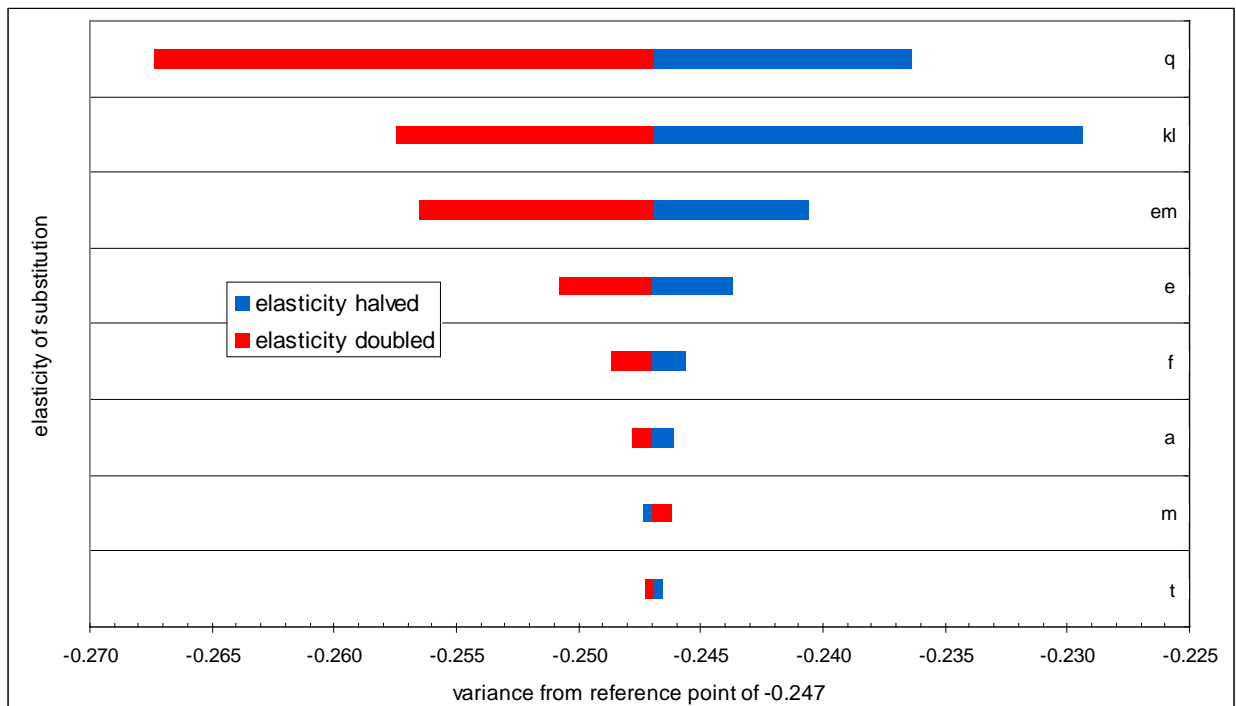


Figure 3-3. Sensitivity of Percent Change in Equivalent Variation to Separate Doubling and Halving of Individual Elasticities of Substitution, $P_{\text{carbon}} = \$50/\text{ton}$.



two elasticities in pairwise fashion, examining all permutations of doubling and halving. The results of this exercise are shown in Figures 4 and 5.

The largest influences on emissions and income can be traced to the elasticities of substitution between intermediate and factor inputs, capital and labor, energy and materials, inter-fuels, and resource (q , kl , em , e , and f , respectively). Varying the materials substitution elasticity (m), the output transformation elasticity between production for domestic and export markets (t), and the armington substitution elasticity between domestic and imported varieties of goods (a), all have much weaker effects. Thus, in further looking at how substitution elasticity uncertainty affects both emissions and changes in equivalent variation, we focus on constructing probability distribution functions for q , kl , em , e , and f .

3.4 Probability Distributions for Key Uncertain Model Parameters

3.4.1 Economic Growth and Energy Efficiency

We assume that the uncertainty in the growth of the simulated economy's primary factor endowments may be adequately captured by the variability of GDP growth. Accordingly, BEA data on the annual rates of growth of real GDP from 1930-2006 were used to estimate a mean annual growth rate of 3.53 percent, with a standard error of 0.58 percent.

3.4.2 The Elasticity of Substitution

The elasticity of substitution measures the curvature of a producer's isoquant or a consumer's iso-utility contour. It is defined as the fractional change in the relative proportions of inputs to production or consumption in response to a fractional change in the marginal rate of substitution—or relative prices in competitive equilibrium. Several multi-input forms of the elasticity of substitution have been proposed (Allen, 1937; Morishima, 1967; Blackorby and

Figure 3-4. Sensitivity of Emissions to Paired Doubling and Halving of Individual Elasticities of Substitution, Pcarbon = \$50/ton.

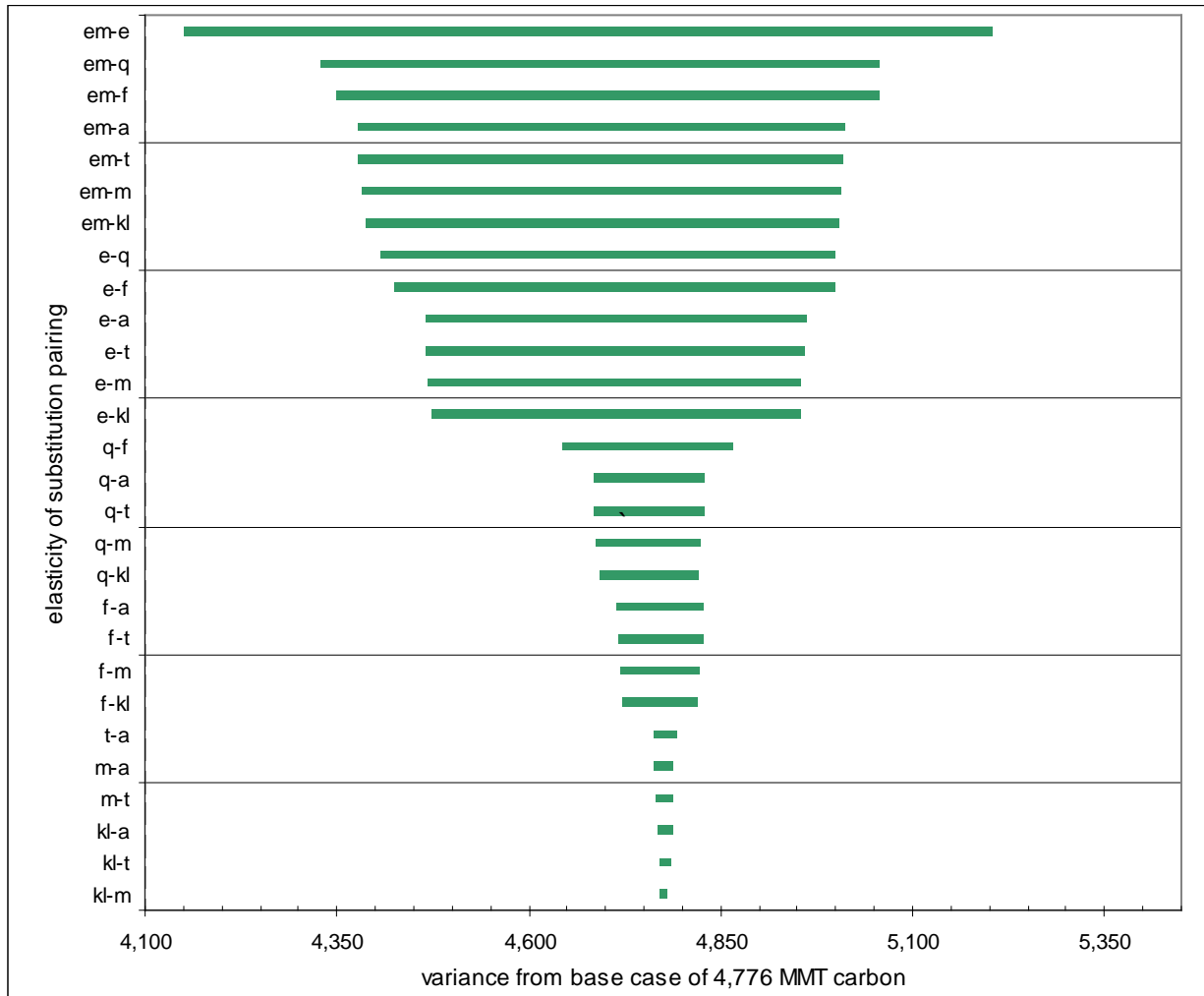
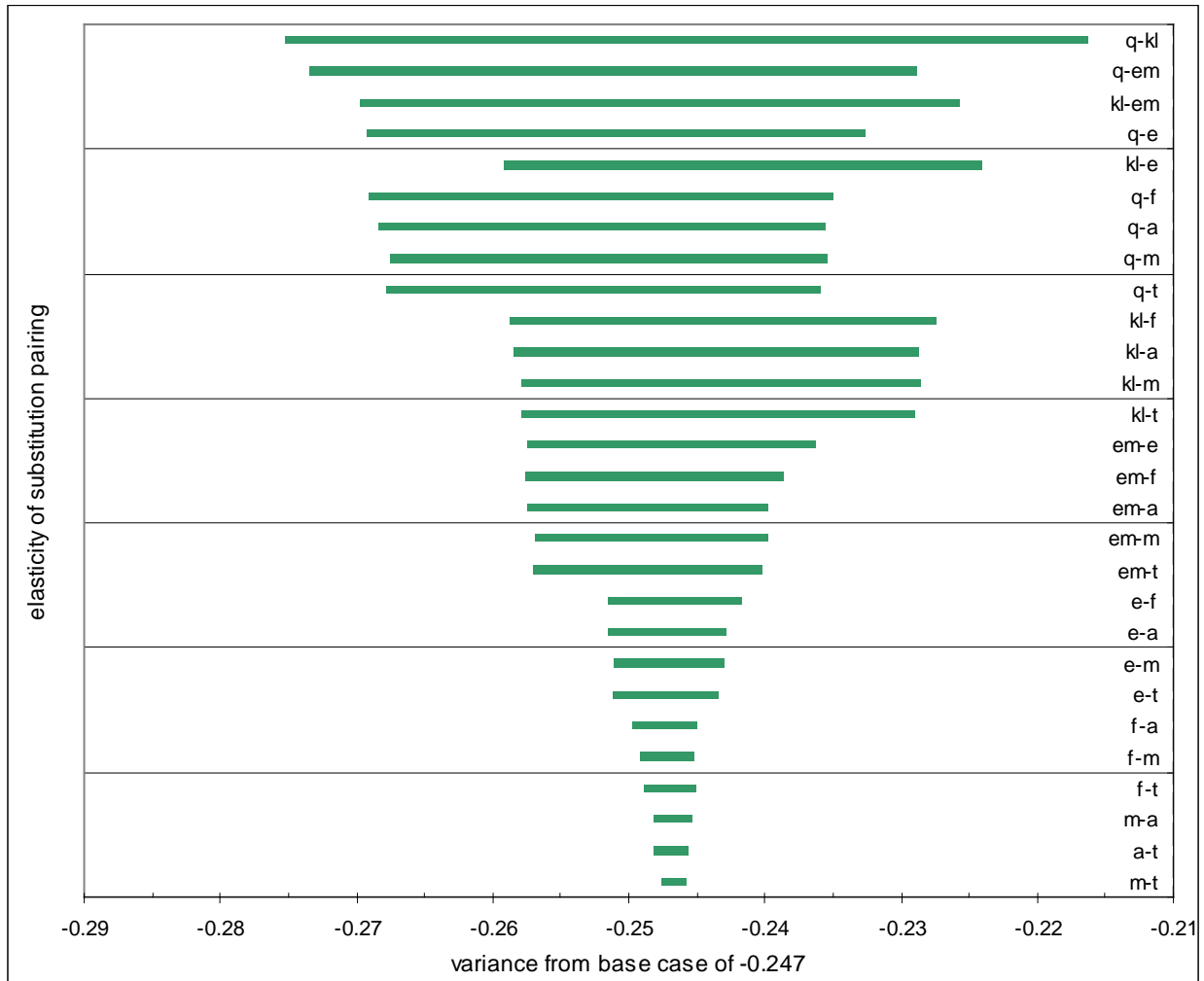


