MIT Joint Program on the Science and Policy of Global Change

Uncertainty in Greenhouse Gas Emissions and Costs of Atmospheric Stabilization

Mort Webster, Sergey Paltsev, John Parsons, John Reilly, and Henry Jacoby

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To inform processes of policy development and implementation, climate change research needs to focus on improving the prediction of those variables that are most relevant to economic, social, and environmental effects. In turn, the greenhouse gas and atmospheric aerosol assumptions underlying climate analysis need to be related to the economic, technological, and political forces that drive emissions, and to the results of international agreements and mitigation. Further, assessments of possible societal and ecosystem impacts, and analysis of mitigation strategies, need to be based on realistic evaluation of the uncertainties of climate science.

This report is one of a series intended to communicate research results and improve public understanding of climate issues, thereby contributing to informed debate about the climate issue, the uncertainties, and the economic and social implications of policy alternatives. Titles in the Report Series to date are listed on the inside back cover.

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Mort Webster[*†], Sergey Paltsev[*], John Parsons[*], John Reilly[*] and Henry Jacoby[*]

Abstract

We explore the uncertainty in projections of emissions, and costs of atmospheric stabilization applying the MIT Emissions Prediction and Policy Analysis (EPPA) model, a computable general equilibrium model of the global economy. Monte Carlo simulation with Latin Hypercube Sampling is applied to draw 400 samples from probability distributions for 100 parameters in the EPPA model, including labor productivity growth rates, energy efficiency trends, elasticities of substitution, costs of advanced technologies, fossil fuel resource availability, and trends in emissions factors for urban pollutants. The resulting uncertainty in emissions and global costs is explored under a scenario assuming no climate policy and four different targets for stabilization of atmospheric greenhouse gas concentrations. We find that most of the IPCC emissions scenarios are outside the 90% probability range of emissions in the absence of climate policy, and are consistent with atmospheric stabilization scenarios. We find considerable uncertainty in the emissions prices under stabilization. For example, the CO_2 price in 2060 under an emissions constraint targeted to achieve stabilization at 650 ppm has a 90% range of \$14 to \$88 per ton CO_2, and a 450 ppm target in 2060 has a range of \$241 to \$758. We also explore the relative contribution of uncertainty in different parameters to the resulting uncertainty in emissions and costs and find that, despite the significant uncertainty in future energy supply technologies, the largest drivers of uncertainty in costs of atmospheric stabilization are energy demand parameters, including elasticities of substitution and energy efficiency trends.

Contents

1. INTRODUCTION

We investigate the uncertainty in future emissions absent greenhouse gas mitigation, and of emissions and abatement costs under four scenarios of atmospheric stabilization taken from the recent analysis of the U.S. Climate Change Science Program (Clarke *et al*., 2007). We follow a formal probabilistic approach (Parson *et al*., 2007), providing an updated view of possible future

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greenhouse gas (GHG) emissions. We follow an approach similar to that of Webster *et al*. (2002), Scott *et al*. (1999), Manne and Richels (1994), Reilly *et al*. (1987), Edmonds and Reilly (1985), and Nordhaus and Yohe (1983), where Monte Carlo techniques are used to simulate a model hundreds of times with samples of parameter values drawn from input distributions to derive estimates of uncertainty for model output variables such as future emissions. The uncertain input variables govern factors that affect emissions growth and the cost of abatement, including labor productivity, population, technology costs, ease of substitution away from CO_2-emitting energy, and resource availability.

While there is considerable literature on uncertainty in future GHG emissions, less attention has been devoted to uncertainty in mitigation costs. Most cost studies have been deterministic (using reference values for model assumptions) supplemented by sensitivity tests of a limited number of key parameters (*e.g.,* Paltsev *et al*., 2007; Weyant and Hill, 1999). Descriptions of cost uncertainty have been limited to meta-analyses of collections of studies (Barker *et al*., 2007) which serve to highlight differences among models but do not deal with uncertainty in a formal sense. Given the interest in long-term targets, within international negotiations, and the heightened focus on uncertainty ranges by the Intergovernmental Panel on Climate Change, studies applying formal methods are called for.

Here such an analysis is developed using the MIT Emissions Prediction and Policy Analysis (EPPA) model, version 4 (Paltsev *et al*., 2005), which is a recursive-dynamic computable general equilibrium model of the global economy. In the EPPA model, the world economy is represented as 16 regions, each with 21 economic sectors linked by domestic and international trade. Probability distributions are developed for more than 100 parameters of the model including correlations among them where appropriate. In contrast to previous work, we have statistically estimated uncertainty in many of the key model inputs, supplementing statistical approaches with expert judgment only where necessary. We sample from these distributions and simulate ensembles of scenarios to develop probabilistic descriptions of a selection of model outputs including emissions, carbon prices, and consumption loss. We also explore the relative contribution to uncertainty from subgroups of the model parameters.

A few clarifications are useful before proceeding. First, the EPPA model does not balance costs and benefits of controlling greenhouse gases to seek an optimal policy response. As applied here, there are no climate damages that feedback on the economy and so estimates of economic cost are those related only to mitigation. Using a classification applied by Weyant (2000), the EPPA model is a policy evaluation model, not a policy optimization model. Second, the exercise is constructed to be explicitly conditional on climate policy assumptions, asking what are the likely ranges of emissions and costs on the condition that there is either no climate policy or a goal of one or another global emissions control paths over time. Other approaches might attempt to explore the likelihood of the world undertaking such mitigation and sample from this policy uncertainty as part of the Monte Carlo exercise or assume a particular behavioral response (*i.e.* mitigation based on cost-benefit analysis). Finally, this study is of parametric uncertainty - the descriptions of uncertainty in results are conditional on the structure of the model as well as on the assumed parameter distributions. However, evidence from past uncertainty work suggests that parametric uncertainty produces a wider range than the differences observed across models with similar baseline assumptions. Put another way, emissions scenarios and abatement cost estimates depend less on the specific structure of the model and more on the assumptions about technology, economic growth, resource availability, and progress on energy efficiency, which are the quantities explored here.

The EPPA model, the assumed uncertainty in parameters, and the Monte Carlo design are described in Section 2. Section 3 presents the results of the analysis, presenting uncertainty in future emissions and in costs under no policy and stabilization cases. We also compare the relative contribution to the uncertainty in these outcomes by different combinations of inputs. Section 4 discusses the key findings.

2. THE EPPA MODEL AND UNCERTAIN PARAMETER DISTRIBUTIONS

2.1 Emissions Projection and Policy Analysis (EPPA) 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. A full description of the model is presented in 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. The economic data from GTAP are augmented with additional data on advanced technologies, greenhouse gases (carbon dioxide, CO_2; methane, CH_4; nitrous oxide, N_2O; hydrofluorocarbons, HFCs; perfluorocarbons, PFCs; and sulphur hexafluoride, SF_6) and air pollutants (sulfur dioxide, SO_2; nitrogen oxides, NO_x; black carbon, BC; organic carbon, OC; ammonia, NH_3; carbon monoxide, CO; and non-methane volatile organic compounds, VOC). The data are aggregated into the EPPA model's 16 regions and 21 sectors as shown in **Table 1**.

Much of the sectoral detail is focused on energy production to better represent advanced technological alternatives that are incorporated using bottom-up engineering detail. Advanced technologies enter endogenously when they become economically competitive with existing ones. Their competitiveness depends on endogenously determined prices for all inputs. These prices in turn depend on depletion of resources, economic policy, and other forces driving economic growth such as savings, investment, energy-efficiency improvements, and labor productivity. The model's 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 base year of the EPPA model is 1997. From 2000 through 2100 it is solved recursively at 5-year intervals. The model is written in the GAMS software system and solved using MPSGE modeling language (Rutherford, 1995). EPPA has been used in a wide variety of applications (*e.g.,* Jacoby *et al*., 1997; Reilly *et al*., 1999; Babiker, Metcalf, and Reilly**,** 2003; Reilly and Paltsev, 2006; Clarke *et al*., 2007; Paltsev *et al*., 2007).

Table 1. Sectors and regions in the EPPA model.

Sectors:	Country or Region:
Non-Energy	***Developed***
Agriculture (AGRI)	USA
Services (SERV)	Canada (CAN)
Energy-Intensive Products (EINT)	Japan (JPN)
Other Industries Products (OTHR)	European Union+ (EUR)
Industrial Transportation (TRANS)	Australia & New Zealand (ANZ)
Household Transportation (HTRANS)	Former Soviet Union (FSU)
Energy	Eastern Europe (EET)
Coal (COAL)	***Developing***
Crude Oil (OIL)	India (IND)
Refined Oil (ROIL)	China (CHN)
Natural Gas (GAS)	Indonesia (IDZ)
Electricity Generation	East Asia (ASI)
Fossil (ELEC)	Mexico (MEX)
Hydro (HYDRO)	Central & South America (LAM)
Nuclear (NUCL)	Middle East (MES)
Solar and Wind (SOLAR)	Africa (AFR)
Biomass (BIOELEC)	Rest of World (ROW)
Natural Gas Combined Cycle (NGCC)	
Natural Gas Combined Cycle with CO_2 Capture and Storage (NGCAP)	
Advanced Coal with CO_2 Capture and Storage (IGCAP)	
Synthetic Gas from Coal (SYNGAS)	
Oil from Shale (SYNOIL)	
Liquid Fuel from Biomass (BIOOIL)	

Note: Agriculture, services, energy-intensive products, other-industries products, coal, crude oil, refined oil, and natural gas sectors are aggregated from GTAP data; industrial transportation and household transportation sectors are disaggregated as documented in Paltsev *et al*. (2004); hydropower, nuclear power and fossil-fuel electricity are disaggregated from the electricity sector (ELY) of the GTAP dataset using data from the International Energy Agency; solar and wind power, biomass electricity, natural gas combined cycle, natural gas combined cycle with CO_2 capture and storage, integrated coal gasification with CO_2 capture and storage, synthetic gas from coal, hydrogen from gas, hydrogen from coal, oil from shale, and liquid fuel from biomass are advanced technology sectors that do not exist explicitly in the GTAP dataset and are modeled as described in Paltsev *et al*. (2005); specific detail on regional grouping is provided in Paltsev *et al*. (2005).

