Quantifying Uncertainty in Scenarios for Integrated Assessment of Climate Change

**Final Technical Report to
Office of Science of the US Department of Energy**

**Principal Investigator:
Mort Webster**

University of North Carolina at Chapel Hill

October, 2005

1. Introduction

The determination of climate policy is a decision under uncertainty. The uncertainty in future climate change impacts is large, as is the uncertainty in the costs of potential policies. Rational and economically efficient policy choices will therefore seek to balance the expected marginal costs with the expected marginal benefits. This approach requires that the risks of future climate change be assessed. The decision process need not be formal or quantitative for descriptions of the risks to be useful. Whatever the decision procedure, a useful starting point is to have as accurate a description of climate risks as possible.

Given the goal of describing uncertainty in future climate change, we need to characterize the uncertainty in the main causes of uncertainty in climate impacts. One of the major drivers of uncertainty in future climate change is the uncertainty in future emissions, both of greenhouse gases and other radiatively important species such as sulfur dioxide. In turn, the drivers of uncertainty in emissions are uncertainties in the determinants of the rate of economic growth and in the technologies of production and how those technologies will change over time.

There have been a number of studies of uncertainty in future carbon emissions (Webster et al, 2002; Manne and Richels, 1994; Nordhaus and Popp, 1997; Scott et al, 1999). In all of these studies, two of the most important drivers of uncertainty in emissions were the economic growth (as driven by labor productivity or equivalent factor productivity growth) and by the autonomous energy efficiency improvement (AEEI) or autonomous energy-saving technological change. The detailed implementation of these growth factors varies with the particular model, but all have one or more parameters that 1) increase production and therefore emissions over time, and 2) decrease the energy used per unit of production, decreasing emissions relative to what they would have been.

Previous uncertainty studies of emissions projections from economic models have used expert judgment to provide the uncertainty in economic growth or its underlying drivers. Experts will necessarily draw upon the information available from their experience, which will almost certainly be annual growth rates for individual countries. However, when applied to the economic models, the growth rates are used for large aggregate regions made up of several countries and for time steps of five or ten years. Finally, the issue of correlation between different regions is difficult, and usually is dealt with by simple assumptions of perfect correlation or perfect independence.

The danger in translating expert opinion on annual growth rates of observable quantities to temporal and regional aggregations in models and in making simplifying assumptions about correlation, such as perfectly correlated or stochastically independent, is that the results may overestimate (or underestimate) the degree of uncertainty implicit in the expert's mind. Assuming, for example, that all regions are perfectly correlated when in fact they are only weakly correlated will overestimate the range of uncertainty in emissions, and therefore in climate impacts.

An alternative approach to quantifying future growth has been the application of econometric time-series techniques for forecasting GDP. A number of studies have explored the nonlinearities and persistence of shocks in GDP for the United States (Cochran, 1988; Stock and Watson, 1988; Cochrane, 1994; Potter, 1995), Canada

(Serletis, 1992), and several OECD countries (Raj, 1992). This type of model provides an alternative method for deriving confidence intervals for future projections of growth. However, there are limits to how far forward in time these projections are robust for, especially with the limited dataset for many countries. We leave the application of time-series models to the full international dataset for future work, and will focus in this study on simpler statistics of observed historical growth.

Because of the long time-horizon used in climate policy studies (typically 100 years), the basis for probability distributions of future economic and energy growth rates or its drivers will necessarily include some expert judgment. Nevertheless, we can use information about past variability and correlation to inform and condition those experts' judgments in an elicitation procedure such as conducted by Morgan and Keith (1995). Or, equivalently, we need to know how to correctly apply expert judgment about uncertainty in individual country annual growth rates to modeling exercises where countries and time are aggregated into larger groups.

This project uses historical experience and observations from a large number of countries to construct statistical descriptions of variability and correlation in labor productivity growth and in AEEI. The observed variability then provides a basis for constructing probability distributions for these drivers. The variance of uncertainty in growth rates can be further modified by expert judgment if it is believed that future variability will differ from the past. But often, expert judgment is more readily applied to projected median or expected paths through time. Analysis of past variance and covariance provides initial assumptions about future uncertainty for quantities that are less intuitive and difficult for experts to estimate, and these variances can be normalized and then applied to mean trends from a model for uncertainty projections. The probability distributions of these critical model drivers, and the resulting uncertainty in projections from a range of models, can provide the basis of future emission scenario set designs.

Section 2 of this report will describe trends in GDP growth for countries and will use this historical record to estimate variability and covariability. I show that descriptions of the uncertainty must be appropriately transformed for any model depending on its regional aggregation and length of time step; distributions are developed for the EPPA, MERGE, and MINICAM models. In section 3, I will present data on energy intensity and discuss alternative methods of estimating AEEI. This section will rely primarily on data from the US, but will also give results for other countries for which data was available. The main result of this exploration is that AEEI is necessarily a model residual, and its correct value depends on other sources of energy intensity change represented in a model. Finally, in section 4, I will give results from uncertainty analyses of the MIT EPPA model using the distributions for AEEI and labor productivity growth. The effects of these uncertainties for future emissions and the costs, in terms of consumption losses and carbon prices, of several policies will be shown.

2. Analysis of Variability and Correlation in Long-term Economic Growth Rates

2.1. Background

One of the primary drivers of uncertainty in projections of future emissions is the amount of economic growth that will occur across countries. There are many factors that contribute to economic growth, including labor productivity, capital productivity, population growth, technical efficiency improvements, and other socioeconomic processes (often referred to as the “residual”) (see, e.g., Ch. 19 in Dornbusch and Fischer (1990)). Ideally, one would develop descriptions of the uncertainty in each of these growth factors. Unfortunately, many of these are extremely difficult to measure. Furthermore, the representation of economic growth varies widely among models in use. Some models simply take GDP as an input. Others have production functions of varying detail. In order to provide results useful to a wide range of researchers, we will limit our exploration to economic growth rates, rather than measuring underlying factors.

There have been a number of studies of uncertainty in future carbon emissions (Webster et al, 2002; Manne and Richels, 1994; Nordhaus and Popp, 1997; Scott et al, 1999). Webster et al (2002) performed uncertainty propagation on the MIT Emissions Prediction and Policy Analysis (EPPA) model (Babiker, 2001). Sensitivity studies revealed that labor productivity growth was one of the most important determinants of future emissions in this model (the labor productivity parameter also captures the effect of population growth). An expert elicitation was performed to obtain probability distributions for future growth of three regions: USA, EU, and China. All other regions in this model (12 in EPPA version 3) used the rescaled distribution of either EU or China, preserving the relative variance. Finally, growth in all regions was assumed to perfectly correlated.

Scott et al (1999) applied Monte Carlo analysis to MiniCAM to explore the relative influence of various parameters. MiniCAM has nine model regions, but grouped the uncertainty in labor productivity into OECD, China, EEFSU, and Non China developing countries. No correlation between these groups was specified, so each group appears to have been treated as independent.

Manne and Richels (1994) conducted uncertainty analysis on Global 2100. This model had five world regions: USA, other OECD, FSU, China, and ROW. In this study, Manne and Richels use the results of an expert elicitation in the form of a poll of experts. One of the uncertainties in their assessment is potential GDP growth. From the poll results, they construct a single probability distribution and apply to all regions, thus assuming perfect correlation.

In summary, previous uncertainty studies of emissions projections from economic models have used expert judgment to provide the uncertainty in economic growth or its underlying drivers. Experts will necessarily draw upon the information available from their experience, which will almost certainly be annual GDP growth rates for individual countries. However, when applied to the economic models, the growth rates are used for large aggregate regions made up of several countries and for time steps of five or ten years. Finally, the issue of correlation between different regions is difficult, and usually is dealt with by simple assumptions of perfect correlation or perfect independence.

The danger in translating expert opinion on annual GDP growth to temporal and regional aggregations in models and in making simplifying assumptions about correlation, such as perfectly correlated or stochastically independent, is that the results may overestimate (or underestimate) the degree of uncertainty implicit in the expert's mind. Assuming, for example, that all regions are perfectly correlated when in fact they are only weakly correlated will overestimate the range of uncertainty in emissions, and therefore in climate impacts.

Because of the long time-horizon used in climate policy studies (typically 100 years), the source of probability distributions for future economic growth rates or its drivers will ultimately include some expert judgment. Nevertheless, we can use information about past variability and correlation to inform and condition those experts' judgments. Or, equivalently, we need to know how to correctly apply expert judgment about uncertainty in individual country annual growth rates to modeling exercises where countries and time are aggregated into larger groups.

This section will answer the following questions:

- How does the variability and correlation differ between annual and larger time-steps such as five or ten years?
- How does variability and correlation differ between individual countries and larger aggregations of various sizes?
- What has been the variability of economic growth rates of different countries/regions in the past?
- What has been the correlation between economic growth rates of different countries/regions in the past?