Figure 3-5. Sensitivity of Percent Change in Equivalent Variation to Paired Doubling and Halving of Individual Elasticities of Substitution, $P_{\text{carbon}} = \$50/\text{ton}$.



Russell 1975), but the Allen form is most commonly used.⁴ Empirical work tends to employ the two-input Allen partial elasticity, whose estimation was greatly facilitated by the development of the pairwise-flexible Translog specification for production and utility functions (Lau 1973; see also Chung 1994).

⁴ Blackorby and Russell (1989) criticize the Allen elasticity for failing to correctly measure the curvature of an isoquant or indifference curve, not utilizing information about the comparative statics of income shares, and exhibiting symmetry only in the case of two inputs. By contrast, despite the superior theoretical properties of the Morishima elasticity, its appeal is diminished by its non-symmetric character, even in the two-input case.

A common fallacy is that the probability distribution function (PDF) of a particular variable may be constructed by gathering empirical estimates of that variable from different sources, treating each point estimate as a random observation, and then calculating the frequency with which these data points fall into different ranges of the variable's magnitude. There are two key problems with this procedure. First, the different estimates are not random observations, so at best the result is a PDF of the variable's *mean*, not the value itself. Secondly, because each estimate is potentially generated using different data, statistical techniques, or even different definitions of the variable itself, to the extent that the input points are not strictly comparable, their frequency distribution is not meaningful.

In conducting meta-analysis, the empirically valid measure of uncertainty is the standard error of each point estimate. The range of standard errors across several different studies gives a robust description of the uncertainty of the variable in question. However, because of the underlying studies' lack of comparability, or the fact that reported point estimates may vary widely in magnitude, the information on variability must be extracted in a way that controls for idiosyncratic factors.

Based on these considerations we constructed PDFs for each elasticity of substitution parameter according to the following algorithm:

1. Point estimates and standard errors were collected from a literature survey.
2. The coefficient of variation (the ratio of the standard deviation to the mean) was computed for each of the estimates in step 1.
3. The coefficients of variation were averaged across estimates.
4. The PDF was defined as a normal distribution with a unit mean and a standard deviation equal to the average coefficient of variation from step 3.

5. Random draws from the distribution were multiplied by the reference value for the corresponding elasticity in Table XX to obtain the sample values for use in Monte Carlo simulations of the model.⁵

We surveyed the empirical economics literature over the last three decades to obtain estimates of key elasticities of substitution for U.S. industrial sectors. These data were used as the basis for constructing probability distribution function (PDFs); accordingly, we used only those studies that reported the standard errors of their estimates.⁶

Berndt (1976) combined six different functional forms with five alternative data construction procedures to estimate the capital-labor substitution elasticity for U.S. manufacturing. In a reanalysis of these data over a longer period, Antràs (2004) found significantly lower estimates after allowing for biased technical change. Early studies by Özatalay et al. (1979) and Pindyck (1979) estimate Allen partial elasticities of substitution by applying a Translog cost function to cross-national time-series data. Atkinson and Halvorsen (1976) apply a Translog normalized restricted profit function to data for U.S. steam electric generating plants to estimate paired interfuel elasticities of substitution among coal, oil, and natural gas.⁷ McKibbin and Wilcoxon (1998) estimate elasticities for twelve aggregated industry sectors using input-demand data for the U.S. developed by Dale Jorgenson and collaborators supplemented by official price series.

A number of issues arise in the use of such information for uncertainty analysis. First, there is a mismatch between functional forms employed by econometric studies (either the Translog or the logit) and simulation models (either Cobb-Douglas or nested CES functions),

⁵ Negative values were rejected as not meaningful and were resampled.

⁶ The majority of studies did not report standard errors for their estimated substitution elasticities. We argue below that this is crucial piece of information, without which there is no basis for determining uncertainty.

⁷ These estimates are analogous but not identical to Allen elasticities. We employ Atkinson and Halvorsen's overall results as opposed to aggregating their detailed estimates across power plants.