2.2 Distributions for Uncertain Parameters

Previously an analysis was conducted of the sensitivity of the EPPA model to determine those parameters that contribute most to uncertainty in emissions and costs (Webster, *et al*., 2002; Cossa, 2004). These parameters can be broadly divided into the following nine groups:

- Elasticities of Substitution
- GDP Growth (based on Labor Productivity Growth)
- Autonomous Energy Efficiency Improvement (AEEI)
- Fossil Fuel Resource Availability
- Population Growth
- Urban Pollutant Trends
- Future Energy Technologies
- Non-CO_2 Greenhouse Gas Trends
- Capital Vintaging

Below, we detail the uncertainty distributions for each of these parameters and the sources and data from which they were constructed. Of these parameters, the uncertainty in the elasticities of substitution, GDP, AEEI, fossil resource availability, population growth rates, and urban pollution trends over time are based on statistical analyses of historical data. For the remaining parameters, the limits of available data and studies led us to use expert elicitation as the basis for input distributions.

2.2.1 Input distributions based on empirical analyses

2.2.1.1 Elasticities of Substitution

Production in EPPA is represented with nested Constant Elasticity of Substitution (CES) functions. Primary input factors include labor, capital, and an energy bundle made up of electricity, coal, oil, and natural gas. Intermediates are represented as fixed coefficient inputs. A schematic diagram of the production function for a typical sector is given in **Figure 1**.[1] These sectors and households are the source of energy demand in the economy. The elasticities of substitution at each level determine the relative ease of substituting one input for another, affecting the cost of emissions reduction policy.

[1] Refining and primary resource using sectors are structured differently as they include the resource (land, or energy resource) or the crude product as an additional input. Elasticities associated with resources affect energy supply and are discussed further below.

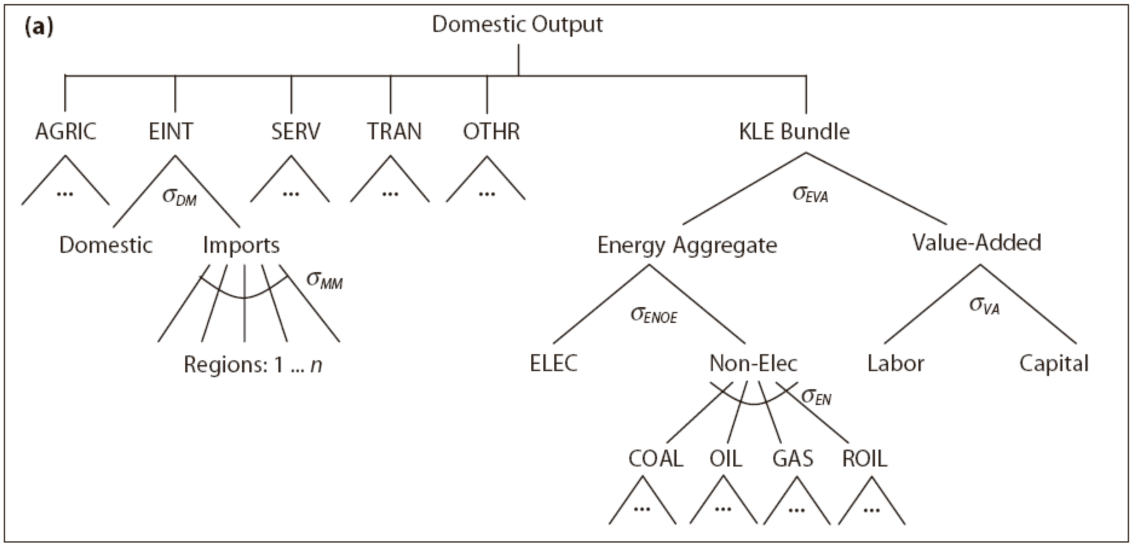


Figure 1. Example of the nest structure for production sectors in EPPA: parameters that govern energy demand (and abatement costs) are substitution elasticities for energy—non-energy, σEVA; labor-capital, σVA; electricity-fuels, σENOE; and that among fuels, σEN.

To construct distributions we use the standard errors from published studies that estimate the value of elasticities of substitution. The constructed distributions are assumed to be normal with a median of 1.0 to describe uncertainty relative to the reference values in EPPA. Thus, the EPPA reference value is retained as the median. The main issue that arises in this construction is how to use the variety of estimates in the literature. Elasticity concepts differ (*e.g.,* Allen versus Morishima elasticities; see Blackorby and Russell, 1989), often econometric studies do not apply the CES function used in EPPA but prefer more "flexible" forms such as the translog, and the level of aggregation can affect the estimated elasticity value. In our survey of the literature, we find that the relative standard errors across different studies are of similar magnitude. Thus, rather than attempt to aggregate across studies, we have in general based our distributions for different elasticities on the most recent effort, and where possible on those that use a functional form and level of aggregation that is most similar to that used in EPPA.

Among the elasticities of substitution shown in Figure 1, the critical ones are labor vs. capital, interfuel substitution within the non-electric energy bundle, interfuel substitution between electricity and other fuels, and substitution between the energy bundle and the value-added (labor and capital) bundle. For the labor-capital elasticities we rely on a study by Balistreri *et al*. (2003) in which they use U.S. data on 28 disaggregated industries to estimate the elasticity of substitution (**Table 2**). For the interfuel substitution elasticity we use a study by Urga and Walters (2003), in which they compared the elasticities estimated by translog and dynamic logit functions. We use the long-run estimates from their dynamic logit, which they show to be the more robust formulation (**Table 3**). We calculate the relative standard errors of the cross-price elasticities, which are proportional to the substitution elasticities. While the Figure 1 production structure includes all fuels and crude oil in the fuels nest, in reality the shares for several are zero or near zero for many sectors. For most sectors, substitution between Refined Oil (ROIL) and Natural Gas (GAS) is the only relevant pair because little coal and no crude oil is used directly. We therefore assume a standard error of ±15% as estimated by Urga and Waters (2003) (See Table 3) for uncertainty in this elasticity for households and for all production sectors except Electricity (ELEC) and Energy-Intensive (EINT). The electric vs. non-electric elasticity uncertainty is also assumed to have a standard error of ±15%, consistent with the estimate for electricity substitution with fuels (Table 3). In the Electricity (ELEC) and Energy-Intensive (EINT) sectors, coal plays a substantial role. For these sectors we use a standard error of ±40%, which is consistent with the Urga and Waters (2003) estimate for coal-oil and coal-gas substitution.

The energy vs. value-added (capital and labor bundle) elasticity is also a critical assumption in EPPA. While much of the empirical literature estimates three or four-factor (*i.e.* KLEM) translog or similar functional forms, relatively recent work by Kemfert (1998) and Kemfert and Welsch (2000) (see **Table 4**) use a CES function in a nest structure that directly estimates an energy-capital/labor elasticity. We use the standard error from the more recent 2000 study, which is ±30%. This assumption is consistent with the relative error in energy-capital and energy-labor substitution elasticities as estimated by Koetse *et al*. (2007) and Medina and Vega-Cervera (2001), which both find uncertainty ranges between 20% and 40% of the best estimate.

Table 2. Labor-Capital Substitution Elasticity Uncertainty.

	EPPA Sector						
Fractile	***AGRI***	***ENOE***	***ELEC***	***EINT***	***OTHR***	***SERV***	***TRAN***
5%	0.03	0.7	0.67	0.72	0.59	1.01	0.67
50%	0.31	0.81	0.99	1.1	1.17	1.51	0.89
95%	1.13	0.93	1.31	1.48	1.76	2.01	1.12

Source: Balistreri *et al*. (2003).
Note: ENOE = Energy sectors other than electricity generation.

Table 3. Interfuel Substitution Elasticity Uncertainty.

Long-Run Cross-Price Elasticities

	Coal		**Oil**		**Gas**		**Elec.**	
	Est.	***Std. Err.***	***Est.***	***Std. Err.***	***Est.***	***Std. Err.***	***Est.***	***Std. Err.***
Coal			0.5259	0.044	-0.3061	0.0430	0.1577	0.018
Oil	0.1002	0.040			0.2357	0.0333	0.0530	0.006
Gas	-0.1243	0.049	0.5020	0.042			0.2751	0.032
Elec.	0.0377	0.015	0.0665	0.006	0.1622	0.023		

Relative Errors

	Coal	**Oil**	**Gas**	**Elec**
Coal		0.08	0.14	0.11
Oil	0.40		0.14	0.11
Gas	0.39	0.08		0.12
Elec	0.40	0.09	0.14	

Source: Urga and Walters (2003).

Table 4. Energy vs. Non-Energy Substitution Elasticity Uncertainty.

	Estimate	**Std. Err.**	**Relative Err.**
Kemfert (1998)	1.18	0.61	0.52
Kemfert and Welsch (2000)	0.43	0.13	0.29

2.2.1.2 GDP and Labor Productivity Growth

The primary driver of GDP growth in the EPPA model is the exogenously specified growth in labor productivity. Previous studies (Webster *et al*., 2002; Manne and Richels, 1994; Scott *et al*., 1999; Edmonds and Reilly, 1985) have used expert judgment to construct probability distributions of future growth in labor productivity or GDP. Here, we use econometric forecasting techniques to estimate the uncertainty in future GDP from past GDP growth. We believe this has significant advantages over expert judgment because there appears to be bias in how experts form opinions about GDP growth and its uncertainty. In particular, the information experts are most familiar with is annual GDP growth for individual countries. Yet in EPPA many of the regions are multi-country areas. Moreover, previous studies derived their estimates from a distribution of growth rates that were applied for the entire century. Expectations about variability of GDP for individual countries are poor indicators of variability for large multi-country regions where poor economic performance in one country is likely to be balanced by average or very good performance in others. We expect, and the historical data confirm, much less variability in growth for multi-country regions than for any of the countries that compose the region. In addition, annual variation in GDP, driven by cyclical economic behavior and response to exogenous shocks, does not provide direct information on the range of long run growth possibilities. Again, analysis of the data showed, not surprisingly, that five-year growth rates were less variable than one-year growth rates, and ten-year growth rates less variable still (see also Webster and Cho, 2006).