We use data (described in the next section) on GDP over the past 50 years, as well as 150 years for a few select countries, to answer these questions. The results are intended to inform future analyses of emissions uncertainty from a range of economic models.

2.2. *Data, Methods, and Assumptions*

The primary data set used is the Penn World Tables (PWT), version 6.1 (Heston et al, 2002). PWT provides data on 168 countries over the period 1950-2000. The primary data we use are the per capita Gross Domestic Product (GDP) based on market exchange rates (not PPP), and the population for each country in each year.

In order to use market price based GDP rather than PPP-adjusted, we calculate GDP from the national account data in PWT 6.1. In the national account data, all five components of GDP are available for each country in each year: C (consumption), G (government expenditure), I (investment), E (exports) and M (imports) both in current local currency and constant (1996 base year) local currency. In addition, the market exchange rates [Local Currency/US\$] for each country in each year are available. To calculate market exchange rate based constant (year 1996) GDP for each country in each year, the following equation was used:

$$GDP_i(t) = [C_i(t) + G_i(t) + I_i(t) + E_i(t) - M_i(t)] / XRATE_i(t) \quad (\text{Eq. 1})$$

where i = country indicator

t = year indicator.

For the longer time series (~150 years) we use data on GDP from International Historical Statistics (Mitchell, 1998a; 1998b) for the United States, United Kingdom, France, Denmark, Finland, Italy, and Canada. The observations of GDP begin in 1790, 1830, 1815, 1820, 1860, 1865, and 1870, respectively.

We are interested in the variability and covariability of the growth rates, so from GDP, we calculate the percentage change from year-to-year, or between time-steps. This provides an observation set for each country/region for which we then calculate the mean, variance and standard deviation.

For example, the mean growth rate r of country i is calculated as:

$$\bar{r}_i = \frac{1}{50} \sum_{t=1951}^{2000} r_i(t), \text{ where } r_i(t) = \frac{GDP_i(t) - GDP_i(t-1)}{GDP_i(t-1)} \times 100 \quad (\text{Eq 2})$$

Variance and standard deviation are calculated equivalently. The correlation ρ between two countries i and j is calculated as:

$$\rho_{ij} = \left[\frac{1}{\sigma_i \sigma_j} \right] \sum_{t=1951}^{2000} (r_i(t) - \bar{r}_i)(r_j(t) - \bar{r}_j) \quad (\text{Eq 3})$$

where σ_i is standard deviation of country i .

In addition to annual changes, we calculate the growth rate of GDP over 5 year steps, and for the countries with observations available 1850-2000, we also calculate 10 and 20-year time steps. These intervals are non-overlapping, i.e.,

$$r_i = \left\{ \frac{GDP_i(1955) - GDP_i(1950)}{GDP_i(1950)} \times 100, \frac{GDP_i(1960) - GDP_i(1955)}{GDP_i(1955)} \times 100, \dots \right\} \quad (\text{Eq 4})$$

We will show sensitivity to the initial year along with the results below.

Calculations are also repeated for regions that aggregate two or more countries, as well as for individual countries. Because the PWT reports per capita GDP, we use the population data to correctly aggregate to a per capita GDP for the combined region. For the region k made up of n countries at time t , the regional per capita GDP is:

$$PCGDP_k(t) = \frac{\sum_{i=1}^n PCGDP_i(t) POP_i(t)}{\sum_{i=1}^n POP_i(t)} \quad (\text{Eq 5})$$

One complication to the calculations is that data is not available for all countries for all years 1950-2000. In fact, for many countries, observations do not begin until 1970 or later. The approach taken is to simply calculate the desired statistics based on the available data. Thus, if a country only has observations 1970-2000, only those data are used to calculate the mean and standard deviation. For correlation, calculations are only performed for years for which both regions have observations.

As an example of a regional aggregation that might be used in an economic model, we use the regional groupings from the MIT Emissions Projection and Policy Analysis (EPPA) model, version 4.0 (Paltsev, 2003). The country/region categories used in this version are listed in Table 1. The issue of missing observations is more problematic when aggregating. The first year of available data for each country differs widely; for some there is no data until the 1980's or 90's. The approach used is to find the earliest year from which data was available for enough countries to constitute a large percentage of the total GDP of that region (based on year 2000 GDP). The table in Appendix 1 shows the details for each region, including first year of data available, percentage of region GDP captured, countries included, and countries excluded. All calculations at all levels of aggregation then use only the included countries for consistency.

Table 1: Regions in EPPA 4.0

Country or Region	
<i>Annex B</i>	<i>Non-Annex B</i>
United States	India
Canada	China
Japan	Indonesia
European Union	Higher Income East Asia
Australia/New Zealand	Mexico
Former Soviet Union	Central and South America
Eastern Europe	Middle East
	Africa
	Rest of World

2.3. Results: 1800-2000

To examine how variation and correlation vary with the length of time step, we begin with an analysis of a few countries for which a long time series of GDP is recorded. The full global analysis below is restricted to 1950-2000, which only allows time-steps of up to five years to be used. Here, we focus on seven countries for which we have GDP observations between the early 1800's and 2000: United States, United Kingdom, France, Denmark, Finland, Italy, and Canada. We use these data to compare the variability of GDP growth rate with annual, five-year, ten-year, and twenty-year time steps.

Figure 1 shows the variability of the GDP growth rate in terms of the coefficient of variation, which is defined as the standard deviation divided by the mean. This is a useful way to compare relative variability between countries with different means. The first result to note is that the variability decreases with the length of the time-step. The variability in ten-year growth rates is much less than the variability in annual growth rates. The second feature to notice is that the biggest decrease in variability is between the annual and the 5-year period lengths. After that, the variability begins to level off. This gives some reassurance that the five-year periods calculated from the 168 country data will reasonably approximate the variability of longer time steps.

The effect of temporal aggregation on correlation varies widely, and does not exhibit a consistent pattern in this small sample set. Figure 2 shows the pairwise correlations between the US and each other country for one, five, ten, and twenty-year time steps. For some country pairs, the correlation is consistent across any length of time period: USA and Canada are consistently correlated, and France and Finland are both independent of US growth regardless of time period. However, the UK and Denmark exhibit positive or no correlation in the short term (1 or 5 years), and negative correlation in the long term (10 and 20 years), but Italy exhibits the opposite pattern. These results are complex interactions of time lags between shocks in different countries, and change significantly over this time horizon. For instance, in terms of 5-year time-steps, USA and Italy were roughly independent (-0.14) during 1850-1900, strongly negatively correlated (-0.77) during 1900-1950, and positively correlated (0.4) over 1950-2000. It is therefore not clear what one can assume over the very long term about correlation at different interval lengths.

Figure 1: Variability on Different Time-Scales (1850-2000)

Figure 2: Correlation over Different Time-Scales

2.4. Results: :1950-2000 (16 EPPA aggregation regions)

2.4.1. Variability

Using the data from the national accounts, we can explore the effects of regional aggregation on variability estimates, in addition to temporal aggregation. We aggregate the national GDP data into the 16 regions in Table 1, and for each, we calculate the mean, standard deviation, and pairwise correlation, for both yearly and 5-year steps respectively. Table 2 shows the mean, standard deviation, and coefficient of variation for each region. The coefficient of variation is also shown graphically in Figure 3. As in the previous section, the variability for five-year periods is less than for yearly periods.

The relative variability also differs among countries. The variance of the Former Soviet Union (RUS) and Eastern Europe (EET) regions are largest, although this is in part due to the transition period in the early 1990s. The variability of growth rates omitting these transition years are also shown in Table 2 and Figure 3; even after removing these years, the standard deviation is nearly +/- the mean growth rate. Of the remaining regions, the variability of long-term growth rates range from 25% of the mean (ROW) to 61% of the mean (Japan). (see [Appendix 1](#))

Table 2: Mean and Standard Deviation of GDP growth rate for Yearly and 5-year steps

Regions	Mean		Std Dev		StdDev/Mean	
	1-year	5-year	1-year	5-year	1-year	5-year
USA	0.04	0.19	0.02	0.05	0.69	0.27
CAN	0.04	0.21	0.02	0.07	0.63	0.32
MEX	0.05	0.28	0.04	0.13	0.76	0.46
EUP	0.03	0.19	0.02	0.08	0.58	0.43
EET	0.03	0.15	0.05	0.18	1.84	1.19
<i>EET*</i>	<i>0.04</i>	<i>0.17</i>	<i>0.04</i>	<i>0.17</i>	<i>0.89</i>	<i>0.99</i>
FSU	0.02	0.13	0.06	0.25	2.75	1.86
<i>FSU*</i>	<i>0.04</i>	<i>0.22</i>	<i>0.04</i>	<i>0.16</i>	<i>0.93</i>	<i>0.72</i>
JPN	0.06	0.33	0.04	0.20	0.65	0.61
EAH	0.07	0.37	0.03	0.10	0.44	0.26
IDN	0.06	0.33	0.04	0.15	0.73	0.47
CHN	0.06	0.36	0.05	0.12	0.72	0.35
IND	0.04	0.24	0.03	0.07	0.73	0.28
AFR	0.03	0.18	0.03	0.08	0.94	0.45
MIE	0.05	0.31	0.05	0.17	0.86	0.56
CSA	0.04	0.23	0.03	0.11	0.74	0.50
ANZ	0.04	0.19	0.02	0.05	0.67	0.26
ROW	0.05	0.26	0.03	0.06	0.58	0.25

* EET and FSU recalculated excluding the transition years of 1989-1993.