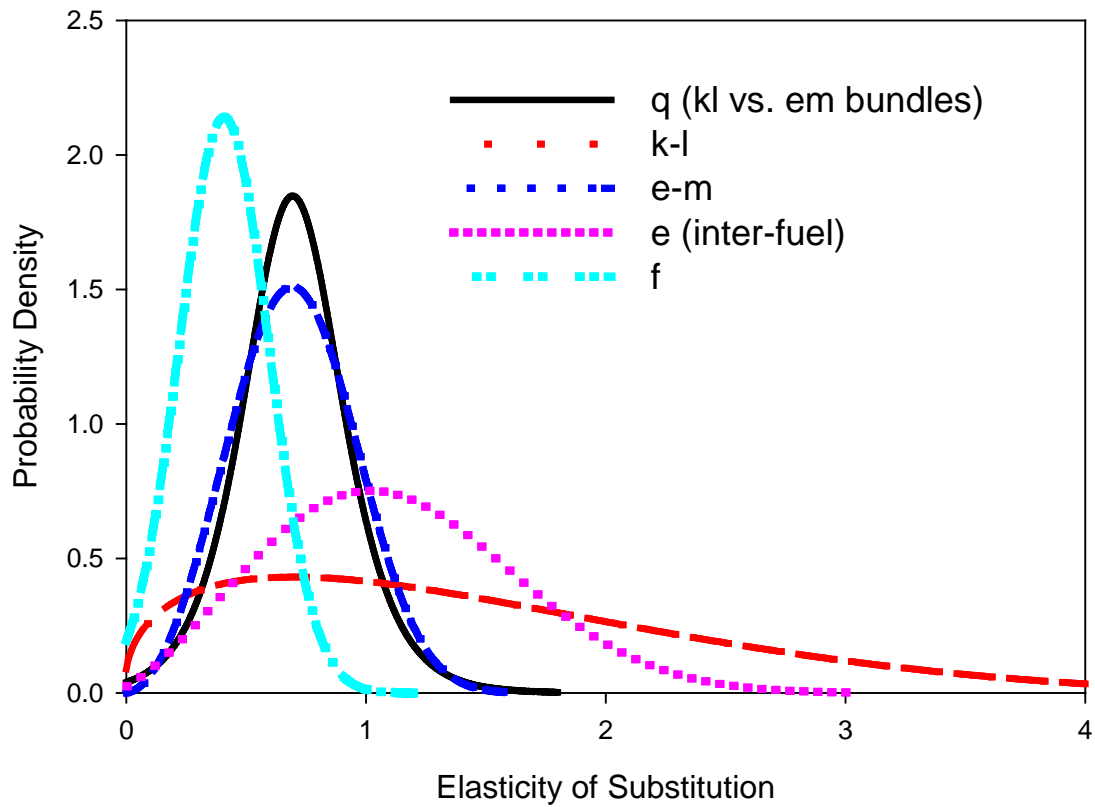
which suggests that the foregoing pairwise elasticity estimates cannot be directly inserted into our model.⁸ A second issue pertains to the fact that elasticities are often estimated using sectorally disaggregate data, while simulation models typically resolve only a few, highly aggregated industry groupings. Because at the more disaggregate level price-induced adjustments in input and output quantities will be spread over a smaller number of firms, the latter representation of production is likely to exhibit a greater degree of reversibility, along with correspondingly larger elasticity values.

Finally, statistical estimation procedures do not generate information on correlations among the standard errors with respect to different pairs of inputs to production and consumption or different sectors for a given pair. For proper stochastic simulation, these correlations are critically important for estimating the uncertainty in costs to the aggregate economy. In the absence of such information, we make a reference assumption that the same elasticity across industrial sectors are perfectly correlated, and that elasticities between different factor pairs are probabilistically independent. Since these assumptions may not be accurate, we will also present results below for alternative assumptions about correlation.

We show (Figure 6) the sampling distributions for each of the five elasticity parameters in terms of their values for the “energy-intensive” sector (since the actual values vary by sector). For kl and e , there is a significant likelihood that the elasticity could be greater than unity, for em and q there is a small likelihood that the elasticity could exceed unity, and the fixed factor f only samples elasticity values below 1.0.

⁸ The former are advantageous in empirical applications because of their linearity, which makes them easy to estimate, and their flexibility, which allows them to locally approximate arbitrarily shaped isoquants or indifference curves in an efficient manner. The latter are globally regular, in that they are guaranteed to result in strictly positive values for output prices, quantities and cost shares (Perroni and Rutherford 1994).

Figure 3-6. Probability Density Functions for Uncertain Elasticity Parameters.



3.5 Results

3.5.1 Abatement

Figure 7 shows the marginal cost of abatement under uncertainty. In the range of interest, a \$23 tax results in 1100mmt and 3050mmt of abatement in 90% of cases, while abatement of 2050mmt (the mean amount required by a 5000mmt cap) costs between \$8 and \$42 per ton CO₂ in 90% of cases.

Under a tax, the marginal cost of abatement is fixed, but the total amount of abatement is uncertain. Possible abatement under a \$23/ton tax, as well as the relative contribution of each uncertain parameter, is shown in Figure 3. Uncertainty in the elasticities of substitution is the largest contributor to uncertainty in abatement, as the effectiveness of the tax largely depends on

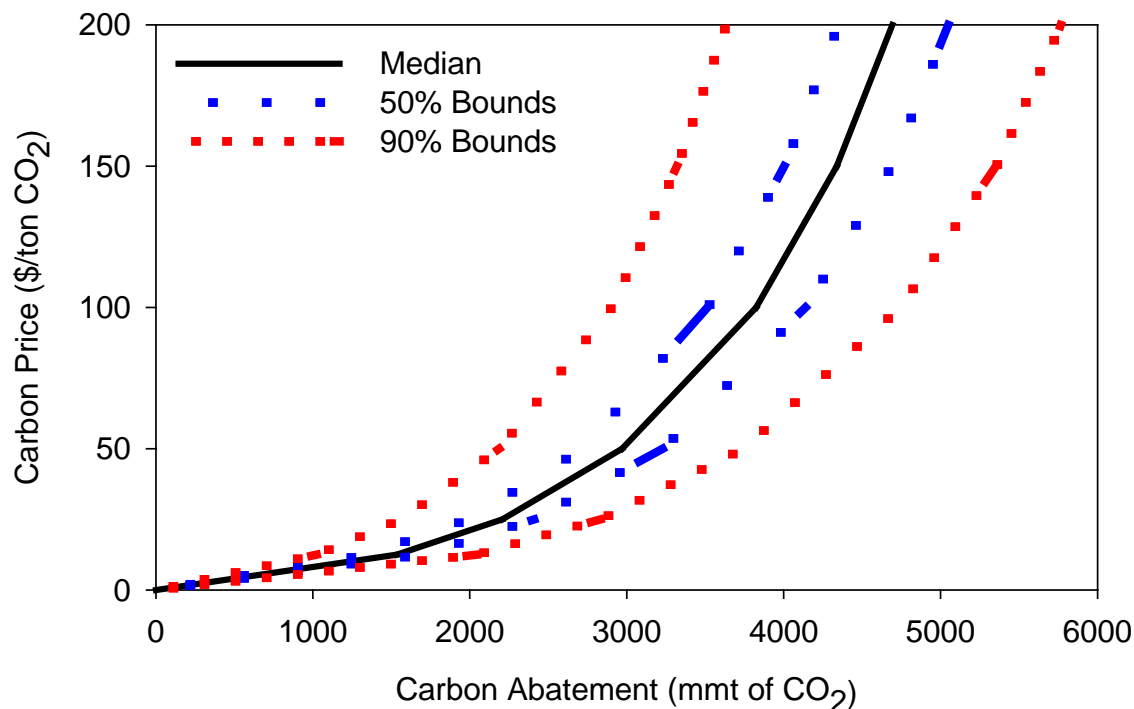


Figure 3-7: Uncertainty in marginal abatement costs in computable general equilibrium model as a result of uncertainty in GDP growth, AEEI, and elasticities of substitution.

whether it exceeds the cost switching to less carbon-intensive energy sources. If elasticities of substitution are not uncertain, a given tax will always produce the same fractional reduction from reference emissions. Thus, GDP growth, as the second-largest contributor to uncertainty in abatement, varies positively with baseline emissions and hence abatement. The opposite is true for AEEI; autonomous improvements in efficiency reduce baseline emissions as well as abatement. Given the 5-95% range of possible abatement when all parameters are uncertain, uncertainty in elasticities of substitution only varies abatement by 81% of this range. GDP uncertainty varies abatement by 50% of the all-uncertain range and AEEI uncertainty by 27%.

The contribution of each uncertainty under a 5000mmt cap is shown in Figure 8. Under a cap, the amount of abatement is always determined by the difference between the cap and no-

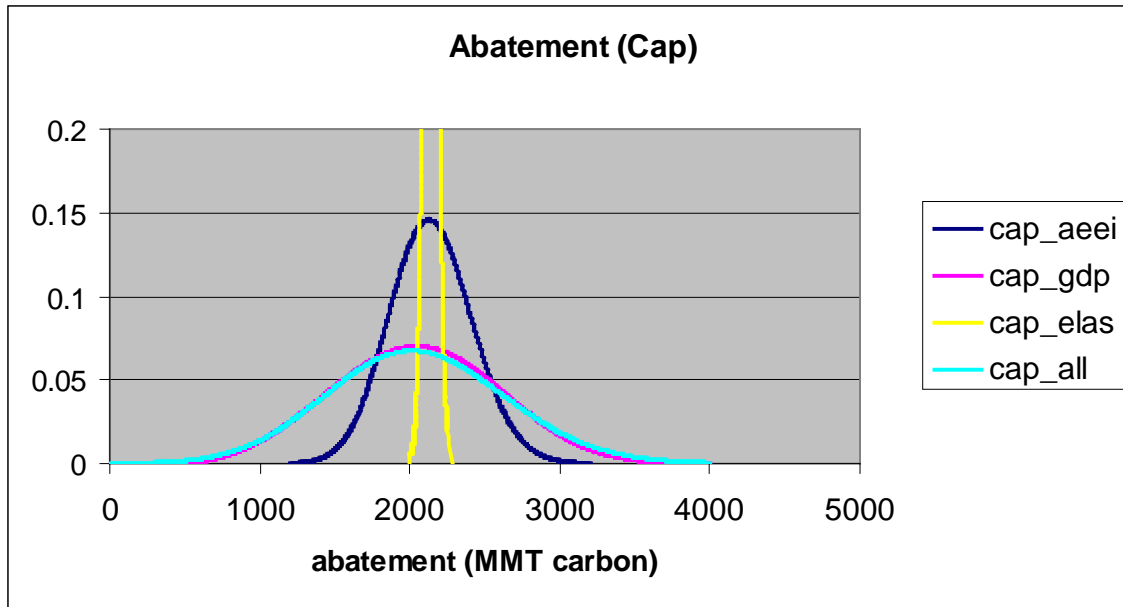


Figure 3-8: PDF of abatement under a cap, and the relative contribution of each uncertain parameter

policy emissions. Thus, uncertain parameters influence the amount of abatement to the same extent that they influence no-policy emissions (Figure 9). GDP is the largest contributor (93% of the all-uncertain range), as a larger economy produces more emissions in the absence of policy. AEEI uncertainty is the next-largest contributor (47% of the all-uncertain range), as improvements in efficiency reduce the amount of no-policy emissions. Uncertainty in elasticities of substitution is almost negligible (6% of the all-uncertain range), as these parameters have little effect on no-policy emissions.