Thus here we simulate growth as a stochastic process where growth prospects are derived for each 5-year EPPA period. The 5-year growth rates are formulated to match the variability obtained from historical data where an economy's 5-year performance is the result of annual performance for which we have good data. Moreover, we use data for the exact regional aggregations we have in EPPA, and so the variation in growth in multi-country regions matches that of those regions historically.

At issue in moving to this formulation was the exact specification of the stochastic growth process. There is a long-running debate in the economics literature (see Stock and Watson, 1988) as to whether variability in economic time series is due to variability in the long-run trend, short-term transient or mean-reverting variability, or some combination of both. Several studies have estimated a structural model with both components (*e.g.,* Harvey and Todd, 1983; Harvey, 1985). In this study, we fit the long-run trend in GDP growth of each region as a random walk with drift. In future work, we will explore the implications of assuming that GDP growth is the sum of a random walk process and a trend-stationary process.

We use historical GDP per capita growth measurements, based on GDP and population data from Maddison (2003). Growth rates are determined by first aggregating GDP and population for all countries in each region (see Paltsev *et al*. (2005) for region definitions). Then the drift term (mean) and shock (standard deviation) are estimated from the time series for each region (**Table 5**). We estimate the standard deviation based on GDP per capita annual growth rates from 1950-2000 for all regions.[2]

Forward projections of EPPA are conducted by applying the estimated uncertainty in growth rates to labor productivity growth (LPG) rates in the EPPA model. Because future growth rates will not necessarily be the same as in the past, we assume that the median trend for each region is the original productivity growth rate in the EPPA reference simulation (Paltsev *et al*., 2005). In other words, the drift term in the random walk procedure is based on EPPA reference growth rates, not the estimated historical mean rate. The random walk generates sample paths in one-year steps from 2010 to 2100. The growth rates for each 5-year step in these sample paths are used as the sample inputs to EPPA, consistent with the model time step (see Webster and Cho, 2006). Finally, the labor productivity growth rates, which are the relevant uncertain parameters in EPPA, are calibrated to produce the desired GDP per capita growth rate (an output of the EPPA model) assuming all other parameters at reference values. The simulated GDP growth of

[2] While data is available for some countries from 1920 or earlier, consistent estimates of variability across regions requires the restriction to years for which data is available for all countries, which is limited to the period of 1950-2000. Using data from earlier years, which include major economic disruptions, for some countries and not others would produce unrealistic biases in the relative variability (*e.g.,* greater volatility in U.S. and Europe than in many developing countries).

Table 5. Mean and Standard Deviation of Historical Per-Capita GDP Growth Rates, and the 5%, median, and 95% projected average annual growth rates for 2000-2100.

	Historical 1950-2000 (%)		Projected Annual Average Growth Rate (%) 2000-2100		
Region	***Mean***	***Std Dev***	***0.05***	***0.5***	***0.95***
USA	2.2	2.3%	1.7	2.1	2.5
CAN	2.3	2.3%	1.7	2.1	2.5
MEX	2.2	5.2%	1.2	2.1	2.9
JPN	4.9	3.5%	1.7	2.2	2.7
ANZ	2.0	1.8%	2.0	2.3	2.6
EUR	2.8	1.6%	1.9	2.1	2.4
EET	1.1	3.9%	2.1	2.8	3.3
FSU	1.1	5.3%	2.0	2.8	3.7
ASI	4.3	4.7%	1.8	2.6	3.3
CHN	4.3	3.7%	2.5	3.1	3.7
IND	2.3	2.7%	2.3	2.7	3.1
IDZ	2.7	5.0%	1.1	2.6	3.9
AFR	1.0	1.8%	2.0	2.3	2.6
MES	2.3	3.3%	1.5	2.1	2.6
LAM	1.7	2.0%	1.7	2.1	2.5
ROW	2.2	3.5%	1.7	2.3	2.8
GLOBAL			2.2	2.4	2.6

an economy over the century in any one of the sampled runs is thus the result of a random walk of varying growth over each 5-year time step of the model. Note that the resulting GDP growth with all inputs varying simultaneously will have a slightly larger variance (see results in Section 3).

An additional assumption is the degree of correlation in GDP shocks across regions. Note that the relevant quantity to correlate is not the mean growth rate (the drift term in the random walk); all countries are assumed to grow over time. Rather, it is the independent shocks (excursions from the mean) to the growth rates that we want to explore for correlation across regions. Empirical estimation of the correlation of variability in historical GDP growth rates from 1950 to 2000 finds no statistically significant correlation between countries and groups of countries, although we recognize the time series is relatively short (Webster and Cho, 2006). Lacking specific evidence for correlation, we assume that the shock to each region's growth is independent of the shocks to other regions for that same time period.

A good way to see the implications of this approach is to examine the GDP growth results from the sampling approach, shown for the U.S. in **Figure 2**. The projections shown are the 5th, 50th, and 95th percentiles from the sample of 400 paths. As a result of our assumption of historical volatility and mean growth from the EPPA reference, the median projection is not necessarily a smooth continuation of the last half of the 20th century, but the 90% probability bounds reflect the past variability. Graphs equivalent to Figure 2 for all 16 regions in EPPA are given in Appendix A. Also, note that the 5th, 50th, and 95th growth rates are for each period. Because century-long growth is composed of stochastic growth for each 5-year period, no single sample run has 95th or 5th (or 50th) percentile growth in every period.

The uncertainty in GDP growth rates for each region and for the global aggregate are described in Table 5 in terms of the average annual percentage growth rate over 2000-2100. We give the 5th, 50th, and 95th percentiles of the projected growth rates. Note that the variability in century-long growth for any region exhibits less variability than in any 5-year time period. Further, global growth is less variable than any individual region due to the absence of correlation in growth shocks described above, with a 5-95% range of 2.2% to 2.6%. In contrast, our previous study (Webster *et al.*, 2002) applied PDFs of labor productivity growth obtained from expert elicitation, and assumed perfect correlation across regions. That study had a 5-95% range of global GDP growth of 1.7% to 2.5%. Our revised approach more realistically allows for the relative performance of different regions to vary and for a region's 100-year growth record to be composed of periods of relatively rapid and relatively slow growth. Even with much more variability in a country or region's performance over time or relative to other regions, the global growth is far less variable. As we will demonstrate in the results section, our current approach reduces somewhat the relative contribution of GDP uncertainty to uncertainty in emissions and costs.

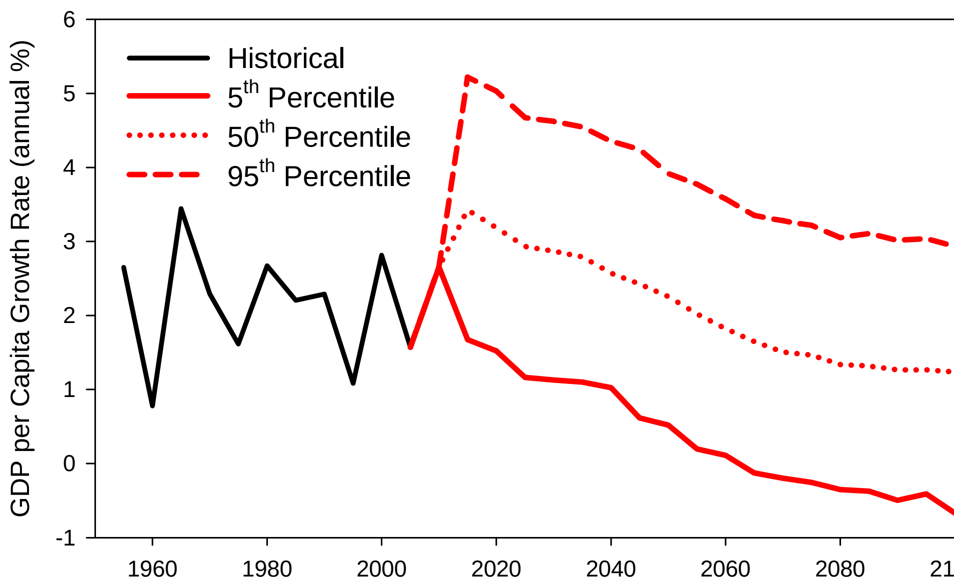


Figure 2. Historical and projected GDP per capita growth rates for the United States. Projections are shown for the 5th, 50th, and 95th percentiles in each period.

2.2.1.3 Autonomous Energy Efficiency Improvement

EPPA assumes an exogenous rate of energy efficiency improvement, as do many other models used for emissions projections (Azar and Dowlatabadi, 1999; Manne *et al*., 1995; Scott *et al*., 1999; Sands, 2004). This parameter is necessary to account for the historical pattern of energy consumption, which cannot be fully explained by changes in energy prices and growth in the size of the economy.

We use historical data to provide a measure of the uncertainty in the AEEI. To do so we used U.S. GDP data from the Penn World Tables (PWT), version 6.1 (Heston *et al*., 2002), energy consumption data from the Energy Information Administration (EIA, 2002), and energy price data are 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 includes prices for crude oil, natural gas, coal, and electricity. We combine these price series into a divisia 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 EIA (2002).