Figure 3: Relative Variability in Annual and 5-year GDP growth rate

The large variation in RUS and EET growth because of the dramatic political and economic changes in the early 1990's raises a dilemma for projecting future growth uncertainty: how should we deal with "surprises" in the socio-economic system? In the past century, we have observed a range of economic shocks, some which affect one or a few nations, others affecting many or all nations. Other examples of these include wars, oil price shocks, and the Great Depression. In simulating growth for the next century to compare climate policy, which types of surprises or large shocks should we include, and which should be left out? Should we leave out wars but include business cycles? Where do we draw the line? This question is beyond the scope of this study, but needs to be considered for this type of analysis.

2.4.2. Correlation

We also calculate the correlation coefficient between each pair of the 16 regions. The results for the five-year periods are presented in Table 3. Since there are at most 10 five-year periods between 1950 and 2000, and in some cases fewer, not all of these are statistically distinguishable from zero. Table 3 also indicates which results are significant at a 95% confidence level. For example, the only region whose long-term growth is significantly correlated with the U.S. is Canada (Figure 4). The statistical significance is determined using a transformation identity from Snedecor and Cochran (1967).

Table 3: Correlation Coefficients for 16 Region aggregation with 5-year time steps

	USA	CAN	MEX	EUP	EET	RUS	JPN	EAH	IDN	CHN	IND	AFR	MIE	CSA	ANZ	ROW
USA	1.00															
CAN	0.71*	1.00														
MEX	0.51	0.83*	1.00													
EUP	0.46	0.74*	0.68*	1.00												
EET	-0.08	0.82*	0.59	0.19	1.00											
RUS	0.47	0.86*	0.69	0.73	0.57	1.00										
JPN	0.31	0.65*	0.55	0.94*	0.17	0.72	1.00									
EAH	-0.10	-0.04	-0.21	0.20	-0.27	0.15	0.34	1.00								
IDN	-0.66	-0.41	-0.30	-0.27	-0.04	0.00	-0.11	0.70	1.00							
CHN	-0.63	0.88*	0.78*	0.76*	-0.52	0.89*	-0.64	-0.09	0.29	1.00						
IND	-0.27	-0.58	0.74*	-0.36	-0.58	-0.38	-0.29	0.09	-0.19	0.37	1.00					
AFR	0.67	0.87*	0.84*	0.87*	0.40	0.88*	0.82*	0.25	-0.11	0.84*	-0.62	1.00				
MIE	0.31	0.71*	0.65	0.76*	0.53	0.36	0.73*	0.29	-0.06	-0.43	-0.56	0.72*	1.00			
CSA	0.18	0.61	0.73*	0.57	0.50	0.30	0.53	0.23	0.18	-0.37	0.76*	0.66	0.90*	1.00		
ANZ	0.34	0.62	0.47	0.72*	0.38	0.34	0.75*	-0.11	-0.59	-0.40	-0.09	0.51	0.73*	0.43	1.00	
ROW	-0.20	0.16	-0.26	0.37	0.13	0.33	0.52	0.34	-0.04	-0.23	0.37	0.11	0.13	-0.20	0.42	1.00

* indicates coefficient is statistically significant at the 95% confidence level.

Figure 4: Correlation with USA on 5-year time steps

2.4.3. Effect of Spatial aggregation

One of the key questions in this research is: how does variability of GDP growth rate change with the level of spatial aggregation? As an initial example, we can compare the relative variability of individual European countries to an aggregate of those countries (EUP), as often used in macro-economic global models. Figure 5 shows the coefficient of variation for 15 European countries and their aggregate. The aggregate has a standard deviation which is 0.5 of the mean, but the variability in individual country growth ranges from 0.47 (Norway) to 1.1 (Switzerland) times the mean. Note that the aggregate variability happens to be nearly the minimum of the individual measures of variability.

For a fuller comparison, we compute pooled estimates of the standard deviation; i.e., all changes in GDP from one period to the next are included in a single calculation regardless of which country it is from. We compute pooled estimates for five levels of aggregation: individual countries, the 16-region EPPA aggregation, a 5-region aggregation for the MERGE model, a two-region aggregation of OECD and Non-OECD, and a single World aggregate. Figure 6 shows the coefficient of variation for these five levels. As with temporal aggregation, the variability is much higher for individual than it is for higher levels of aggregation. This is true for both annual and five-year growth.

To examine how individual region's GDP growth distribution varies across models with different time dimensions, we construct PDF of GDP growth rates for regions across models. For consistency of analysis in terms of countries included in aggregation across models, GDP data over 1965-2000 are used for 100 countries (see [APPENDIX 2](#)). The following tables show that the fitted distribution of annualized 3 year step GDP growth rate which is normalized by its mean and scaled by the ratio of coefficient of variation of 3 year step GDP growth to model specific time dimension.

Figure 5: Range of Variability of Individual European Countries and EU Aggregate

Figure 6: Relative Variability at Different Levels of Aggregation

Table 4: PDFs of GDP growth rate for EPPA 16 regions

EPPA	PDF	Mean	s.d	5%	50%	95%	Mean**
USA	Logistic (1.01854, 0.13688)	1.02	0.25	0.62	1.02	1.42	3.22%
CAN	Logistic (1.04559, 0.18018)	1.05	0.33	0.52	1.05	1.58	3.40%
MEX	ExtValue (0.76688, 0.42676)	1.01	0.55	0.30	0.93	2.03	4.25%
EUP	ExtValue (0.85558, 0.25122)	1.00	0.32	0.58	0.95	1.60	2.82%
EET	Logistic (1.0240, 1.0563)	1.02	1.92	-2.09	1.02	4.13	3.65%
EET*	ExtValue (0.55043, 0.89364)	1.07	1.15	-0.43	0.88	3.21	4.71%
FSU	Logistic (1.2891, 1.1776)	1.29	2.14	-2.18	1.29	4.76	1.80%
FSU*	ExtValue (0.72449, 0.57232)	1.05	0.73	0.10	0.93	2.42	3.99%
JPN	ExtValue (0.80471, 0.32030)	0.99	0.41	0.45	0.92	1.76	4.64%
EAH	ExtValue (0.87387, 0.28447)	1.04	0.36	0.56	0.98	1.72	6.71%
IDN	Logistic (1.04217, 0.12255)	1.04	0.22	0.68	1.04	1.40	6.45%
CHN	ExtValue (0.86229, 0.26495)	1.02	0.34	0.57	0.96	1.65	6.47%
IND	Logistic (1.02412, 0.14808)	1.02	0.27	0.59	1.02	1.46	4.73%
AFR	ExtValue (0.77129, 0.37236)	0.99	0.48	0.36	0.91	1.88	3.30%
MIE	ExtValue (0.79433, 0.37864)	1.01	0.49	0.38	0.93	1.92	4.89%
CSA	ExtValue (0.73858, 0.54228)	1.05	0.70	0.14	0.94	2.35	3.79%
ANZ	ExtValue (0.86607, 0.26300)	1.02	0.34	0.58	0.96	1.65	3.32%
ROW	Logistic (1.03084, 0.097771)	1.03	0.18	0.74	1.03	1.32	4.76%