Possible abatement for all four policies with all parameters uncertain is shown in Figure 7. As shown in the previous figures, a tax allows for a more limited range of possible abatement than does a cap. If base emissions are higher than expected in the “no uncertainty” case, a cap will abate more than a tax; if emissions are lower than expected the tax will require more abatement. Abatement under the intensity target is roughly equivalent to a tax: if base emissions are higher than expected the intensity target allows for less abatement than a cap, and requires

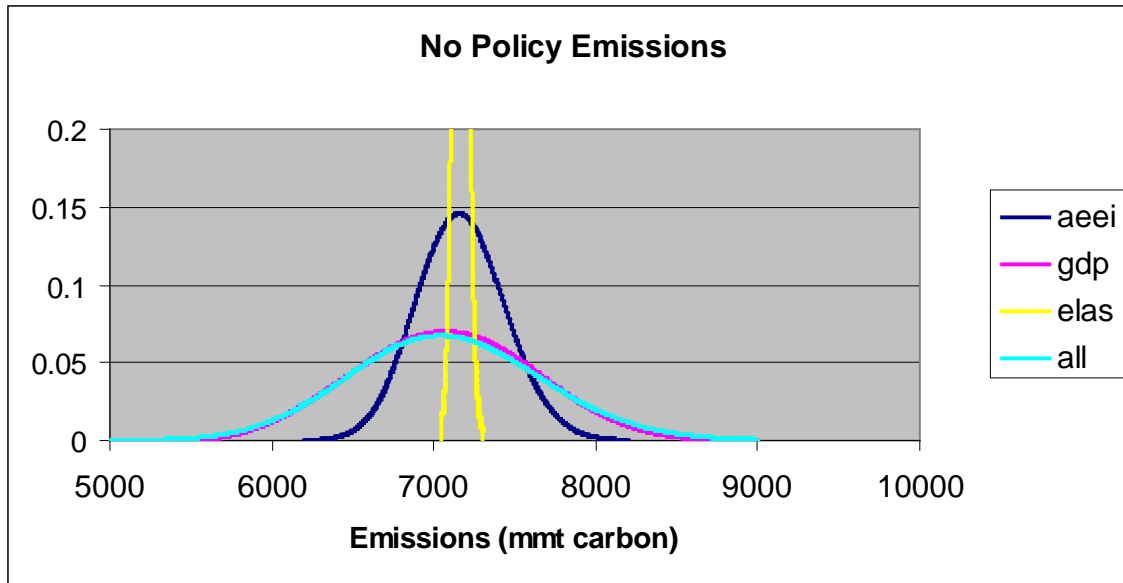


Figure 3-9: PDF of BAU Emissions, and the relative contribution of each uncertain parameter

more abatement than a cap if base emissions are lower. A safety valve requires the least amount of abatement of the four policies, as it combines the “easiest” options of the cap and tax. Where the cap requires little abatement (and hence is low-cost), the quantity instrument (cap) applies; where the cap requires a lot of abatement (and is high-cost) the price instrument (tax) applies.

3.5.2 Carbon Price

Possible carbon prices for the four policies, with all parameters uncertain, are shown in Figure 10. The tax holds the carbon price constant at \$23/ton, while the cap requires a tax ranging from less than \$5/ton to over \$80/ton. The safety valve is a hybrid of these policies; if the market price under a cap is less than \$23/ton then that cost applies. If the market price under the cap is more than \$23/ton, the safety valve is “triggered” and a \$23/ton tax applies. Since the cap and tax used to design the safety valve are equivalent in the no-uncertainty case, the safety valve is expected to behave like a tax with approximately 50% probability. Lowering the trigger price

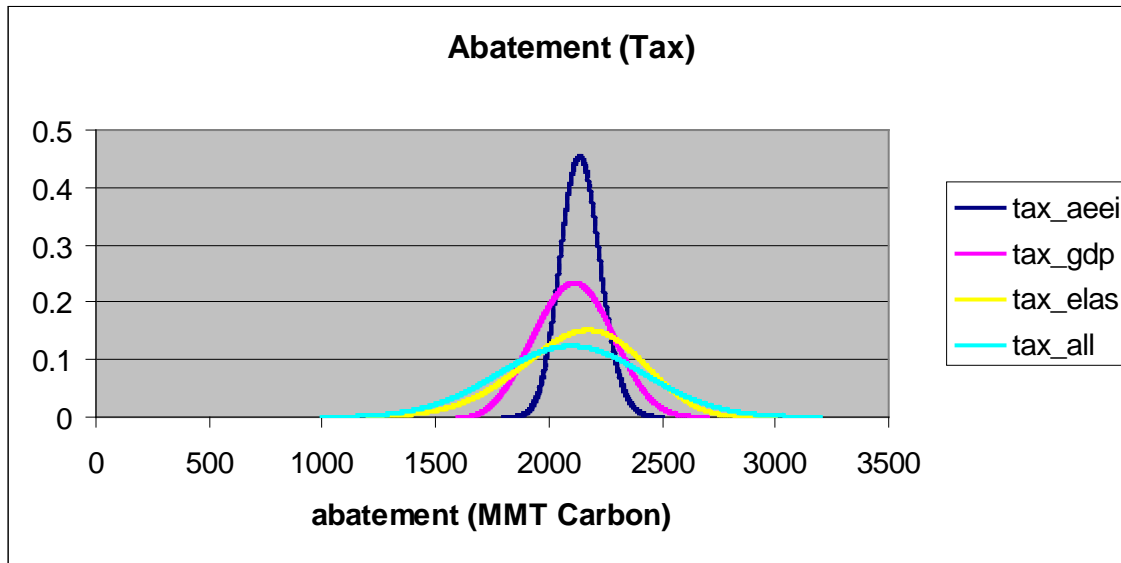


Figure 3-10: PDF of abatement under a tax, and relative contribution of each uncertain parameter

or making the cap more stringent will increase the probability that the safety valve behaves like a price instrument.

The carbon price under an intensity target behaves similar to a cap, but has a narrower range. If base emissions are low, the intensity target requires more abatement than a cap, and thus imposes a higher carbon price. If base emissions are high, the intensity target allows a more relaxed target than a cap, and thus a relatively lower carbon price. It is important to note that an intensity target behaves more like a tax in terms of abatement, and more like a cap in terms of carbon price. The intensity target “chooses” the quantity to abate by maintaining a constant emissions/GDP ratio, which substantially narrows the range of abatement to more closely mirror a tax. However, as under a cap, elasticities of substitution have little influence in determining the amount of abatement required, but are the most important factor in determining how much

that abatement will cost. This effect causes carbon prices under both the cap and intensity target to be highly variable.

3.5.3 *Welfare Loss*

Welfare loss, or percent change in equivalent variation, is shown for each policy in Figure 9. The safety valve causes the smallest change in welfare, but also requires the least abatement (and lowest carbon prices) of the four policies. Welfare loss varies only slightly under a tax, and more considerably under a cap and intensity target (Figure 9). The reason for this large variation in welfare loss under a cap and intensity target is the same as for carbon price; the amount to abate is chosen with little regard to elasticities of substitution. Under a cap, welfare loss will be small if base emissions are low, and large if base emissions (and hence abatement) are high. Under an intensity target, welfare loss will be small if both AEEI and substitution elasticities are favorable (as abatement is chosen only with respect to GDP), and more substantial if they are not.

3.5.4 *Net Benefits*

A cubic marginal cost curve was fit to each of the 1000 scenarios, and integrated to determine the total cost of abatement. Marginal benefits of abatement were set at the reference tax, \$23/ton. Net benefits were calculated by subtracting total costs from total benefits. Because the tax always abates to \$23/ton, i.e. the point where marginal cost equals marginal benefit, the tax is by definition optimal in terms of net benefits. This result is shown in Figure 10, as is the result that both the safety valve and intensity target are always preferable to a pure cap in terms of net benefits. This relationship has also been demonstrated analytically. The distinction between the safety valve and intensity target is less clear from the graph; the curves for these

“second-best” policies cross each other, indicating that one is not stochastically preferable to the other.