We specify a simple aggregate model after those widely used in demand modeling (*e.g.,* Bohi, 1981; Yatchew and No, 2001; Li and Maddala, 1999) where the good's own-price and GDP are the main explanatory factors and we allow for an additional time trend effect—the residual AEEI:

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

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 reflect changing prices of the sectoral output resulting from the changing energy input price. If a growing economy exhibited constant returns to scale (CRS) we would expect θ=1. To the extent that structural change occurs with growth in GDP, shifting the economy toward rising or falling energy intensity either directly in final consumption or indirectly through non-price structural shifts in the economy, that structural shift will be captured by θ > or <1.

Econometric evidence indicates that the short-term price effect differs from the effect in the long-term (Bohi, 1981). Explanations range from short-term irreversibilities of the capital stock, other inertia in consumer response, expectations, and even potential price-induced technical change. A common approach for estimating long run effects is to introduce a lagged dependent variable, the Koyck lag transformation (Kmenta, 1971), but this means that the lagged response applies equally to all independent variables.

The Koyck transformation eliminates the problem of explicitly including prior period data on independent variables such as in a geometric lag distribution

$$E_{t-1} = \alpha + \beta_0 \left(P_{t-2} + \lambda P_{t-3} + \lambda^2 P_{t-4} + \cdots\right) + \varepsilon_t$$

where $0 \le \lambda < 1$, by observing that E_{t-1} captures the early year effects of independent variables. Thus, the Koyck transformation is:

$$\ln E_t = \alpha(1-\lambda) + \lambda \ln E_{t-1} + \beta(1-\lambda)\ln P_{t-1} + \theta(1-\lambda)\ln GDP_{t-1} + \gamma(1-\lambda)t + \eta_t \quad (2)$$

where $\eta_t = \varepsilon_t - \lambda\varepsilon_{t-1}$, λ is the strength of the lag effect. The directly estimated parameters are the short-run response and, as shown in Kmenta (1971), include the factor (1-λ). The long run effect is thus derived by dividing the estimated parameter by that factor. We estimate equation (1) (**Table 6**) and equation (2) (**Table 7**) with different omissions and restrictions on the estimated parameters.

Equation (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, and is consistent with estimates of the aggregate economy's short-run price elasticity (Bohi (1981), especially Table 3-1). Neither the GDP nor the residual time trend is significantly different than zero. The estimated values show a weak effect of GDP and show the residual time trend to be slightly energy using. The main reason for this is that GDP and time are highly correlated (correlation = 0.99). Dropping the time trend (specification 2) produces a significant coefficient on the GDP elasticity but still considerably weaker than a constant returns to scale value of 1.0. With the formulation restricted to be CRS (specification 3), the AEEI is 2.0 percent per year.

Considering the Koyck transformation (Table 7) produces a statistically significant and large lag effect when the GDP elasticity is unrestricted (specifications 1-2). The estimated values of 0.60 to 0.77 mean that the long run response is 2.5 to nearly 4.5 times larger than the short run response. The time trend in this formulation is significant and suggests an energy-using bias but the GDP elasticity is insignificant. Restricting the GDP elasticity to CRS (specification 3) produces a smaller lag effect and an AEEI that somewhat above 2% per year not that dissimilar from the CRS specification without the lag. The most robust result across these formulations is the price elasticity, which is consistently inelastic. With the lag effect in specifications 1 and 2, the estimated short-run price elasticity is less than half the value without the lag (-0.08 to -0.11) Thus, even with the strong lag effect, the long run price elasticity is only about 30 to 50 percent larger (rather than 2 ½ to 4 ½ times) than without the lag.

The strong correlation between GDP and time makes it nearly impossible to estimate separate effects. In considering applications to the EPPA model, its production function approach produces a model that, except for some shifting consumption shares, is a constant returns to scale representation of the economy. In the lagged effects model, while the estimated value of the AEEI varies depending on the specification, the standard errors of the estimates are consistently in the 30% and 40% range, relative to the best estimate. As in other cases we assume a normal distribution, normalized to a mean of 1.0 and a standard deviation of 0.4, and apply the sampled value as a multiplicative factor for the regionally varying AEEIs as specified in EPPA. We assume the AEEI is driven in part by technology which would be to some extent commonly available across the world. We therefore impose a correlation of 0.9 among sampled values for all regions.

The reference assumptions in the EPPA model differentiate the rate of AEEI among regions and between non-energy and energy sectors of the economy (Paltsev *et al*., 2005). 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 and in some cases even increased in intensity. 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. We assume that the median path of AEEI for each region is the reference assumption for that region. The uncertainty, sampled for each region with correlation among other regions, is then applied to scale the time path of energy efficiency up or down relative to the median path.

2.2.1.4 Fossil Fuel Resource Availability

All fossil energy resources are modeled in EPPA4 as graded resources whose cost of production rises as they are depleted. The production structure for fossil energy sectors, plus the depletion model and representations of backstop technologies, completely describe fossil fuel production. Two critical values are the total physical amount of the resource and the elasticity of substitution between the resource and other inputs in the production function. The latter determines the cost increase as depletion occurs. The full description of the resource model and reference values for the available resources of each type in each region and the elasticity values are given in Paltsev *et al*. (2005).

Table 6. Energy consumption as function of price, GDP, and time effects.

	Estimated Parameters (Standard errors)					Calculated Values
Specification (eq. 1)	***α Constant***	***β Price elasticity***	***θ GDP 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. (θ=1)	-9.8** (0.21)	-0.24** (0.047)	1	-0.0206** (0.00080)	2.0 (0.08)	-

** Significant at p<0.05 level

Table 7. Energy consumption as function of price, GDP, and time with lagged effects.

	Estimated Parameters (Standard errors)					Calculated Values		
Specif-ication (eq. 2)	α ***Const.***	β ***Price elas. (short-run)***	θ ***Inc. elas.***	γ ***Residual time trend***	λ ***Lag in dep. variable***	***Long-run AEEI % per year***	***Long-run price elas.***	***Long-run GDP elas.***
1. LAG, Pr, GDP, t	13.4 (4.5)	-0.082† (0.043)	-0.31 (0.20)	0.012** (0.0054)	0.77** (0.16)	-5.5 (2.5)	-0.35	-1.3
2. LAG, Pr, GDP	3.5** (1.5)	-0.11** (0.044)	0.14** (0.055)	-	0.60** (0.16)	-	-0.29	0.36
3. ($\theta = 1$)	-11.7** (3.8)	-0.22** (0.061)	1	-0.022** (0.002)	0.10 (0.20)	2.4 (0.24)	-0.24	1.1

†Significant at p<0.1 level;   **Significant at p<0.05 level

As a data source for the uncertainty in the available resources, we rely on the most recent global resource assessment by the U.S. Geological Survey (Ahlbrandt *et al*., 2005). The report gives a detailed assessment of fossil resources in terms of undiscovered, reserve growth, remaining reserves, and cumulative production for geologic formations in all regions except the U.S., which was previously assessed in Gautier *et al*. (1996). A Monte Carlo analysis is used to assess the uncertainty in global aggregate resources, and is reported in terms of 5th and 95th percentiles (**Table 8**). For uncertainty in the global resources in EPPA, we use the 5th and 95th percentiles relative to the median for the world excluding the U.S., which gives a range of 40% to 175% of the median value. We again normalize the distribution to retain as the median value the reference regional resource estimate specified in EPPA, and these are sampled with correlation among oil and gas resources of 0.9 (*i.e.* less global crude oil available for use implies that there is also less global natural gas resource in the ground). Similarly detailed assessments for shale oil are not available. We assume one standard deviation bounds of 50% and 200%. The normalized probability density functions for fossil resources are shown in **Figure 3a**.

With regard to the supply elasticity, Dahl and Duggan (1996) provide a detailed survey of the literature. They find a wide range of estimated elasticities, from 0.41 to 7.90 across coal, oil and natural gas with a best estimate of 1.27. Similar ranges are reported for coal supply elasticities by the IEA (1995) and for oil and natural gas by Krichene (2002). We assume a probability distribution for the supply elasticities as shown in **Figure 3b**, ranging from 0.5 to 2.0. Each fuel is sampled independently from this distribution (*i.e.* no correlation).

Table 8. Uncertainty in Available Supply of Fossil Fuels.

		Oil (Billion Barrels)				Natural Gas (Trillion Cubic Feet)			
		F95	*F50*	*F5*	*Mean*	*F95*	*F50*	*F5*	*Mean*
World Excluding U.S.	***Undiscovered Conv.***	334	607	1107	649	2299	4333	8174	4669
	Reserve Growth (conv.)	192	612	1031	612	1049	3305	5543	3305
	Remaining Reserves				859				4621
	Cum. Production				539				898
	Total	526	1219	2138	2659	3348	7638	13717	13493
	Relative to Median	***43%***		***175%***		***44%***		***180%***	
U.S.	***Undiscovered Conv.***	66		104	83	393		698	527
	Reserve Growth (conv.)				76				355
	Remaining Reserves				32				172
	Cum. Production				171				854
	Total	345		383	362	1774		2079	1908
	Relative to Mean	***95%***		***106%***		***93%***		***109%***	

Source: Ahlbrandt *et al*., 2005

Note: Blanks are shown where results were not provided in the original source.