Table 5: PDFs of GDP growth rate for MiniCAM 14 regions

Mini	PDF	Mean	s.d	5%	50%	95%	Mean**
USA	Logistic (1.009316, 0.068716)	1.01	0.12	0.81	1.01	1.21	3.22%
CAN	Logistic (1.022880, 0.090462)	1.02	0.16	0.76	1.02	1.29	3.40%
WEU	ExtValue (0.93038, 0.12113)	1.00	0.16	0.80	0.97	1.29	2.91%
ANZ	ExtValue (0.93277, 0.13202)	1.01	0.17	0.79	0.98	1.32	3.32%
JPN	ExtValue (0.90196, 0.16080)	0.99	0.21	0.73	0.99	1.38	4.64%
EEU	Logistic (1.01205, 0.53029)	1.01	0.96	-0.55	1.01	2.57	3.65%
EEU*	ExtValue (0.77431, 0.44862)	1.03	0.58	0.28	0.94	2.11	4.71%
FSU	Logistic (1.14512, 0.59119)	1.15	1.07	-0.60	1.15	2.89	1.80%
FSU*	ExtValue (0.86167, 0.28732)	1.03	0.37	0.55	0.97	1.72	3.99%
CHN	ExtValue (0.91849, 0.14958)	1.00	0.19	0.75	0.97	1.36	6.43%
MIE	ExtValue (0.89675, 0.19009)	1.01	0.24	0.69	0.97	1.46	4.89%
AFR	ExtValue (0.88517, 0.18693)	0.99	0.24	0.68	0.95	1.44	3.30%
LAM	ExtValue (0.86875, 0.27225)	1.03	0.35	0.57	0.97	1.68	3.79%
KOR	Logistic (1.019918, 0.057598)	1.02	0.10	0.85	1.19	1.02	7.64%
SEA	Logistic (1.023282, 0.058089)	1.02	0.11	0.85	1.02	1.19	6.03%
IND	Logistic (1.012115, 0.074340)	1.01	0.13	0.79	1.01	1.23	4.73%

Table 6: PDFs of GDP growth rate for MERGE 5 regions

MERGE	PDF	Mean	s.d	5%	50%	95%	Mean**
USA	Logistic (1.011385, 0.083993)	1.01	0.15	0.76	1.01	1.26	3.22%
OECD	ExtValue (0.91493, 0.13819)	0.99	0.18	0.76	0.97	1.33	3.52%
FSU	Logistic (1.17738, 0.72255)	1.18	1.31	-0.95	1.18	3.31	1.80%
FSU*	ExtValue (0.83094, 0.35118)	1.03	0.45	0.45	0.96	1.87	3.99%
CHN	ExtValue (0.90037, 0.18286)	1.01	0.23	0.70	0.97	1.44	6.43%
ROW	ExtValue (0.91811, 0.15845)	1.01	0.20	0.74	0.98	1.39	4.22%

* EET and FSU recalculated excluding the transition years of 1989-1993.

** Mean of annualized GDP growth rate of actual data point

2.4.4. Sensitivity to initial year

It is important to show how the variation changes by taking different initial year in calculation of more than 1 year-step GDP growth rates since the result would be quite different depending on initial year selected if the variation is sensitive to initial year. As shown in Figure #, however, most of regions are not sensitive to initial year in 5 year step GDP growth in terms of mean and standard deviation.

2.4.5. Market rate vs PPP (PPPvsMR.xls)

To Mort, Reminder!!! Why PPP adjusted GDP should be addressed compared with MR.

To compare how basic statistics differ using different economic output metric, the identical calculation with MR GDP has been performed for PPP adjusted GDP which is provided in PWT.6.1.

Figure # shows that regardless of which metric is used, there is not much difference in variation of GDP growth rates. Also correlation coefficient of growth rates for PPP adjusted GDP is 95% bounds of that for MR GDP.

Figure 7: Sensitivity to initial year in GDP growth rate

Figure 8: Comparison of MR versus PPP

3. Representing Energy Intensity Changes with AEEI

3.1. Background

- What is AEEI,
- Why AEEI is important
- Relationship between AEEI and price elasticity

There are numerous studies that estimate the trend in energy intensity and attempt to discriminate between price and non-price driven energy bias in technical change. The results of these estimates vary widely depending on the specific method used in the estimation. Direct estimates of the rate of change in energy intensity tend to find large rates of decline in energy intensity (Nordhaus, 1994, Kydes, 1999). Analyses of structural change in economies show that this explains a significant portion of the decline in intensity (Howarth and Schipper, 1991; Howarth et al, 1993). Econometric estimates that explicitly model technical bias, often disaggregated by sector, find that a residual autonomous trend is either quite small or non-existent (Hogan and Jorgensen, 1991; Sue Wing and Eckaus, 2005; Kaufmann, 2004; Popp, 2001).

There are a variety of macroeconomic models used to project greenhouse gas emissions and estimate the costs of restricting these emissions. They vary across many dimensions, but most relevant for this discussion, they differ in terms of the number of regions, the number of production sectors, the functional form of the production function, and the representation of technical change. Most such models represent technical progress in part with an autonomous energy efficiency improvement (AEEI) parameter (Azar and Dowlatabadi, 1999). The first documented instance of AEEI was by Edmonds and Reilly (1985), where they justified a declining coefficient of energy use with the historical experience of decreasing energy intensity with increasing economic output.

Many of the widely used climate policy models use nested constant elasticity of substitution (CES) production functions. The CES family of production functions (which includes Cobb-Douglas and Leontief functions) are homogenous of degree one, and this property is actually required for models that are solved using the mixed complementarity approach (Perroni and Rutherford, 1998). The relevant feature of models with homogeneous of degree one functions is that doubling the economy (*ceteris paribus*) will double the use of all inputs, production of all goods, and the consumption of all goods. In other words, there is no structural change that occurs with economic growth in these models. Changing relative prices (e.g. of energy relative to capital and labor) can lead to “structural change” in that consumer and producers will substitute less energy intensive goods for relatively more energy intensive goods when their prices rise because of the rising cost of energy. But such induced structural change is relatively minor because the energy value share (and thus cost increase) of even relatively energy intensive goods is not that great. Casual observation of historical trends suggest that it is not relative input price change that has driven structural change but rather it is a feature of consumer preferences as they depend on income. With rising incomes, consumers demand a different set of goods, more services and less basic materials, and these goods are coincidentally less energy intensive. While efforts are often made to model more realistic

structural change in applied general equilibrium models, in reality they do not fully capture this phenomenon. The AEEI thus brings the aggregate behavior of these models in line with historical trends.

An example of one of these models, the MERGE model (Manne et al., 1995) has a single production sector for each of its five geopolitical regions. The production function is at its top level a nested CES function, with its value added bundle (labor and capital) and its energy bundle (electric and non-electric energy) both Cobb-Douglas functions. The elasticity of substitution between the value-added bundle and the energy bundle is 0.4 for USA and other OECD countries, and 0.3 for other regions. The AEEI is assumed to be 0.5% per year.

A different example is the Emissions Projection and Policy Analysis (EPPA) model (Babiker et al., 2002). EPPA has 16 world regions, and 10 production sectors. The production functions' form vary by sector, but all are nested CES functions. The elasticity of substitution between energy and non-energy primary factors is 0.1 for electricity, 0.4 for agriculture and primary energy sectors, and 0.5 for all other sectors. AEEI is assumed to be 1% per year.

There are a wide variety of other models that make different assumptions. Table 1 summarizes the assumptions about AEEI and the price elasticity of energy for several prominent models. AEEI for most models ranges between 0.5% and 1.0% per year.

Table 7: Typical values of AEEI in assessment models

Model Name	AEEI (%/year)	Price Elasticity of Energy	Source
EPPA	1.0	-0.4	Babiker et al., 2002
ERB	1.0	-0.7	Edmonds and Barnes, 1992
MiniCAM	0.0 ~ 2.6 varies by region, time	?	Scott et al., 1999
MERGE	0.5	-0.4 (USA, OECD) -0.3 (other)	Manne et al., 1995
CETA	0.25	-1.0 (Cobb-Douglas)	Peck and Teisberg, 1992
SGM	Varies by sector and country; e.g. 0.5 for USA Other Goods; 1.0 for household oil	-0.1	Brenkert et al (2004)
WW	1.0	-0.7	Walley and Wigle, 1991

3.2. Analysis of energy intensity growth rates for EPPA 16 regions

Table 8 shows a simple statistics of annual growth rate of energy intensity (Energy Consumption/GDP) for EPPA 16 regions. Most developed countries or regions shows decreasing growth rate of energy intensity while some fast growing economies also shows decreasing growth rate such as China, India, and Indonesia. (Add text?)

Table 8: Summary statistics of annual energy intensity growth rates

	Mean	Standard Deviation
USA	-1.22%	1.87%
CAN	-0.79%	2.37%
MEX	0.44%	2.20%
EUP	-0.40%	2.01%
EET	-1.76%	3.83%
RUS	1.00%	3.03%
JPN	-0.21%	2.98%
EAH	0.34%	2.37%
IDN	-1.18%	3.93%
CHN	-3.87%	3.37%
IND	-1.29%	3.19%
AFR	0.62%	1.93%
MIE	3.57%	7.74%
CSA	-0.03%	1.86%
ANZ	-0.33%	2.99%
ROW	0.08%	2.28%

Source: World Development Indicator (see APPENDIX 3)

3.3. Data, Methods, and Assumptions

We begin by examining historical experience. The data used in this study includes GDP from the Penn World Tables (PWT), version 6.1 (Heston et al, 2002), energy consumption and energy price data from the International Energy Agency (IEA, 2004) on 8 individual countries, United States, United Kingdom, Canada, France, Germany, Italy, Japan, and Mexico and 1 aggregate, OECD. GDP data is available from 1950 to 2000, but the energy consumption and energy price data are available from 1960 and 1978 onward, respectively. For United States, the Energy Information Administration (EIA, 2002) provide more detailed data on energy consumption and price from 1970, some analysis below are extended further only for US.