Whether a safety valve or intensity target yields higher net benefits is determined by the relative carbon prices under the policy, as is seen in Figure 11. These carbon prices, by definition, represent the marginal cost of abatement in each scenario. When the safety valve behaves as a price instrument, and thus imposes a tax equal to the marginal benefits, it is always optimal to the intensity target. When neither policy abates to the point where marginal cost equals marginal benefit, the policy which abates closer to this point is preferred. For example, if the carbon price under the intensity target is \$15, and under the safety valve the price is \$10, the intensity target is preferred because \$15 is closer to \$23 (the optimal price). Similarly, if the carbon price under the intensity target is \$40, and under the safety valve the price is \$10, the safety valve is preferred because \$10 is closer to \$23. In terms of expected net benefits, the intensity target performs slightly better than the safety valve Table 3, indicating that is preferred under uncertainty.

The above findings apply only when these “second-best” policies are designed based on the reference “no-uncertainty” case. In practice, the design of these policies is likely to be somewhat arbitrary, and thus the rest of this paper is devoted to exploring the relative advantage of these policies when these assumptions are relaxed.

Using the probability distributions for the elasticity parameters described above, we perform Monte Carlo simulations with a sample size of 1,000. We calculate the resulting uncertainty in carbon emissions and welfare loss from the parametric uncertainty for both price and quantity instruments, focusing on a reference policy of \$50/ton carbon tax.

Under reference elasticity values, this level of carbon tax results in 1785 MMT of carbon reduced, a 37% reduction in emissions. Under uncertainty, we impose a price instrument of \$50/ton and a quantity restriction of 1785 MMT reduction.

As first explained by Weitzman (1974), the carbon price results in uncertain levels of emissions abatement, and the emissions target results in uncertainty in the carbon price (Figure 6). The tax of \$50/ton yields a 95% probability range of abatement of 1300 to 2180 MMT C, or 25% to 50% reduction in carbon emissions. The emissions target gives carbon prices with a 95% range of \$35 to \$80/ton to achieve the required abatement. The effect of the two policy instruments varies in their welfare effects as well. The welfare loss pdf's from the carbon tax, measured as equivalent variation, has a 95% range of 0.14% to 0.27% relative to the no policy case (Figure 7). In contrast, the emissions target exhibits greater variability in its welfare impacts, with a 95% range of 0.15% to 0.40%.

We can illustrate the relative uncertainty in price and quantity instruments more generally by performing Monte Carlo simulations for a range of carbon prices, and graphing the resulting percentiles of abatement vs. carbon price (Figure 8). The abatement uncertainty from carbon tax can be seen in the horizontal distance between the 95% bounds for a given tax level, and the marginal cost uncertainty in an emissions target can be seen in the vertical distance between the bounds for a given level of abatement. One of the benefits of general equilibrium analysis is the ability to estimate the ultimate economic impacts on consumer welfare of policies that affect some sectors of the economy more than others. Although the "costs" of a climate policy are often described in terms of the carbon price, this is the marginal cost of the policy, not the actual welfare loss. For a range of carbon prices up to \$200/ton, we compute the uncertainty in the projected welfare losses for the U.S. economy in 2010.

As noted above, the results of a stochastic simulation depend on the assumptions about the correlation structure across the uncertain parameters. As a reference assumption, the results to this point are obtained assuming that there is no correlation (i.e., probabilistic independence) between different elasticities. In other words, the sample value for the capital-labor elasticity of substitution contains no information about the corresponding sample for the inter-fuel substitution elasticity. For the different industrial sectors, we assume perfect correlation ($\rho = 1.0$); i.e., the sample value for the substitution elasticity between capital-labor is the same for all sectors in that simulation. We now test the sensitivity of these assumptions by assuming different correlation structures and comparing the results to the standard *base case* shown above. We restrict the sensitivity tests to a single policy case, the carbon tax of \$50/ton.

We test three additional cases, one where the different substitution elasticities are all positively correlated with each other with a correlation coefficient of 0.5, one where the different elasticities are correlated with each other with a coefficient of 0.9, and one where the elasticities for each production sector are probabilistically independent from all other sectors. The effects of increasing the correlation between elasticities is a slight increase in the variance of emissions; the standard deviations are 226, 268, and 263, respectively for the standard, correlation of 0.5, and correlation of 0.9 (Figure 11). But the larger effect is a decrease in the mean emissions as the strength of correlation increases. The effect of correlation between elasticities on the uncertainty in welfare loss is similar, with a slight increase in variance and an increase in the mean welfare loss (Figure 12).

The effect of imposing zero correlation across sectors is more pronounced than that of varying correlation across elasticities (Figures 11 & 12). For both emissions and welfare losses,

the impact is significant reduction in variance, but no appreciable difference in the mean outcome.

Figure 3-11. Emissions Uncertainty over Four Scenarios, $P_{\text{carbon}} = \$50/\text{ton}$.

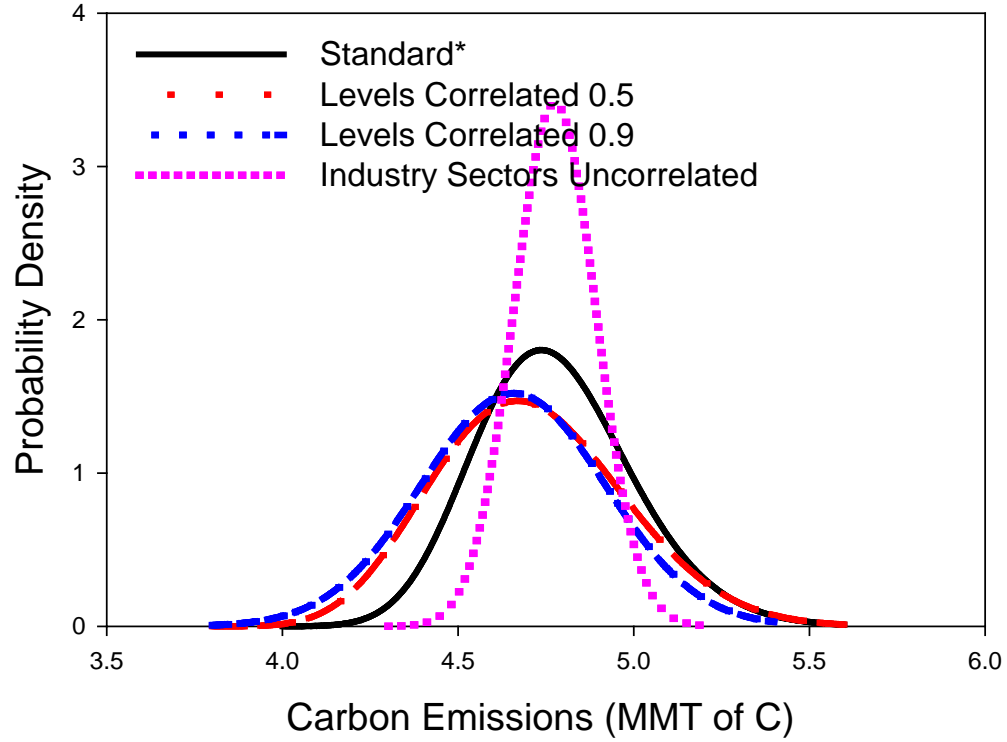
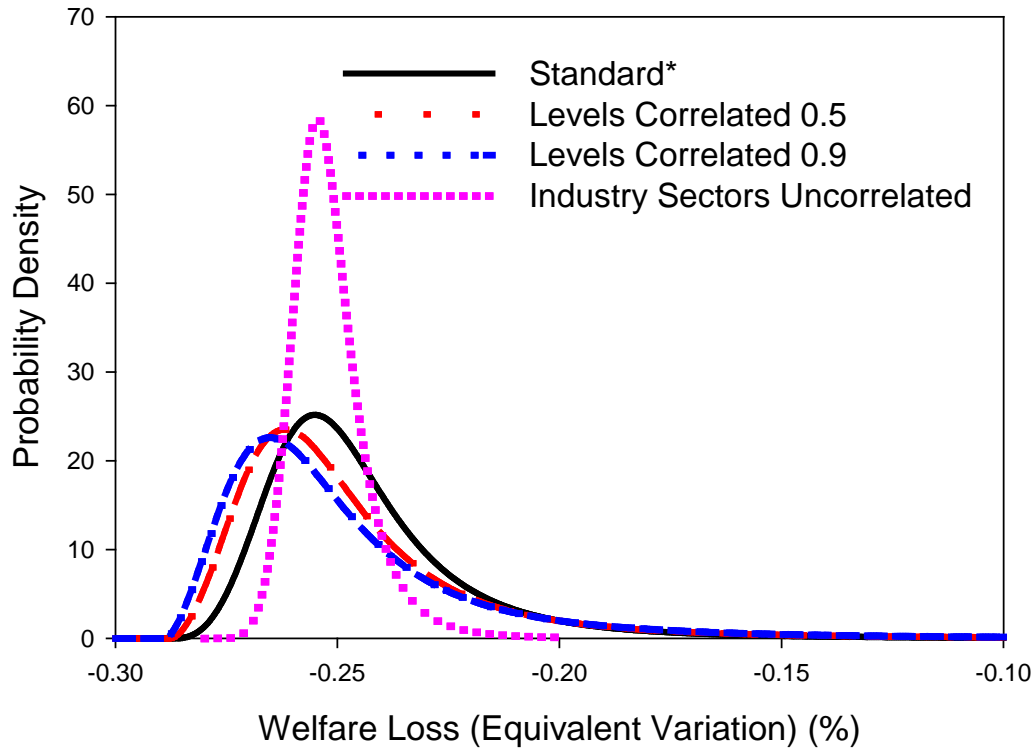


Figure 3-12. Welfare Loss Uncertainty over Four Scenarios, $P_{\text{carbon}} = \$50/\text{ton}$.