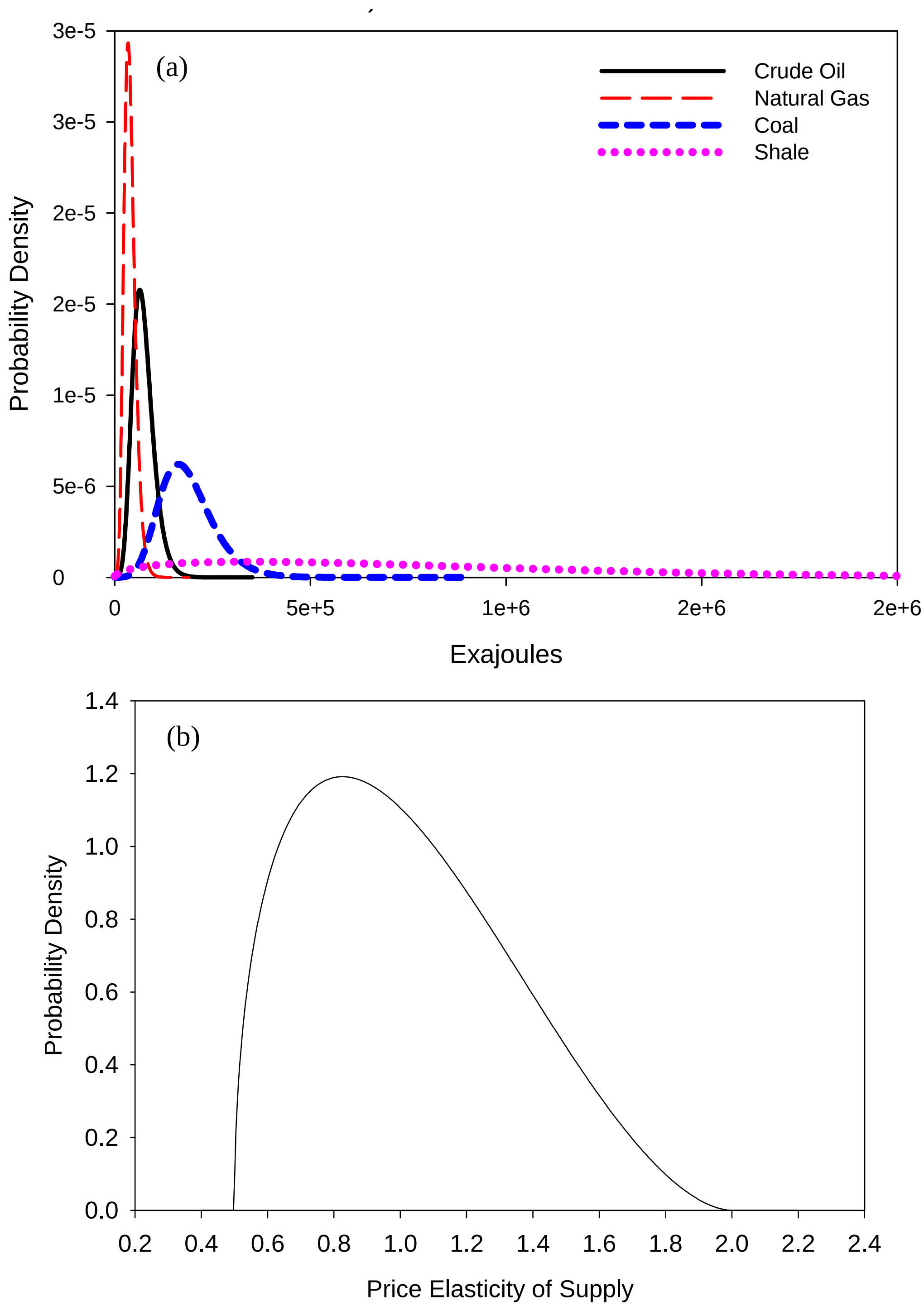


Figure 3. PDFs for (a) total fossil resources available for depletion, and (b) price elasticity of supply for fossil fuels.

2.2.1.5 Population Growth

The uncertainty in population growth is taken from World Population Prospects: the 2006 Revision (UN, 2007). The UN projections consist of a medium, a high, and a low case projection to 2050. The relative likelihood of these scenarios is not given; for the purposes of developing a probability density function, we assume that the high and low cases (**Figure 4**) represent one standard deviation about the medium case, which is taken to be the median (**Figure 5**). We apply each sample of population growth to 2050, relative to the reference growth rate, to the reference growth path for each region. This procedure generates population growth for the world as shown in Figure 4. The assumption that the population growth rate uncertainty is perfectly correlated across regions is an extreme one; however as shown in the results below, population growth even under this assumption has only a weak influence on emissions and cost uncertainties.

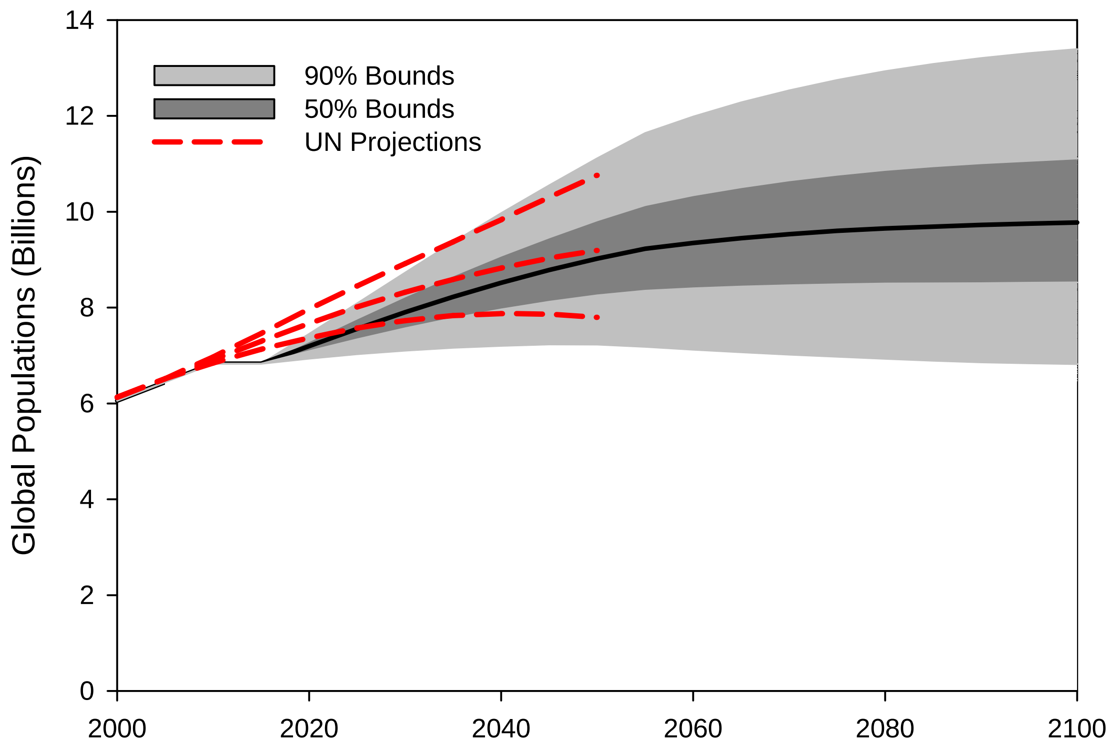


Figure 4. Shaded regions show the 50% (darker) and 90% (lighter) ranges of the EPPA population projections to 2100, and lines show the UN population projections to 2050 (source: UN, 2007).

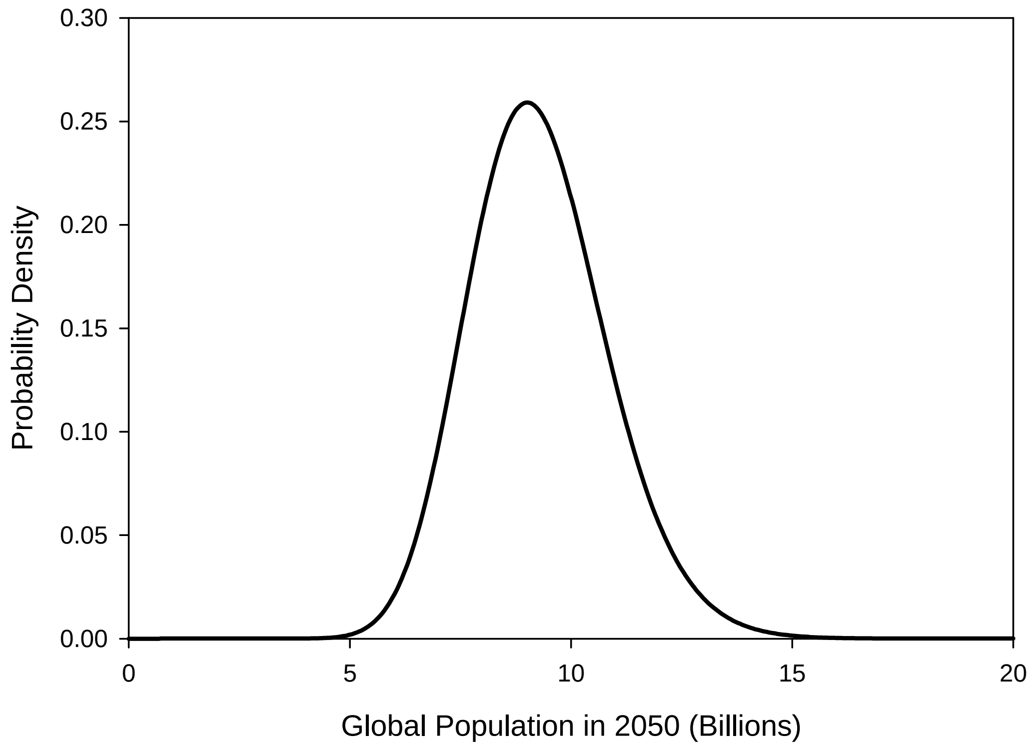


Figure 5. PDF of global population in 2050.

2.2.1.6 Urban Pollutant Trends

One area of significant improvement to the treatment of uncertainty, compared with our earlier study (Webster *et al*., 2002), is in the parameters of the urban pollutant emissions (See Mayer *et al*, 2000 for details on urban emissions modeling in EPPA3). Here we take advantage of an approach developed by Stern (2006, 2005; Stern and Common, 2001) in which he uses observed emissions to estimate a stochastic emissions frontier. Hence, we model the emissions of urban pollutants with an activity-specific emissions factor as in previous versions, relating the economic activity in each economic sector of the model to the emissions produced of each substance. However, we now model the evolution of these factors over time according to:

$$F_{i,j,t} = F_{i,j,0} \exp(\gamma_j t) \quad (3)$$

where $F_{i,j,t}$ is the emissions factor for economic sector i, pollutant j, and time t, $F_{i,j,0}$ is the emissions factor in the initial year, and γ_j is the uncertain trend parameter for pollutant j.