Price data from IEA includes prices for crude oil, natural gas, coal, and electricity. We combine these series into an overall price index by weighting each fuel by its value share of total energy. Quantities of each fuel used for non-electric and electric are also obtained from IEA (2002). The electricity value share includes hydroelectric and nuclear generation as well as fossil fuel sources.

3.4. Energy Intensity and Energy Prices

The basic energy characteristics of the aggregate US economy are shown in Figure 1. This figure shows the changes in 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, much higher than typical assumptions for AEEI in forecast models.

Figure 9: GDP, Energy Consumption, and Energy Prices in U.S. 1970-2000

To examine how the relation between energy consumption, energy price and GDP has changed historically over a long term, we expand the time horizon back to 1860 (each series is indexed so that 2000 = 1.0). Energy consumption and GDP have risen at a similar rate up to 1940 and Energy consumption has grown faster than GDP since 1940 while energy price has decreased, in general, with several shocks. (see APPENDIX 4).
[Add text?](#)

Figure 10: GDP, Energy Consumption and Energy price in U.S 1860-2000

There are several factors that may account for this change in the energy/GDP ratio. One factor is the short-term price response by industry. This can explain the falling energy intensity when energy prices are rising, before 1986. Other factors are needed to explain the 1986-1999 continued decrease in energy intensity when prices were falling. Price responses can come in the form of either short-term adjustments, or because of delays in capital stock turnover, longer-run price-responses. Structural change, shifting production and consumption levels between sectors with different energy using characteristics, is a second candidate. A third general factor is non-price driven technological change, which occurs independent of relative factor price changes and shows up as a bias in the technical change over time.

We begin with some simple calculations as a way to illustrate the relationship between the price and non-price components. With an assumed price elasticity of energy demand (ε_D) we can predict next period's energy use assuming no non-price intensity change based on observed changes in GDP and energy prices (assuming no technical change occurs). Specifically, an initial prediction of energy consumption in each period is generated by:

$$PE_t = \frac{GDP_t}{GDP_{t-1}} * (1 + \frac{\Delta P_{t-(t-1)}}{P_{t-1}} * \varepsilon_D) * E_{t-1} \quad (\text{Eq 6})$$

Where PE_t is the predicted energy consumption in year t , GDP_t is the GDP, $\Delta P_{t-(t-1)}$ is the change in energy prices between time $t-1$ and time t , and E_{t-1} is the energy consumption in time $t-1$. A residual can then be calculated as the improvement needed to 'correct' this prediction, as the ratio of the predicted energy consumption to actual energy consumption in year t .

$$RES_t = \frac{PE_t}{E_t} \quad (\text{Eq 7})$$

The average of the residuals over a T years gives an upper bound measure for the AEEI:

$$AEEI = \left(\sum_t RES_t \right) / T \quad (\text{Eq 8})$$

This measure is an upper bound in the sense that a model with only an instantaneous price response by factor substitution and no other mechanisms at all, this residual autonomous trend would be needed to make projections consistent with historical experience.

Figure 11 : Simple direct estimate of AEEI from 1979-2000

	CAN	FRA	GER	ITA	JPN	MEX	UK	USA*	OECD
Mean	1.21%	1.25%	2.47%	2.63%	0.14%	6.49%	2.64%	1.96%	2.01%
Standard Deviation	3.16%	4.77%	4.80%	3.49%	4.51%	5.57%	4.13%	2.01%	1.46%

See Appendix 5

* USA is from 1971 to 2000

By varying the assumed elasticity, we can find different values of AEEI that are then consistent with the data. Equations (1)-(3) and the data define a linear relationship between AEEI and energy price elasticity, shown in Figure 2. The value of AEEI that matches observed economic trends ranges from less than 1% per year to 2.2% per year, for elasticities of -1.5 to 0 , respectively.

In Figure 2, we also plot the approximate position of several economic-energy models from the literature, based on published assumptions of energy price elasticity and AEEI. These models generally do not fall on the line defining the upper bound because they all represent some of the structural processes that contribute to intensity changes other than immediate factor substitution. Examples of such features include income elasticities of energy consumption (ERB) and structural shifts in the consumption bundle with increasing income (EPPA). The AEEI or residual needed for each model is therefore a function of 1) the assumed responsiveness to price, and 2) the set of non-price processes included in the model.

Figure 12: AEEI vs. Price Elasticity in U.S.1970-2000

The most important point is that, while we may not be able to definitively partition the relative contributions of substitution and autonomous technical change in explaining reality, we can identify combinations of assumptions that are more or less consistent with experience. Regardless of the “true” value of AEEI in reality, if one even exists, there is clearly an appropriate choice of AEEI for a model with a price elasticity of -0.5 . This information can then be used in an expert judgment process where we can modify these assumptions to the extent that experts expect future experience to depart from the past. Estimates such as those provided here give a point of departure for such a process.

3.4.1. Simple Econometric Estimates of AEEI:1970-2000 (8 countries)

Next, we explore a few simple econometric estimations of energy intensity for each country. We present below four simple alternative models as a means of illustrating the range of possible model formulations. These models are not proposed as an advance on the estimation literature; in fact they are simpler than most recent studies. Rather, the following is an illustration of the fact that the AEEI (or residual) component depends on the factors included in the estimated equation, and an exploration of the magnitude of the residual effect at an aggregate level comparable to energy models used for climate policy. We estimate four different equations for this illustration. Equations 1 and 2 estimate energy consumption and equations 3 and 4 estimate energy intensity. Equations 1 and 3 only include terms for short-term price response and the residual, while equation 2 includes a third term to represent structural change and equation 4 includes terms representing long-term price response.

The simplest estimation we can begin with is to regress energy consumption on energy price and GDP:

$$\ln(E_t) = \alpha + \beta_1 \ln(P_t) + \beta_2 \ln(GDP_t) \quad (\text{Eq 9})$$

This estimation is done in terms of logged variables so that the coefficients can be interpreted as elasticities.

(Due to data shortage second equation is only applied to USA) The second equation adds a term for the share of energy intensive industries in GDP in the above regression to explore whether structural change accounts for some of the apparent non-price induced efficiency increase, estimating:

$$\ln(E_t) = \alpha + \beta_1 (\ln P_t) + \beta_2 \ln(GDP_t) + \beta_3 \ln(EL_t) \quad (\text{Eq 10})$$

Five industrial sectors of US accounted for 71% of the energy consumed in manufacturing during 1974-1998 (see also Howarth et al, 1993), and for 26% of the energy consumed by the “Industrial Sector” as defined by the EIA (2002), which includes all manufacturing, construction, mining, and agriculture. These sectors are 1) stone, clay, and glass products, 2) primary metal industries, 3) paper and allied products, 4) chemicals and allied products, and 5) petroleum and coal products. These sectors, as well as manufacturing in general, have been falling steadily as a share of GDP in the U.S. economy over the latter half of the 20th century. In 1950, the energy intensive manufacturing sectors were 7.2% of GDP, in 1970 they were 5.7%, and by 2001 they had fallen to 3.4% of GDP. This is due to the increasing share of production by service sectors; energy intensive output has grown by a factor of 20 since 1947, but total GDP has grown by a factor of 40. These computations used additional data on energy use by sector from the EIA Manufacturing Sector Energy Trend Data: 1985-1998 (EIA, 2003) and on value added by industry from the Bureau of Economic Research’s Gross Domestic Product by Industry data (BEA, 2003).

The previous two estimates of energy consumption as a function of energy price and GDP may not be the best way to extract an estimate of the autonomous non-price trend. An alternative is to directly estimate the energy intensity, which is equal to energy consumption divided by GDP, as a function of energy prices and an autonomous time trend variable, t :

$$\ln(E / GDP_t) = \alpha + \beta_1 \ln(P_t) + \beta_2 t \quad (\text{Eq 11})$$

We estimate the logged intensity as a function of logged price, but do not take the log of the time trend.