3.6 Discussion

In this study, we have used a CGE model of the US to show the uncertainty in impacts from various carbon reduction policies. The uncertainty in impacts shown here is the result of uncertainty in the elasticities of substitution between production factors. As potential policy responses are considered by lawmakers, the cost impact of any policy is a critical piece of information. Because costs cannot be known in advance with certainty, the most useful form this information is the description of the uncertainty in the costs. Thus, uncertainty studies of the type presented here form part of the necessary background for a public debate on potential policy responses.

For any given policy constraint, the uncertainty in costs, as well as in resulting emissions, depends on the economy's ability to respond and adjust to the new constraints. For near-term

policies focused on the next decade or so, we are mainly interested in the ability of existing production processes to adjust. Over the longer term, other uncertainties become more critical, such as how investment in research and development of new technologies responds to the new incentives, and on how likely new technology developments are as a result of increased investment and effort.

In this paper, we have summarized an extensive survey of the estimation literature to find what is known about elasticities of substitution between production factors. One finding is that there are numerous gaps in the available information that would be needed to conduct an uncertainty analysis with more confidence. One such gap is the difference in the functional forms used in most estimation studies as compared with the functional forms used in CGE models. Another is the relative dearth of information on some of the most influential elasticities, in particular the substitution between sector-specific fixed factors and other production factors, and between nested bundles of capital-labor for bundles of energy-materials. Many studies in the literature do not report standard errors of their estimations, providing no information at all about the uncertainty. Finally, traditional statistical methods yield no information on correlation across factors and across sectors, which also significantly determines the uncertainty in outcomes. Future contributions to any of these gaps would greatly improve our ability to estimate the uncertainty in policy costs.

4. Probabilistic Scenarios

4.1. Background

The problem of designing effective and appropriate policy to address global climate change is one of reducing and managing the risks of severe climate impacts in the future. Therefore, scientific guidance for climate policy should characterize the uncertainties and risks

for decision makers. Among the most useful contributions that scientific assessment can make to the policy process are to 1) help to *frame* the debate between policy options; and 2) provide *intuition* about the tradeoffs between alternatives. These contributions are more important than precise predictions of outcomes. For a decision under risk, this means providing information about the range of possible outcomes, their relative likelihood, and how the risks of undesirable outcomes are altered by the policy alternatives.

One very useful tool for structuring and communicating assessments is a set of scenarios. A set of scenarios are sketched of future conditions (or alternative sets of future conditions), used as inputs to exercises of analysis or planning. There are several objectives for designing scenarios for assessments. First and foremost, they provide a set of common assumptions to a group or community of scientists jointly contributing to an assessment exercise. Second, a set of scenarios reduces the number of cases to study from the infinite continuum of possible futures to a manageable set, making detailed analysis of each alternative future feasible. This leads to the third objective, which is to span a useful range of the uncertainty. Scenarios are especially useful for problems of decision under uncertainty, since they can provide a way to test the robustness of a policy against possible “worse case” outcomes. This creates a tension between designing one or more scenarios that describe extreme enough outcomes to be a useful test of robustness, while on the other hand, scenarios should have enough likelihood of being realized to be worth the time and effort to consider. A fourth objective for designing scenarios is to enhance communication with decision makers and the public by providing a detailed storyline that describes each possible future. Finally, a more subtle but critical objective in designing scenarios is the frame the overall debate over options. A scenario set that reflects a narrower range of uncertainty may lead to different decisions than one with a wider range of uncertainty.

This effect is often implicit and unintentional, but can have a powerful effect and should therefore be considered carefully by scenario designers.

Previous scenarios designed for exercises such as the Intergovernmental Panel on Climate Change (IPCC) assessments, the U.S. National Climate Impacts Assessment, and others have generated several debates over the most useful methods to design and construct scenarios. One of these debates is whether explicit probabilistic approaches should be used in the design process and whether probabilities or likelihoods can be associated with scenarios. This paper addresses the controversy over probabilistic approaches to scenario design. Often, this debate is framed as a choice between storyline approaches and purely probabilistic approaches. We use probabilistic methods to design two alternative sets of emissions scenarios for use in climate change assessment. We argue that storylines and probabilities are not mutually exclusive but rather complement each other in the design process.

4.2. Probabilistic vs. Storyline Approaches

We begin by exploring the current arguments within the climate science community over whether to use probabilistically based scenario designs or to use a storyline approach to scenario design. The best example of the storyline approach is the IPCC Special Report on Emissions Scenarios (SRES) (Nakicenovic et al, 2000). The SRES authors developed this set of scenarios, “to represent the range of driving forces and emissions in the scenario literature so as to reflect current understanding and knowledge about underlying uncertainties,” (Nakicenovic et al, 2000). They developed four different narrative storylines to “describe consistently the relationships between emission driving forces and their evolution,” each of which represents a different complete picture of how the world might develop socially, economically, and technologically over the next century. Six different integrated assessment models were then used in conjunction

with the four narratives to develop a total of 40 scenarios. Out of these 40, six were selected as “marker scenarios” to provide common assumptions for modelling efforts in the wider climate change community.

The advantages of the SRES approach are that it provided a small set of common scenarios that have been used extensively in the climate research community, and that the intuition for the scenario assumptions is enhanced by the storyline. One criticism of the SRES, however, is that no statement as to the relative likelihood was attached to the scenarios (Reilly et al., 2001). In fact, the authors explicitly avoided any statement of probabilities, and instead defined all scenarios as equally plausible.

The probabilistic approach to scenario design is grounded in the practice of using probability distributions to formally characterize and communicate the uncertainty in a particular outcome variable (e.g., global mean temperature change in a given decade). The advantages of this approach are that it organizes our current knowledge about possible outcomes and their relative likelihood, and that it allows for the explicit exploration of risk-reducing strategies through policy (Webster 2003). Critiques of this approach are that communication is limited by the less intuitive nature of probability distributions, the difficulty in linking the results from one set of possible assumptions across multiple outputs, the reliance on expert judgment for socio-economic future trends, and the false sense of accuracy that may be accorded to numerical probabilities.

The perspective of the authors is that these two approaches are not necessarily mutually exclusive. We propose, and illustrate with an example below, that storyline scenarios can be constructed based on the results of a probabilistic uncertainty analysis, after which the discrete scenarios can be communicated and used as common assumptions.

4.3. Simple Example of a Probabilistic Scenario Design

The example here builds upon the uncertainty analysis in Webster et al (2002), and uses it to design small sets of emissions scenarios as an illustration of the proposed approach.

The Method

The steps in designing a set of probabilistic scenarios are:

1. Conduct sensitivity analysis of parameters,
2. Construct probability distributions for key parameters,
3. Perform uncertainty propagation (Monte Carlo),
4. Use distributions of outcomes (emissions) to identify interesting targets,
5. Find an appropriate set of parameters that give the target emissions, and
6. Choose a small set of scenarios: combinations of parameter assumptions and their resulting outcomes.

This approach assumes that one or more modelling frameworks are being used to assist in the development of internally consistent scenarios. The first step requires that all uncertain assumptions in the model be tested to find which exert the greatest influence over the model outcomes of interest. The second step entails the development of a probability distribution for each of the most important assumptions. This can be done with the use of historical observed data and measurements, reliance on expert elicitation, or on some combination of both. The third step is the use of the parameter distributions to perform uncertainty analysis of the model and obtain probability distributions of the model outcomes. These first three steps are described in detail in Webster et al (2002).

The resulting probability distributions of projected outputs of interest can be used to locate percentile values to define scenarios, such as shown in Figure 1. This is the fourth step of the procedure, selecting a useful set of possible outcomes. Using the probabilistic information available from this approach, specific fractiles of the distributions can be chosen around which to construct scenarios. For example, one could construct scenarios that bound +/- one standard deviation, enclosing a 67% probability, and +/- two standard deviations, enclosing 95%. Other useful probability bounds include 50% and 99%. For some questions, we may be interested in an even more extreme probabilistic upper bound case, such as one with a one in one hundred or one in one thousand level of risk.