The uncertainty in the time trend γ for SO_2 is based on data and analysis by Stern (2006, 2005; Stern and Common, 2001), in which he uses observed emissions to estimate a stochastic emissions frontier for 15 different countries. We estimate the global trend in emissions consistent with his range of estimated emissions frontiers projected over the next century. The mean trend for SO_2 is consistent with a value for γ in equation 1 of -0.03, with a standard deviation of 0.1. The fitted PDF is shown in **Figure 6**.

The trend for NO_x is revised from that of SO_2 based on the expert judgment of the authors. Unlike SO_2, which has both straightforward end-of-pipe options for removal from exhaust flows and options for substituting low-sulfur fuels, NO_x is much more difficult to either remove or to prevent from forming during combustion. Therefore the prospects for reducing global NO_x emissions from activities that combust fossil fuels are less likely than they are from SO_2. We modify the distribution of the time trend parameter for NO_x to span a range (with 95% probability) of global emissions that stabilize at 2000 levels to growth at nearly double the rate in reference EPPA projections. The PDF for the NO_x parameter is shown in Figure 6.

For other urban pollutants, for which there is much less data and fewer available studies of time trends, we assign either the SO_2 or the NO_x time trend distributions as appropriate. We assume that black and organic carbon have end-of-pipe removal options similar to SO_2, and use the SO_2 trend distribution. All other urban pollutants, VOC, CO, and NH_3, are similar to NO_x in the difficulty of prevention during combustion or removal from exhaust flows, and we assume the NO_x time trend distribution. We assume that the uncertainties in urban emissions trends are perfectly correlated across all regions.

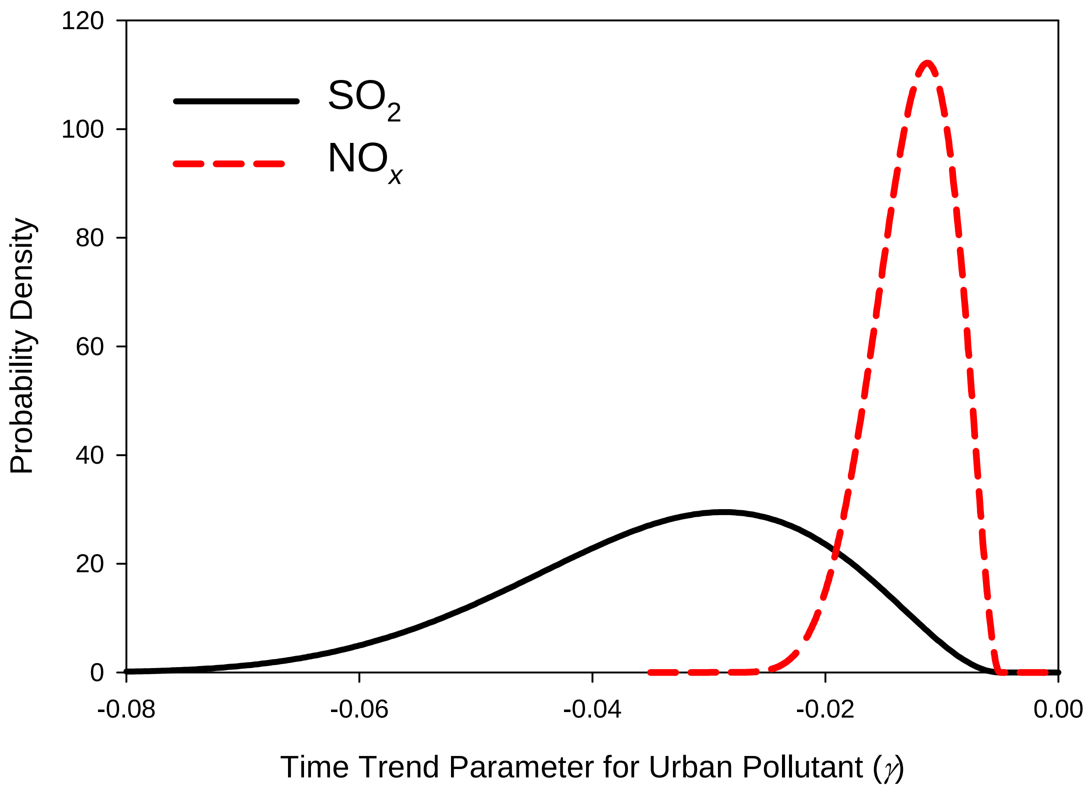


Figure 6. Probability density functions assumed for the time trend parameters for urban pollutants.

2.2.2 Distributions Based on Expert Elicitation

2.2.2.1 Expert Elicitation Methodology

The distributions assumed for the remaining uncertainty parameters – future energy technology/fuel costs, costs of methane and nitrous oxide abatement, and capital stock vintaging – are based on expert elicitation. Here, we briefly review the methodology used to perform these assessments, and then present the elicited data and resulting distributions.

Expert elicitation is not always straightforward: it relies on probabilistic judgments that can be biased (Tversky and Kahneman, 1974; Morgan and Henrion, 1990). It also requires using judgments from multiple experts who often disagree. Various protocols have been developed to address these difficulties including the Stanford/SRI assessment protocol (Staël von Holstein and Matheson, 1979) and the Morgan-Henrion (1990) protocol. Both of these define clear steps to follow.

1) Introduction/Motivation: Both of the above protocols begin with a short "motivating" phase during which experts are explained the background of the analysis (why are we interested in doing an uncertainty analysis on this parameter?).

2) Technological discussion: Morgan and Henrion include a phase prior to the elicitation itself during which experts explain their view on how to approach the issue: what would be the most convenient way to define the parameter, how could we model the uncertainty.

3) "Structuring" the elicitation: Experts come to a consensus on an unambiguous form of the quantity to be assessed so that they will be able to give reliable judgments on its uncertainty. In this phase is also useful to make clear what sort of data they will be asked to provide and to familiarize them with probabilistic vocabulary.

4) The "conditioning" phase: This phase helps experts think in terms of cognitive biases or judgment anchoring. Morgan and Henrion advise a review of the psychological literature related to issues associated with expert elicitation to help experts become more aware of the kind of biases that may affect their judgments.

5) The "encoding" phase: The key part of the process, encoding consists of asking experts to provide characteristics of the probability distribution function that provide the basis for fully specifying it later. This may consist of asking experts to give a low and a high-end point (the 5% and 95% fractiles for example) and then to ask them for the median (the 50% fractiles). Another possibility is to ask for the two extremes (the 0% and 100% fractiles), the mode (most likely value) and a level of variance. Each expert may use a different methods as long as information is obtained that is sufficient to later compare PDFs obtained from different experts.

6) The "verifying" phase: Experts can be asked about scenarios that would lead to different values than the one predicted. Detail reasoning and explanation of all the assumptions behind a judgment will help the thinking process. Finally one should try to obtain redundant information in order to check the coherence of each judgment.

7) Combining PDFs: One can require the experts to come to a consensus (Dalkey, 1967) or mathematically combine the results (Genest and Zidek, 1986; Clemen and Winkler, 1999) by for

example weighting equally each prediction. We chose in this paper to combine the different assessments.

In the elicitations performed for this analysis, we presented to our experts a simple protocol that tried to gather all the phases described before. The protocol used in the elicitations for this paper was composed of five stages:

- Introduction: explain the purpose of the meeting.
- Choice of parameter:
  - Define exactly the parameter. Is everyone comfortable with it? Would anyone know an easier way to think about it?
  - Specify that each parameter will be analyzed independently from others
  - Begin with a specific country/sector
- Double-checking: has this job been done before? Are there any other elicitation studies available on this quantity?
- Elicitation: high end / low end / median (recursive step)
  - Write down the first estimate. Give ways to easily figure out what you are asking for:
    - High/Low estimates = 19 chances out of 20 it is not higher/lower
    - Median = half of the potential values are lower/half higher
  - Scenario linking:
    - To which scenario does this value correspond?
    - Could you think of any scenario that would lead to a higher/lower value?
    - Can you think of reasons that lower/higher values are not possible?
  - Output checking: ask for an output that would result from these estimates
  - Calibration with other experts/consistency with current model
  - Scope extension: without any additional elicitation, is it possible to apply these estimates to other sectors/countries?
- Compile estimates: do experts accept that their estimates will be compiled with the others to have a single PDF?

Before the interview, in order to give experts a broader view of the process they were about to go through, each was given the chart in **Figure 7**, summarizing the different stages to show in a clear way the recursive process of writing down estimates. The methodology for these expert elicitations are described in more detail in Cossa (2004).

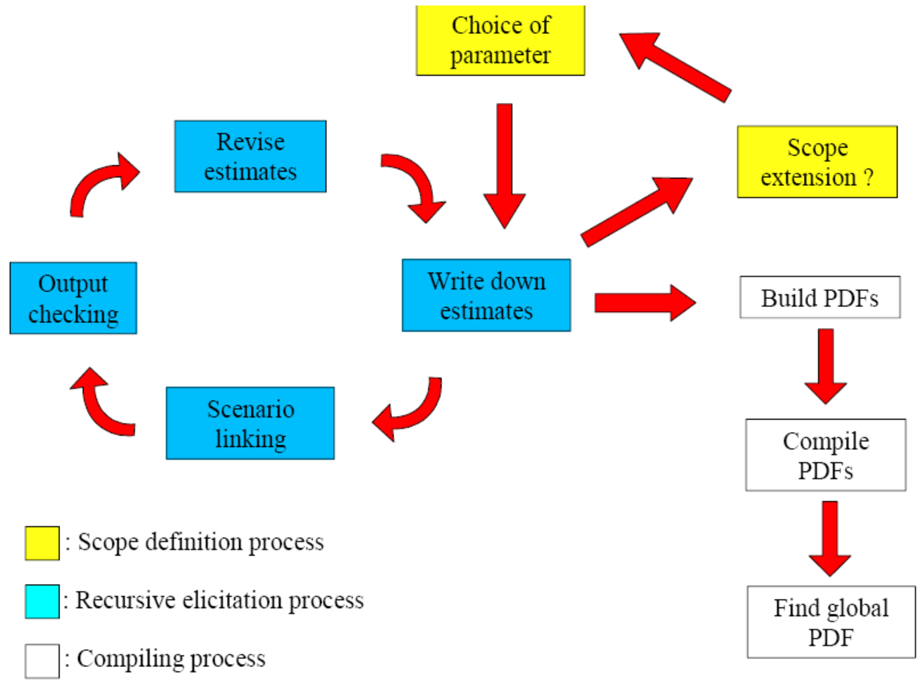


Figure 7. Diagram of Expert Elicitation Process for Uncertainty Judgments.