3.4.2. Short-run and Long-run price elasticity of energy demand.

The previous three estimation equations only include the current period energy price index. However, the price elasticity of energy demand in the short-term differs from the long-term elasticity. While production technologies are fixed in the short-run and so little substitution is possible when prices change, the technological possibilities for adjustment over the long-run are much greater. When estimating long-run elasticities,

two additional unknowns are how many prior periods to include, and how strong the effect of past periods is on the dependent variable. One approach is to estimate with a geometric lag distribution

$$\ln(E / GDP_t) = \alpha + \beta_0 \left(\ln(P_t) + \lambda \ln(P_{t-1}) + \lambda^2 \ln(P_{t-2}) + \dots \right) + \varepsilon_t \quad (\text{Eq 12})$$

where $0 \leq \lambda < 1$. We can estimate this using the Koyck transformation (Kmenta, 1971), in which we estimate:

$$\ln(E / GDP_t) = \alpha(1 - \lambda) + \beta(1 - \lambda) \ln(P_t) + \lambda \ln(E / GDP_{t-1}) + \gamma t + \eta_t \quad (\text{Eq 13})$$

where $\eta_t = \varepsilon_t - \lambda \varepsilon_{t-1}$, λ is the strength of the lag effect, $\beta(1 - \lambda)$ is the short-run price elasticity, and β is the long-run price elasticity. The residual term γt is included to capture any residual bias in energy intensity that is not a short or long-term price response.

Table 9: Summary of Estimation Results (USA only: 1970-2000)

Estimation Equation #	Dependent Variable	Independent Variables	Price Elasticity	GDP / Time Elasticity (AEEI)	Equivalent Annual Rate of AEEI
Eq. 9	Energy Consumption	Energy Price GDP	-0.2* (0.04)	0.33* (0.02)	1.5%
Eq. 10	Energy Consumption	Energy Price GDP Share of EI	-0.17* (0.02)	0.5* (0.02)	1.3%
Eq. 11	Energy Intensity	Energy Price Time	-0.26* (0.04)	-0.021* (0.0007)	2.1%
Eq. 13	Energy Intensity	Energy Price Lagged Effects Time	SR: -0.046* LR: -1.03	-0.005* (0.002)	0.5%

* Statistically significant at the 5% level.

To. Mort, Check the number.

SR:-0.07067*

LR:-0.28528*

Table 10: Summary of Estimate Results (8 regions except #2 model over 1978-2000)

Estimation Equation #	Dependent Variable	Independent Variables	Region	Price Elasticity	GDP / Time Elasticity (AEEI)	Equivalent Annual Rate of AEEI
Eq. 9	Energy Consumption	Energy Price GDP	CAN	0.03 (0.07)	0.57 * (0.03)	3.4%
			FRA	0.07 (0.04)	0.85 * (0.05)	4.1%
			GER	0.07 (0.04)	0.85 * (0.05)	3.9%
			ITA	0.10 * (0.04)	0.54 * (0.06)	3.0%
			JPN	-0.09 (0.07)	0.73 * (0.07)	4.0%
			MEX	-0.03 (0.04)	1.10 * (0.06)	5.4%
			UK	0.07 (0.05)	0.25 * (0.04)	1.6%
			OECD	-0.49 * (0.06)	0.22 * (0.03)	1.5%
Eq. 11	Energy Intensity	Energy Price Time	CAN	0.39 (0.30)	-0.02 * (0.00)	1.8%
			FRA	0.10 (0.05)	0.00 * (0.00)	0.3%
			GER	-0.05 (0.05)	-0.02 * (0.00)	2.1%
			ITA	0.08 (0.08)	-0.01 * (0.00)	0.8%
			JPN	-0.19 * (0.09)	0.00 (0.00)	0.4%
			MEX	0.03 (0.04)	0.00 * (0.00)	-0.4%
			UK	0.08 (0.05)	-0.02 * (0.00)	1.8%
			OECD	-0.40 * (0.15)	-0.02 * (0.00)	2.0%
Eq. 13	Energy Intensity	Energy Price Lagged Effects Time	CAN	SR:-0.004 LR:0.008	-0.01 * (0.00)	0.6%
			FRA	SR:0.077 LR:0.114	-0.01 * (0.00)	0.2%
			GER	SR:-0.041 LR:-0.067	-0.01 * (0.01)	1.3%
			ITA	SR:0.007 LR:0.022	0.00 (0.00)	0.2%
			JPN	SR:-0.053 LR:-0.162	0.00 (0.13)	0.0%
			MEX	SR:-0.025* LR:-0.097*	0.00 (0.19)	0.7%
			UK	SR:0.048 LR:0.088	-0.01 * (0.00)	0.9%
			OECD	SR:-0.342 LR:-0.392	-0.01 * (0.01)	1.7%

* Statistically significant at the 5% level. * ITA:1978-1999 *MEX:1980-200

ADD text?

Table 9 summarizes the estimation results for the aggregate US economy, which we briefly discuss here. The first regression has an R-squared of 0.91 and all coefficients are significant at $p < 0.001$. The results give a price elasticity of energy demand for the whole economy of -0.20 with a standard error of 0.04 . This is consistent with previous estimates of the aggregate economy short-run price elasticity (Bohi, 1981; Table 3-1). The elasticity of energy consumption with respect to GDP is 0.33 with a standard error of 0.02 . In other words, after controlling for price effects, a 1% increase in GDP will only result in a one-third percent increase in energy consumption. This is equivalent to an AEEI of 1.9% per year over those 30 years.

The second regression has an R-squared of 0.97 and all coefficients are significant at $p < 0.001$. The price elasticity is similar with a value of -0.17 and a standard error of 0.02 . The elasticity of the energy intensive share parameter is 0.35 with a standard error of 0.04 ; a 1% fall in the energy intensive share of GDP would lead to a 0.35% fall in energy consumption by the economy. Since the share of energy intensive industries have fallen about 40% since 1970, this implies that energy consumption by the economy should have decreased by 14%, *ceteris paribus*. The coefficient for GDP in this case increases to 0.50 with a standard error of 0.02 , which implies an autonomous energy efficiency improvement of 1.3% per year, not including price effects or the effect of the falling share of energy intensive manufacturing. The issue of trends within different sectors of the economy is in fact very important to accurately representing energy intensity changes. We explore this issue more fully in Section 5 below.

The third estimation of energy intensity has an R-squared of 0.98, and all coefficients are significant at $p < 0.001$. The price elasticity in this case is -0.26 with a standard error of 0.04 . The coefficient on the time trend is -0.021 (0.0007), which is equivalent to an annual decrease in energy intensity of 2.1% per year due to non-price effects. Adding a term for the energy intensive share of GDP, the autonomous time trend coefficient is -0.018 (0.002), equivalent to an annual decrease of 1.75% per year in energy intensity.

The results of the fourth estimation accounting for lagged price effects yields:

Strength of Lag Effect (λ):	0.96
Short-term price elasticity ($\beta(1 - \lambda)$):	-0.046
Long-term Price elasticity (β)	-1.03
Constant (α):	-6.95
Time Trend (γ):	-0.005

These results suggest that the short-run price elasticity is much smaller than our previous e These results suggest that the short-run price elasticity is much smaller than our previous estimates above, and that the long-run price elasticity is quite large. These estimates for the elasticities are again not inconsistent with the range of prior empirical estimates (Bohi, 1981). This estimate still has a residual time trend in energy intensity, but much weaker than the other estimations at 0.5% per year. The long-term price response accounts for more than 1%/year of the AEEI estimated by the simpler equations.

But this result raises an important issue for the choice of model parameters: many models, for example CGE models, represent substitution elasticities in production functions for the current period, or short-run elasticities. The results of this estimate

indicate the response to energy price changes occurs more gradually over a much longer period of time. Indeed, the lag strength parameter is very close to unity. If a model does not represent these longer term adjustments to past price changes, this effect should then be rolled into the residual change in energy intensity. The residual will then no longer represent solely an autonomous non-price efficiency gain, but will nevertheless be a necessary correction to be consistent with past experience. An alternative is to formulate a dynamic model with long-run elasticities. Because many models have time-steps of several years, typically 5 or 10, their price elasticity is essentially a long-run response. Also, models that vintage capital stock, such as the EPPA model, also simulate a short and long run elasticity because full adjustment can only occur after all the vintaged capital has turned over.

There are three simple points from this illustration. The first point is that the estimated AEEI will necessarily depend on the estimating equation. The more phenomena explicitly represented in the model, the lower the remaining residual trend in energy intensity change. The second point is that structural change is a significant contributor to the observed decline in energy intensity, as has been shown by others. This accounts for as much as 0.5%/year decline in intensity. The third point is that long-term price-driven substitution is a very significant contributor to observed intensity decline, accounting for more than 1.0%/year.

3.4.3. Using different price index (calculated vs IEA index)

Besides the total energy price index that we calculated by weighting value share of each source, IEA provides household and industry combined total energy price index over 1978 to 2000.

Figure 13. Price Indices Comparison for U.S.