The selection of a set of possible values for an outcome, for example global CO₂ emissions or global mean temperature change, does not by itself constitute a set of scenarios. For each targeted outcome value there are many possible combinations of the uncertain input assumptions that would yield the target result within some small error. The task in the fifth step, then, is to choose one such representative assumption. One obvious choice is to choose the set of input parameter values that are the most likely, in the sense of having the highest joint density. However, alternative criteria can be used to select one set of assumptions out of many that give a particular result, as will be illustrated below.

An Example

The model used for this example is the MIT Emissions Projection and Policy Analysis (EPPA) model (Babiker et al., 2001). An uncertainty analysis of emissions from EPPA is described in Webster et al (2002). In that analysis, two key uncertain parameters that drive carbon emissions were found to be labor productivity growth (LPG) and the autonomous energy efficiency improvement rate (AEEI). Probability distributions of these parameters were

developed from experts' subjective judgements about the uncertainty in future trends. Monte Carlo simulation was then performed to obtain the probability density function (PDF) for global CO₂ emissions (Figure 1), as well as for emissions of other greenhouse gases and local air pollutants.

We now use the results of this analysis to design a set of emissions scenarios for the 21st century. The next step is to choose a set of targets around which to design scenarios. One of the primary outcomes for an emissions scenario is carbon emissions. We define seven targets at the percentiles of 5%, 10%, 33%, 50%, 66%, 90%, and 95% from the CO₂ distribution. These target outcomes are shown in Figure 1.

A complication to designing emissions scenarios is the fact that emissions of multiple species are relevant to climate projections, and the uncertainty in these emissions is neither completely uncorrelated, nor is it perfectly correlated. Thus, the distribution of methane emissions depends strongly on whether model assumptions are leading to CO₂ at 5%, median, or 95% levels. For this scenario set, we assume that other greenhouse gases and aerosols are at their median levels conditional on the seven CO₂ cases described above. In addition, we add four scenarios that result in non-CO₂ greenhouse gases at 10%, 33%, 66%, and 90% conditional on CO₂ at its median, and four additional scenarios that result in urban pollutant emissions (SO₂, NO_x, etc) at their 10%, 33%, 66%, and 90% conditional on CO₂ emissions at their median.

The final step, given a target level for emissions, is to define the scenario by choosing the underlying parameter assumptions that result in those emissions. For any given outcome, many different possible assumptions can result in roughly the same outcome. In this example, there are 289 combinations of assumptions about the AEEI and LPG parameters that result in 20 GtC in 2100 within +/- 0.01 GtC (Figure 3). This is because that one can increase the growth rate of

the economy (LPG) and also increase the rate of energy efficiency improvements (AEEI) and still get the same carbon emissions. One of these sets of assumptions must be chosen as a representative scenario for the median CO₂ case. This is where a storyline approach can complement the probabilistic approach. A particular storyline can provide a guide or basis for selecting a particular set of assumptions out of the many candidates. In the absence of a storyline to supplement this design, we choose the pair of assumptions with the highest joint density.

Note that the probability of this scenario is not 50%. 50% describes the likelihood that carbon emissions will be lower than or equal to the emissions in this scenario. The probability of this particular set of characteristics is vanishingly small, as is any single set out of an infinite continuum.

We repeat this process for each of the targeted emissions, selecting the maximum joint density assumption that results with some small error of the target emissions level. Together, these fifteen scenarios, designated by the target emissions level and the representative underlying assumptions that result in those emissions, comprise one complete set of emissions scenarios that could be used.

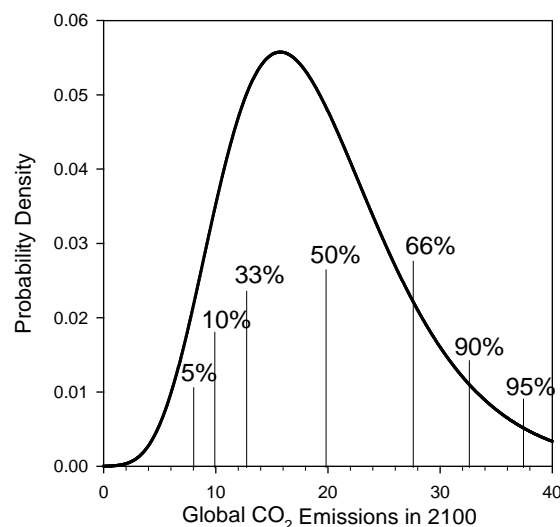


Figure 4-1: Probability distribution of global CO₂ emissions in 2100, and fractiles used to define targets for scenario design.

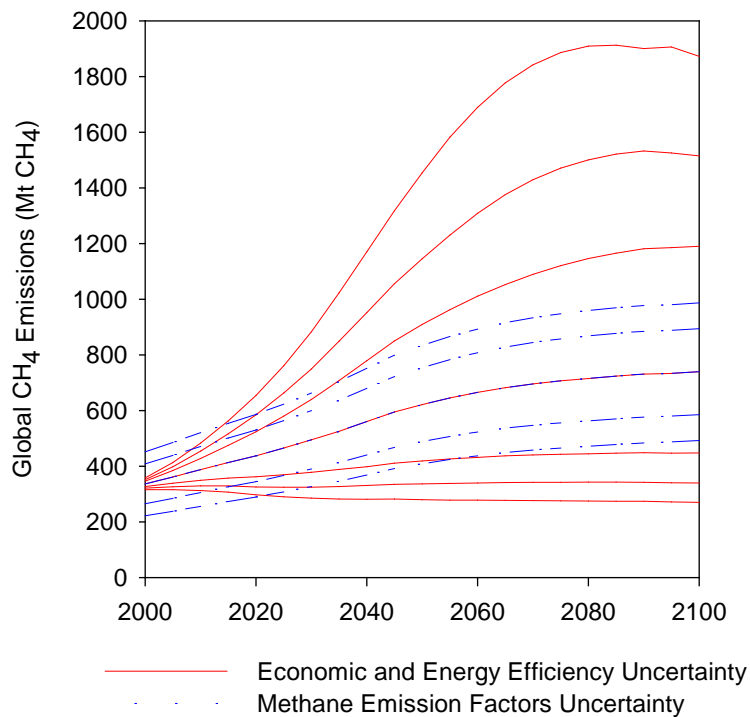
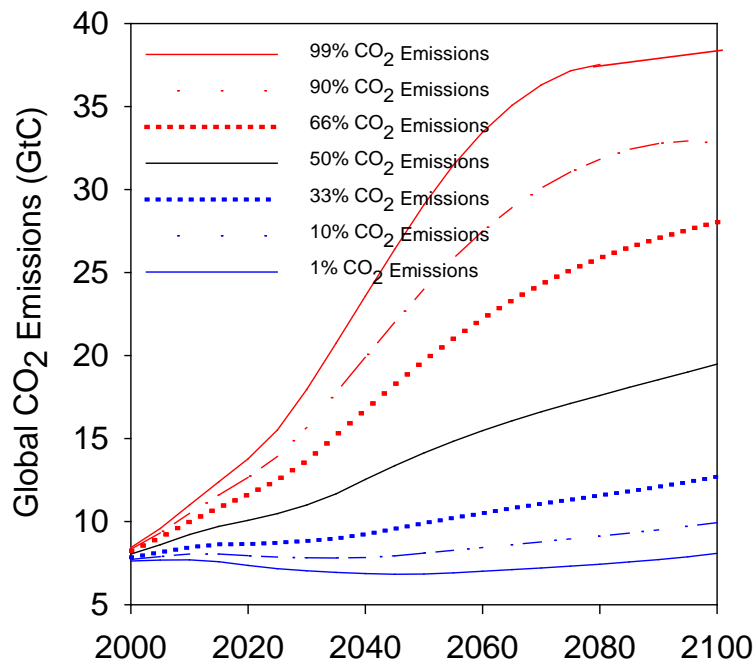


Figure 4-2: a) CO₂ emissions from seven scenarios that result in desired fractiles; b) CH₄ emissions from scenarios that vary economic growth, energy efficiency, and emissions factors.