2.2.2.2 Future Energy Technologies

Projections of energy and emissions data are highly dependent on the deployment of advanced technologies. These technologies endogenously enter if and 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, climate policy, and other forces driving economic growth such as the savings, investment, and the productivity of labor. These advanced technology options are summarized in **Table 10**. Three technologies produce substitutes for conventional fossil fuels (gas from coal, a crude oil product from shale oil, and a refined fuel from biomass). The remaining five are electricity generation technologies (biomass, wind and solar, natural gas combined cycle with and without carbon capture and sequestration, and advanced coal with carbon capture and sequestration).

Each advanced technology is represented with a nested production structure similar to the conventional technology with which it competes. We identify a multiplicative mark-up factor that describes the cost of the advanced technology relative to the existing technology against which it competes in the base year. This markup is multiplied by input share parameters in the production function of the advanced technology so that the cost shares, at base year prices, no longer add up to 1.0. Thus, as this sum greater or less than 1.0, the technology is more or less costly than the technology against which it directly competes in base year prices. The reference assumptions for each mark-up factor are given in Paltsev *et al*. (2005).

Cossa (2004) performed the elicitation on five backstop technologies: synf-oil, gasified coal, natural gas combined cycle with (NGCC) and without carbon capture (NGCAP) and finally advanced coal with sequestration (IGCAP). He asked experts about their uncertainty in capital and labor markup factors for these technologies. He consulted five different experts: Professor Henry Jacoby, Dr. Sergey Paltsev and Dr. John Reilly for fossil backstops and Mr. Howard Herzog and Mr. Jim McFarland for combined cycle and carbon capture backstops. The elicited fractiles are given in **Table 9**. The fractiles from the different experts were then averaged, and the averaged fractiles used to construct probability density functions, with mean and standard deviations given in Table 10.

As noted by Jacoby *et al*. (2006) observations on penetration rates for new technology typically show a gradual penetration, for which there are numerous contributing factors. EPPA4 replicates the penetration behavior that is typically observed by endowing the representative agent with a small amount of a specialized resource. The endowment of this resource grows as a function of output in the previous period. Capacity expansion is thus constrained in any period by the amount of this fixed factor resource and the ability to substitute other inputs for it. As output expands over time the endowment is increased, and it eventually is not a significant limitation on capacity expansion. The rate of penetration as a function of the previous period's capacity is also treated as uncertain, with mean and standard deviation indicated in Table 10.

Wind and solar sources of electricity supply are treated differently in the model and required different treatment in the uncertainty analysis. Wind and solar are represented as imperfect substitutes for conventional electricity supply, in order to represent the intermittency of the resource. This is represented with an elasticity of substitution between the output from the wind and solar and the output of other electricity supply technologies. Choice of the substitution elasticity creates an implicit supply elasticity of wind in terms of the share of electricity supplied by the technology. Thus, this elasticity is the key parameter that describes the potential extent of penetration of this electricity source. The uncertainty in the elasticity of substitution is given in Table 10, and is based on Cheng (2004).

Table 9. Fractiles for Advanced Technology Markup Factors from Expert Elicitation.

	Fractile	Expert 1	Expert 2	Expert 3
Synthetic Oil Markup	***5%***	2.0	2.1	2.5
	50%	3.5	4.3	4.3
	95%	5.0	5.8	6.0
Coal Gasification Markup	***5%***	3.4	1.9	3.9
	50%	4.3	3.0	5.2
	95%	6.5	6.5	6.9
		Expert 4	**Expert 5**	
Advanced Coal with Carbon Capture	***5%***	1.1	1.1	
	50%	1.1	1.2	
	95%	1.4	1.3	
Natural Gas with Carbon Capture	***5%***	1.1	1.1	
	50%	1.2	1.2	
	95%	1.3	1.2	
Natural Gas Combined Cycle	***5%***	0.8	0.9	
	50%	0.9	0.9	
	95%	1.0	1.0	

Table 10. Uncertainty in Advanced Energy Technology Assumptions.

Input Factor Markups	**Mean**	**Std. Dev.**
Shale Oil	3.20	0.77
Coal Gas	3.94	0.82
Advanced Coal with CCS	1.18	0.10
Advanced Gas with CCS	1.15	0.05
Advanced Gas without CCS	0.90	0.04
Bio-Oil	3.94	0.82
Bio-Electric	3.94	0.82
Elasticity of Substitution		
Wind and solar	0.25	0.20
Penetration Rates		
New Tech Penetration Rate	2.25	1.13

Table 11. Assessed uncertainty in elasticity of substitution for CH_4 emissions (smaller numbers make emissions reductions more costly).

Regions	5%	50%	95%
USA	0.01	0.02	0.04
JPN	0.01	0.01	0.02
EUR	0.01	0.01	0.02
ANZ	0.01	0.02	0.03
FSU	0.005	0.01	0.02
EET	0.01	0.02	0.03
CHN	0.01	0.03	0.06
IND	0.01	0.01	0.02
MES	0.005	0.01	0.02
LAM	0.01	0.01	0.02
ASI	0.01	0.03	0.08
ROW	0.005	0.01	0.02

Table 12. Assessed uncertainty in elasticity of substitution for N_2O emissions (smaller numbers make emissions reductions more costly).

Fractile	OECD	LDC	FSU	EET
5%	0.01	0.01	0.007	0.008
50%	0.02	0.02	0.009	0.011
95%	0.02	0.02	0.011	0.014

2.2.2.3 Methane and Nitrous Oxide Elasticities

The costs of reducing methane (CH_4) and nitrous oxide (N_2O) emissions under a policy constraint are implemented in EPPA by using a nested CES production function where conventional inputs can be substituted for CH_4/N_2O emissions (Reilly *et al*., 2006; Hyman *et al*., 2003). The assumed value of the elasticity of substitution between emissions and conventional inputs determines the shape of the marginal abatement curve. We represent uncertainty in the costs of reducing CH_4 and N_2O in terms of uncertainty in these elasticities of substitution. An expert elicitation of this uncertainty was performed by Cossa (2004), as described above, using experts at the U.S. Environmental Protection Agency. This assessment produced the uncertainty in elasticities of substitution, which vary by region, shown in **Tables 11** and **12**. These fractiles are used to develop probability density functions for these parameters.

2.2.2.4 Capital Vintaging

Capital stock is dynamically updated for each region and sector, as determined by the capital vintaging procedure (Jacoby and Sue Wing, 1999; Paltsev *et al*., 2005). In each period a fraction of the malleable capital is frozen to become part of the non-malleable portion. Letting K^m represent the malleable portion of capital and K^r the rigid portion, the procedure can be described as follows. New capital installed at the beginning of each period starts out in a malleable form. At the end of the period a fraction ϕ of this capital becomes non-malleable and frozen into the prevailing techniques of production. The fraction $(1 - \phi)$ is that proportion of previously-installed capital that is able to have its input proportions adjust to new input prices to take advantage of intervening improvements in energy efficiency driven by the AEEI or by changing prices—essentially allowing the possibility of retrofitting previously installed capital. We treat the share of vintaged (non-malleable) capital as uncertain. The fractiles were obtained through expert elicitation of 5 experts (Cossa, 2004), whose results are shown in **Table 13**. The probability density function is constructed using the average of these fractiles, and is shown graphically as a probability density function in **Figure 8**.

Table 13. Fractiles of Vintaged Capital Fraction from Expert Elicitation.

Fractile	Experts				
	Jacoby	*Reilly*	*Paltsev*	*Eckaus*	*Loeschel*
5%	30%	30%	20%	44%	20%
50%	50%	60%	45%	59%	35%
95%	80%	100%	80%	70%	70%

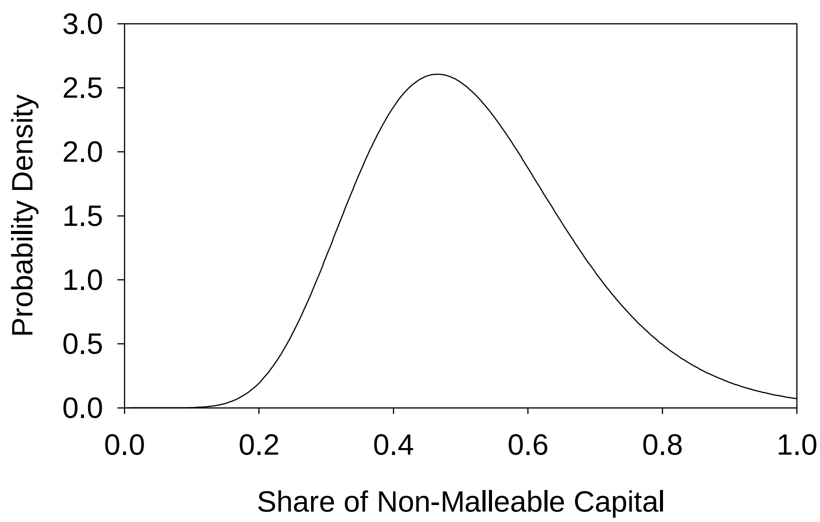


Figure 8. Probability density function for share of vintaged capital.