Table 11: Summary of Estimation Results using each price index (USA: 1978-2000)

Estimation Equation #	Dependent Variable	Independent Variables	Calculated Price Index			IEA Price Index		
			Price Elasticity	GDP / Time Elasticity (AEEI)	Equivalent Annual Rate of AEEI	Price Elasticity	GDP / Time Elasticity (AEEI)	Equivalent Annual Rate of AEEI
Eq. 9	Energy Consumption	Energy Price GDP	-0.55* (0.037)	0.19* (0.017)	1.4%	-0.11 (0.076)	0.29* (0.070)	2.1%
Eq. 10	Energy Consumption	Energy Price GDP Share of EI	-0.50* (0.498)	0.23* (0.033)	1.7%	-0.06 (0.055)	0.46* (0.062)	3.0%
Eq. 11	Energy Intensity	Energy Price Time	-0.37* (0.129)	-0.02* (0.002)	2.2%	-0.11 (0.010)	-0.02* (0.003)	2.0%
Eq. 13	Energy Intensity	Energy Price Lagged Effects Time	SR: -0.173 LR:-0.290	-0.01* (0.005)	1.2%	SR:-0.086 LR:-0.179	-0.01* (0.004)	1.0%
Eq. 8	n/a	n/a	2.36% s.d.: 1.84%			2.27% s.d.: 2.77%		

* Statistically significant at the 5% level.

[Add text?](#)

3.5. Detailed analysis of US aggregate Energy Intensity 1970-2000

3.5.1. Sectoral Composition

In a previous section, we econometrically estimated the contribution of the fall in the share of energy-intensive industries in GDP, and found it to be significant in size as well as statistically. Here, we further explore how energy intensity has changed within different sectors of the US economy over 1970-2000. Multi-sector models often tend to assume a common AEEI value, but this may not be appropriate or consistent with observations.

In 1960, nearly half of US energy was consumed by the industrial sector. But this share has fallen steadily so that industry's share by 2000 was little more than a third, while the shares of energy used by commercial and transportation grew, and residential share held steady at 20% (Figure 3). The first question to ask is: why has industry's share of energy consumption fallen? One reason is that the industrial share of GDP has fallen over the last half century. The share of GDP by value-added from all industrial sectors have fallen by 36% since 1970 and by 48% since 1947 at an average rate of 1.5% per year (Figure 4). Similarly, the manufacturing sectors within industry have fallen at an average rate of 1.8% per year, and the five energy intensive manufacturing sectors have fallen at a rate of 1.7% per year. However, this is not because of falling output over this time period. In fact, output from the energy intensive industries has grown by a factor of nearly 5 since 1970 and by a factor of 20 since 1947. The main reason for the falling share is the shifting ratio between services (non-industrial sectors of the economy) and industry. If the energy intensity were held constant over this time, this effect alone would account for a decrease of up to 0.25% per year.

The other main reason for why the industrial share of energy has fallen is due to the improvement of the energy efficiency in the industrial sector, independent of its share

of the economy. Figure 5 shows the decline in energy intensity for 1974 to 1998 for energy intensive industries, all manufacturing industries, the whole industrial sector (as defined by EIA¹), and all commercial industries (as defined by EIA²). A longer time series shows that energy intensity declined an average of 4%/year over 1950-2001. The rate of intensity decline was 2.4% in the 1950's, 2.1% in the 1960's, 7% in the 1970's, 5.6% in the 1980's, and 2.6% in the 1990's.

The commercial share of energy consumption, in contrast with industrial, increased slightly over the period 1950-2000 (Figure 3). Since 1950, consumption of energy has increased 56%, from 11% to 18% of total energy consumed. Unlike the industrial sector, the commercial sector has increased as a share of GDP over this time period (Figure 4). Commercial sectors have grown as a share of GDP by 58% since 1950, from 36% of the economy in 1950 to 59% in 2001. But the energy intensity of each dollar of production has fallen over this time period. The energy intensity of the commercial sector has fallen 92% since 1950, at an average rate of 4.8% per year. The intensity declined by an average of 3%/year between 1950 and 1970, and at an average rate of 6%/year between 1970 and 2000. Thus the total energy consumed by this sector is the net of two opposite effects: increasing share of the economy and decreasing energy intensity.

The other two broad sectors of energy use in the economy are residential and transportation. These sectors are more difficult to analyze than commercial and industrial because there is no "value-added" for the unit of economic value to use in determining energy intensity. We will show results for different possible indicators, including both physical and economic units, but it is less obvious what the best denominator is.

Figure 6 shows the energy intensity of the residential sector by three different denominators: income, population, and number of households. Each series suggests different degrees of price responsiveness. If energy consumed per dollar of median household income is used, the energy intensity of residential use fell dramatically over 1960 to 1980, and slowed substantially after 1980. This suggests that residential energy use is relatively unresponsive to price, since energy prices fell during the 1960's, rose during the 1970's, and fell during the 1990's. On average, the intensity per dollar has fallen at 8% per year over this time period. If, however, we examine energy use per capita, the intensity seems somewhat responsive to price in the sense that energy intensity increased rapidly until 1973, and risen very little since that time. The energy intensity of residential use per capita has increased an average of 1% per year, but most of this increase occurred in the 1960's (1.9%/year before 1980 as compared with 0.1%/year after 1980). Finally, one can measure residential energy usage by the number of households, rather than using population and not controlling for changing demographics of household size, as a simple proxy for a detailed study of energy using appliances in the home over time (beyond the scope of this study). Data since 1967 shows much more marked responsiveness to energy prices, with intensity rising in the late 1960's, falling in the 1970's, and gradually rising since the mid-1980's. The energy intensity by household has

¹ In terms of 1972 SIC codes and BEA classification, EIA's definition of the "Industrial" sector includes all industrial codes under agriculture, mining, construction, and manufacturing.

² EIA's definition of the "Commercial" sector includes wholesale trade, retail trade, finance, insurance, real estate, and services subcategories.

increased at an average rate of 0.03%/year, but this is the net effect of falling by 0.28%/year before 1985 and increasing by 0.37%/year.

Figure 14: Share of Energy Consumption by Sector

Figure 15: Share of GDP by Industry Sub-Group

Figure 16: Energy Intensity by Industry Sub-Groupings

Each of these alternative measures of residential energy intensity implies a different AEEI. Income implies a large AEEI (most changes non-price driven), per capita implies a smaller AEEI, and household intensity implies a small or zero AEEI since intensity appears to track energy prices. In general, although an economic measure, such as the income intensity, is desirable over physical measures, it is not clear that this

Figure 17: Residential Energy Intensity by Income, Population, and Household

really informs the price / non-price causes of energy intensity, and rather is an indicator of the income elasticity of residential energy use. The per capita and per household measures are probably better indicators, and they show that unlike industrial and commercial energy use, the energy intensity in the residential sector has been fairly constant or even rising slightly over recent decades.

Transportation energy intensity yields similar results to residential intensity in that reductions in energy intensity have been smaller than that experienced by industrial and

commercial industries. The energy intensity and the changes in intensity in transportation vary widely depending on the mode. The largest reductions in energy intensity have been made by commercial air transportation, which has fallen an average of 3.0% per year since 1970, and 1.5% per year since 1990. Air travel accounts for just over 50% of non-auto passenger miles traveled. The largest share of passenger miles traveled is by private automobiles and light trucks, which accounted for 90% in 1970, and has fallen to 80% by 2000. The energy intensity of passenger automobiles has fallen by an average of 1.0%/year since 1970. But this is offset by the increasing use of light duty trucks and sport utility vehicles, which are much more energy intensive (Figure 8), and have increased their share of passenger miles from 10% in 1970 to almost 30% in 2000. Including all private vehicles, energy intensity has decreased an average of 0.5%/year since 1970. All forms of transportation other than private automobiles (purchased transportation), has reduced its energy intensity by an average of 2.3%/year from 1970 levels, mainly driven by the efficiency gain of domestic air travel. The change in energy efficiency of total transportation, weighted by passenger miles traveled, averaged 0.8% per year for 1970-2000 and 0.55%/year for 1990-2000.

The data for residential and transportation, especially private automobile, energy intensity suggest that unlike firms (commercial and industrial), individual consumers are significantly less price responsive in their energy usage (Table III). In fact, given the price changes observed over 1970-2000 and depending on assumed elasticities of demand, one could interpret the change as an increase in energy intensity that partly offsets the price response. For example, in automobiles, increasing vehicles and miles per vehicle on the road has mostly offset the increase in technical efficiency. The analysis of differences in energy efficiency changes by sector has important implications for the use of estimates in economic models. If one's analysis uses a model with a single sector for the economy of a nation or region (e.g., MERGE), the estimates of aggregate efficiency improvement from sections III and IV are appropriate. However, models with even crudely disaggregated sectors, which may separate out energy intensive industries from others, services, or even transportation, should not use aggregate efficiency numbers and apply them equally to all sectors. This practice would yield patterns of energy use, emissions, and costs of emissions reductions that are not consistent with experience. At a minimum, energy use by firms tends to improve at different rates and respond to energy prices very differently than individual consumption of energy and transportation as a final good.