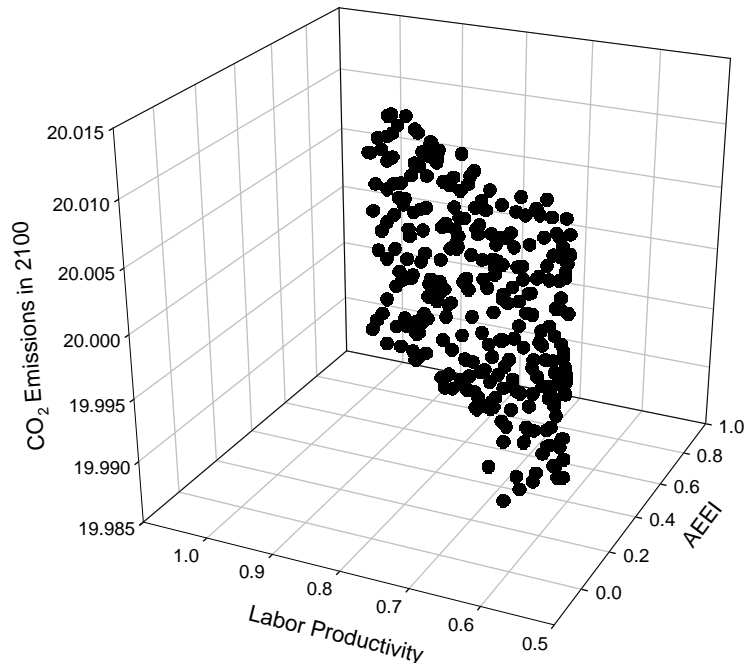


Figure 4-3: Combinations of uncertain assumptions that result in median CO₂ emissions

Table 4-1: Fifteen Multi-Gas Emissions Scenarios

Scenario #	CO ₂ Emissions	Other GHGs	Urban Pollutants
1	99%	50%	50%
2	90%	50%	50%
3	66%	50%	50%
4	50%	50%	50%
5	33%	50%	50%
6	10%	50%	50%
7	1%	50%	50%
8	50%	90%	50%
9	50%	66%	50%
10	50%	33%	50%
11	50%	10%	50%
12	50%	50%	90%
13	50%	50%	66%
14	50%	50%	33%
15	50%	50%	10%

4.4. Integrated Approach to Emission Scenario Design

Using percentiles from distributions of emissions is a simple way of using probabilistic bounds to guide scenario design. However, because emissions scenarios serve as common assumptions for climate and impacts projections, the design can be improved by considering the role that emissions play in climate modeling and that the focus of climate projection assessments is on impacts, not emissions.

From a climatic perspective, emissions are primarily interesting only in terms of their aggregate impact on total radiative forcing in the climate system. Designing scenarios that span the probability space across multiple emissions will not necessarily result in a useful spread across the probability distribution of radiative forcing, or provide efficient coverage with a small number of scenarios. Other possible impacts for design could be global mean temperature change, some aggregate index of regional/local physical impacts, or an economic valuation. As an illustration here, we focus on scenarios that efficiently cover radiative forcing as an impact.

The total net radiative forcing that results from the 15 emissions scenarios from the previous example are not spread evenly or efficiently across the probability distribution of forcing (Figure 4). A more efficient approach would be to design scenarios to explore percentiles of the radiative forcing distribution. Then one can choose one set of multi-gas emissions that will result in each desired radiative forcing based on one of several criteria. For example, one might choose to design scenarios at the 5%, 50%, and 95% values for radiative forcing (Figure 4).

As was true for alternative parameter assumptions that result in a given emissions level, there are multiple emissions of CO₂, other greenhouse gases, and aerosols that result in the same net radiative forcing change (Figure 5). Different criteria can be used to choose a particular

combination of emissions for one scenario. For example, one might choose the highest CO₂ forcing that gives a particular total radiative forcing target, the lowest CO₂ forcing, the highest aerosol forcing, and so on. Because of different lifetimes of species, radiative forcing strength, and differing costs of reductions, it may be useful to choose several distinct alternative scenarios with the same net forcing. For the median forcing, an alternative set of ten scenarios (Figure 2b) contains three that give 5% RF with different combinations of emissions, four that give 50% RF and three that give 95%.

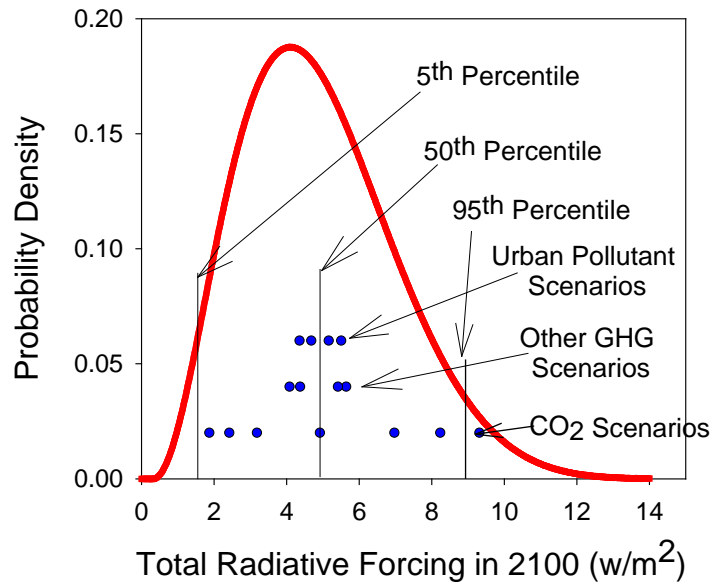


Figure 4-4: Probability distribution of total change in radiative forcing 2000-2100, three percentiles for scenario design, and the radiative forcing of the Section 3 emissions scenarios.

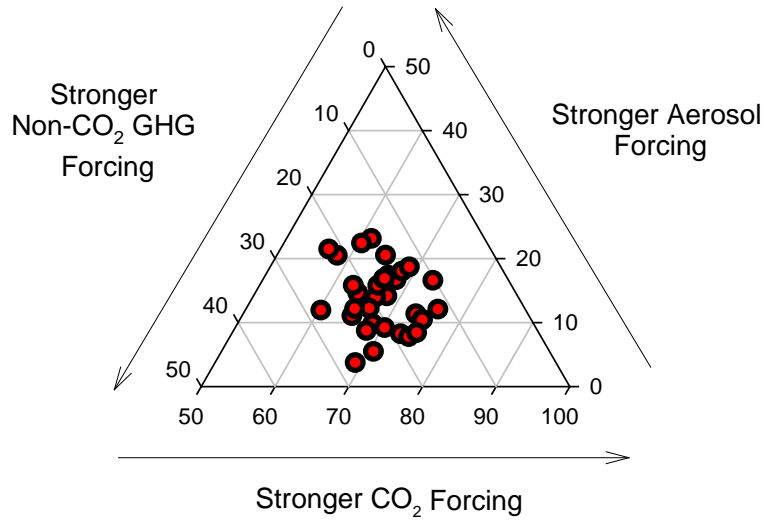


Figure 4-5: Different multi-gas emissions with the median net radiative forcing change.

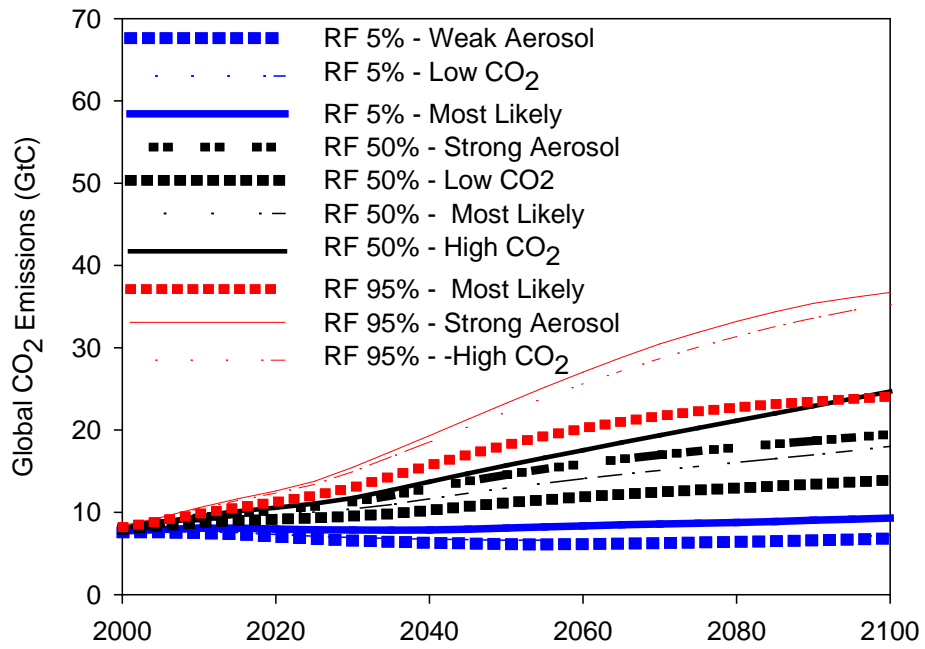


Figure 4-6: Alternative set of emissions scenarios based on radiative forcing.

Table 4-2: Proposed Set of 10 Scenarios

Scenario #	RF Fractile	Characteristics
1	5%	weak aer, low oghg
2	5%	low CO ₂
3	5%	most likely
4	50%	strong aer
5	50%	low CO ₂
6	50%	most likely
7	50%	high CO ₂
8	95%	most likely
9	95%	strong aer
10	95%	high CO ₂

4.5. Challenges

This simple illustration has several limitations, including the fact that even better bases for design exist, such as global mean temperature change or cumulative forcing. Critics may still object to the use subjective probabilities for some quantities. In the end, we still a means of designing scenarios that are most useful and efficient for scientific assessment to advise policy. Probabilistic methods provide one aide in this design problem.

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