A final problem with some models is with respect to changes in the relative share of sectors over time. As shown above (Figure 5), services have grown significantly as a share of output in the U.S. over the past half-century, while manufacturing has fallen as a share. However, computable general equilibrium models and other numerical models usually make mathematical assumptions, for example that consumption is homogeneous of degree one, in order to make the model numerically solvable. Without explicit changes built into the consumption function over time, this will result in constant relative shares of the different production sectors over the time horizon of the model. As seen here, this would influence the overall energy intensity pattern, and would not reflect observed changes in intensity that come from falling shares of more intensive industries. To the extent that AEEI is a residual parameter for a given model to capture all effects not represented elsewhere in the model, this shift in the energy bias would be appropriate

to include in AEEI for a multi-sector model. Equivalently, one could assume that consumption shares shift over time. The important point is that one or the other method must be used to avoid misleading results.

Table 12: Summary of Sector Specific Energy Intensity Trends (Annual Rates)

Sector	Rate of Intensity Change	Change in Share of GDP
Energy Intensive	-5.4%	-1.7%
Manufacturing	-5.6%	-1.8%
Industrial	-4.0%	-1.5%
Commercial	-4.8%	+1.8%
Residential	Per \$ HH Income: -8.0% Per Capita: +1.0% Per Household: +0.03%	-
Transportation	Total: -0.8% Autos: -1.0% All Private Road: -0.5% Commercial Air: -3.0% All non-private: -2.3%	-

Figure 18: Residential Energy Intensity by Income, Population, and Household

4. Simulation & Uncertainty

This paper has examined a range of values for autonomous energy efficiency improvement and corresponding values for energy price elasticities of demand that are

consistent with US historical experience over 1970-2000. To explore the implications of alternative values of AEEI-elasticity, in this section we use a computable general equilibrium (CGE) model to project GDP, energy consumption, and carbon emissions.

The Emissions Projection and Policy Analysis model (EPPA) Version 4 is a component of the MIT Integrated Global Systems Model (IGSM), developed to enable detailed studies of the effects of climate policies. The main advantage of CGE models is their ability to capture the influence of a sector-specific (*e.g.*, energy, fiscal, or agricultural) policy on other industry sectors, on consumption, and also on international trade. EPPA is a recursive-dynamic and multi-regional model covering the entire the world economy (Babiker *et al.*, 2001). It is built on the economic and energy data from the GTAP dataset (Dimaranan & McDugall, 2002; Hertel, 1997). It has been used extensively for the study of climate policy (Jacoby *et al.*, 1997; Babiker *et al.*, 2000, 2002; Viguier *et al.*, 2001; Bernard *et al.*, 2003; Paltsev *et al.*, 2003; Reilly *et al.*, 2002; McFarland *et al.*, 2003), climate/multi-gas interactions (Reilly *et al.*, 1999; Felzer *et al.*, 2004), and to study uncertainty in emissions and climate projections for climate models (Webster *et al.*, 2002, 2003). Table IV provides an overview of the basic elements of the model, with greater details in Babiker *et al.* (2001) and Paltsev *et al.* (2003, 2004), and for the non-CO₂ GHGs Hyman *et al.* (2003).

Table 13: Countries, Regions, and Sectors in the EPPA Model

Country or Region	Sectors	Factors
Developed United States (USA) Canada (CAN) Japan (JPN) European Union+a (EUR) Australia & New Zealand (ANZ) Former Soviet Unionb (FSU) Eastern Europe (EET)	Non-Energy Services (SERV) Energy-Intensive Products (EIT) Other Industries Products (OTHR) Transportation (TRAN) Agriculture (AGRI)	Capital Labor Land Crude Oil Resources Natural Gas Resources Coal Resources Hydro Resources Shale Oil Resources Nuclear Resources Wind/Solar Resources
Developing India (IND) China (CHN) Indonesia (IDZ) Higher Income East Asiac (ASI) Mexico (MEX) Central & South America (LAM) Middle East (MES) Africa (AFR) Rest of Worldd (ROW)	Energy Coal (COAL) Crude Oil (OIL) Refined Oil (ROIL) Natural Gas (GAS) Electric: Fossil (ELEC) Electric: Hydro (HYDR) Electric: Nuclear (NUCL) Electric: Solar and Wind (SOLW) Electric: Biomass (BIOM) Electric: Natural Gas Combined Cycle (NGCC) Electric: NGCC with Sequestration (GGCAP) Electric: Integrated Gasification with Combined Cycle and Sequestration (IGCAP) Oil from Shale (SYNO) Synthetic Gas (SYNG)	
Emissions of Climate Relevant Substances		

Substances 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	Sources Combustion of refined oil, coal, gas, biofuels and biomass burning, manure, soils, paddy rice, cement, land fills, and industrial production.
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^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, Phillipines, Singapore, Taiwan, Thailand.

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

One of the representations for technological change in the EPPA model is the AEEI parameter. It is defined as an input factor that is applied to energy inputs into the production/consumption bundle. This factor falls over time, so that by 2100, for example, with a 0.5%/year trend one needs only 0.66 as much energy input as in 1997 to make one unit of output, with a 1%/year, 0.44 as much energy is needed, and with 2%/year, 0.19 as much energy is used (Figure 8). In EPPA, there are 11 production sectors, as well as consumption, government, and savings sectors. An energy efficiency trend can be defined for each sector for each region of the world, although some sectors (e.g., savings/investment) do not use energy as an input and thus would have no effect.

4.1. Model Simulation

As discussed above, the results from this analysis are expected to become one component of input for constructing probability distributions of future economic growth. We do not necessarily expect future economic growth to resemble the past, in terms of mean, variance, or correlation. Rather, these results provide guidance and conditioning in obtaining expert judgment about future growth or its determinants.

Nevertheless, it is a useful check to perform an uncertainty analysis of a model using historical variability unaltered, and to compare this to the results of previously obtained expert judgments (without this analysis) based implicitly on national annual growth rates. In this section, we will use the EPPA model to compute the effect on carbon emissions uncertainty of using this data to fit distributions for future uncertainty in economic growth, and compare to the results of prior expert distributions (Webster et al, 2002).

We have used the 5-year growth rates computed from the 50-year data set for each aggregate region in the EPPA model, and have fit a probability distribution to each. We then obtain 1000 samples using Latin Hypercube Sampling (Iman and Helton, 19XX). We perform this procedure twice: once sampling for each region independently, and once by imposing the observed correlations (Table 3) on the samples. For the comparison, we obtain two other sample sets, with and without correlation, from the expert elicited PDFs from Webster et al (2002). For this simple illustration, we attribute all uncertainty in growth to the labor productivity augmentation factor in EPPA, and assume all other parameters in the model are certain.

The resulting uncertainty in global carbon emissions by 2100 for each of the four cases is shown in Figure 7. Several differences are worth noting. First, the emissions uncertainty resulting from assuming historical variability has a lower mean than results from the expert PDFs. Secondly, the expert case with correlation, because it assumes all

regions are perfectly correlated, has the largest variance. Since this does not correspond with the observed degree of correlation, this probably overstates the variance in emissions. By contrast, the uncorrelated expert judgment case has the smallest variance in global emissions, due to the fact that higher growth in some regions is frequently offset with lower growth in others. Finally, the difference in emissions uncertainty between the correlated and the uncorrelated historical rates is relatively small. The effect of correlation is smaller because the imposed partial correlations are weak; the majority of pairwise correlations are less than 0.7.

One important caveat to these results is that the treatment of uncertain growth was to simply modify the growth path over time to be higher or lower based on each sample, and the growth of region in any particular sample falls smoothly over time. In other words, there are no random shocks over time to any region. Future uncertainty studies can employ econometric time-series techniques described in the introduction to produce samples for a Monte Carlo simulation that vary stochastically over time within each run, as well as between runs.

Figure 19: Global Carbon Emissions:
Comparing Historical Rates to Expert Elicited Growth Rates

4.1.1. Methods

- Procedure to take sample (Latin Hypercube Sampling)
- How to fit a probability distribution of GDP growth rate
- How to convert GDP growth rate into labor productivity growth rate - normalization to factor distributed around 1.0

2.5.2 Results – near term projections

Show short-term stochastic growth to 2010

2.5.3 Results – Long-term Projections

Show LT uncertainty only

Show LT + ST uncertainty

4.2. Discussion