2.2.3 Correlation among Parameters

A critical assumption in any uncertainty analysis, in addition to the assumed distributions of individual parameters, is the correlation assumed among parameters when sampling. In general, the stronger the correlation between two parameters, the greater the uncertainty is in the model outcome (except when two parameters have opposing effects on the outcome). The empirical basis for estimating the degree of correlation among parameters treated here is limited. One exception is for the GDP growth rates across nations, for which the evidence shows only very weak correlation (Webster and Cho, 2006), and this weak correlation is implicitly represented in the random walk with drift procedure (since all regions have positive drift).

We have imposed correlation across subsets of parameters for which, on the basis of expert elicitation (Cossa, 2004), there are theoretical reasons to believe that a higher sample value for one implies a greater probability of a high sample value for another. These parameters all reflect aspects of technology, and the expert judgment was that different regions and sectors would at some level reflect similar technology characteristics because all regions would have access to general improvements in technology through normal processes of technology diffusion. The sets of parameters which are highly correlated are: AEEI across regions, the elasticity of substitution between capital and labor across sectors, the methane and nitrous oxide elasticities (which determine abatement costs) across regions, and the time trends for urban pollutants across different pollutants. In addition, the total available resources of oil and natural gas are assumed to be correlated (coal and shale resources are probabilistically independent). These groups of correlated parameters are summarized in **Table 14**. All other parameters in this study are assumed to be probabilistically independent. Note, however, that most other technology parameters do not explicitly vary by region (e.g. cost, and supply elasticities) and so in these cases parameters among regions are perfectly correlated.

Table 14. Correlated Subsets of Uncertain Parameters.

Parameter	**Correlated Across (dimensions of matrix)**	**Correlation Coefficient**
AEEI	Regions (16x16)	0.9
Elasticity of Substitution (L,K)	Sectors (8x8)	0.8
Methane Elasticities (cost)	Regions (16x16)	0.8
N_2O Elasticities (cost)	OECD, LCD, FSU, EET (4x4)	0.8
Fossil Resources	Oil, Natural Gas (2x2)	0.9
Urban Pollutant time Trends	Urban Pollutants (7x7)	0.9

2.3 Policy Scenarios

We explore the uncertainty in five scenarios developed for the U.S. Climate Change Science Program (CCSP) Assessment Product 2.1a (Clarke *et al*., 2007). These scenarios included a reference or no policy scenario and four scenarios that for the earth system models used in the exercise stabilized radiative forcing. They were developed to provide insight into discussions of climate policy, particularly with regard to the implications of stabilization for emissions trajectories, energy systems, and mitigation cost. In Clarke *et al*. (2007), projections were developed for these scenarios from three different integrated assessment models, one of which was the MIT modeling framework that includes the EPPA model. However, the full range of uncertainty under each of these scenarios was not explored in the CCSP report. Here we build on that exercise by performing an uncertainty analysis of the EPPA model under each of these policy constraints using the MIT-based emissions scenarios in the CCSP report.

The CCSP scenarios used here are a thought experiment, in which we explore the consequences of one path of policy constraints over time without learning or revision along the way. The purpose of this approach is not to provide a prediction of what will occur; indeed, we expect that some uncertainties will be reduced over time, and that long-term greenhouse gas reduction objectives will be revisited to respond to this new information.[3] Rather, the purpose is to compare the uncertainty in economic and emissions outcomes under alternative paths in order to provide insight into the implications of several distinct levels of policy stringency, and to provide a basis for analysis of the uncertain climate effects of these scenarios.

The CCSP exercise developed a reference level of emissions and a set of 4 stabilization scenarios described as Level 1, 2, 3, and 4 (Clarke *et al*., 2007) that were developed to meet the radiative forcing targets shown in **Table 15**. Each level referred to additional radiative forcing from GHGs. The radiative forcing levels led to CO_2-only stabilization levels of approximately 450, 550, 650, and 750 ppm with varying additional concentration increases of other GHGs given the models used. For the MIT IGSM the CO_2-equivalent concentrations were 523, 675, 812, and 925 ppm for levels 1 through 4, respectively. Here we implement the *emissions paths* developed by the MIT ISGM for the CCSP exercise.[4] They are applied as constraints on GHG emissions, which are imposed identically across all parameter samples (*i.e.* all 400 samples for the Level 1 scenario impose the same emissions constraints). **Figure 9** shows the global CO_2 emissions over time under each of the five scenarios for reference parameter assumptions in EPPA (*i.e.* no uncertainty). When these emissions levels are propagated through an earth

[3] For studies of this type, see Webster *et al*. (2008b), Yohe *et al*. (2004), Kolstad (1996), and Ulph and Ulph (1997).

[4] Using those emissions paths with a different earth system model, and different versions of the IGSM will lead to different concentrations and radiative forcing. Both the EPPA and earth system components of the IGSM have been updated since the CCSP exercise was completed, and so the reference projections have changed. In the uncertainty exercise parameters that affect trace gas cycles are varied and so we do not expect them to meet the same radiative forcing or concentration targets. Our goal here is to evaluate the emissions scenarios in the CCSP report, not necessarily the concentration or radiative forcing targets.

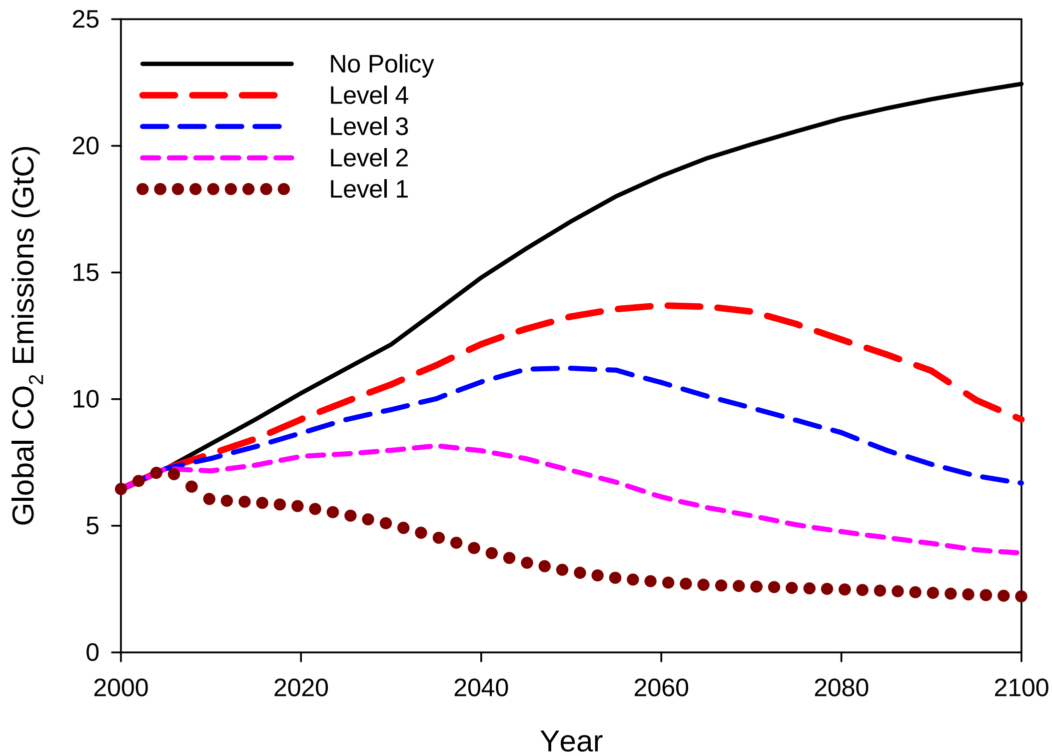


Figure 9. Reference projections of global CO_2 Emissions under No Policy and concentration stabilization targets of 750, 650, 550, and 450ppm, as defined in Clarke *et al*. (2007).

Table 15. Definitions of Concentration Stabilization Cases.

	Total Radiative Forcing from GHGs (W/m^2)	Approximate Contribution to Radiative Forcing from non-CO_2 GHGs (W/m^2)	Approximate Contribution to Radiative Forcing from CO_2 (W/m^2)	Corresponding CO_2 Concentration (ppmv)
Level 1	3.4	0.8	2.6	450
Level 2	4.7	1.0	3.7	550
Level 3	5.8	1.3	4.5	650
Level 4	6.7	1.4	5.3	750
Year 1998	≈2.1	0.65	1.46	365
Preindustrial (1750)	—	—	—	278

Source: Clarke *et al*. (2007), Table 1.2

system model with uncertainty in the physical science parameters, these radiative forcing and concentrations will necessarily vary from these targets in most of the simulations.

Several other assumptions in constructing the stabilization scenarios are important to note (see Clarke *et al*., 2007 for details on each of the following). Policies are modeled as greenhouse gas emissions constraints with tradable permits both among regions and across GHGs. It is assumed that the policies to achieve stabilization are applied globally after 2012; *i.e.* no differentiation among nations in terms of when emissions constraints are introduced. The timing of emissions reductions was calculated under reference assumptions for EPPA to minimize costs over time ("when flexibility"). Finally, the allocations of emissions permits across regions under the stabilization scenarios, as in the CCSP report, were designed to impose equal marginal costs of abatement across all regions in each period, under the reference assumptions for all parameter values. This allocation is neither a recommendation nor a prediction of what will occur, but rather is a simple and transparent assumption. Because the regional economic impacts from emissions reductions are strongly influenced by the initial allocation, we report below only global aggregate economic losses.

3. RESULTS

We perform Monte Carlo simulation of the EPPA model, using Latin Hypercube sampling (Iman and Helton, 1988) from the parameter distributions described in Section 2. The simulations presented here are based on 400-member ensembles, and each sample is simulated under No Policy and under the four stabilization cases described in section 2.3.

3.1 Uncertainty in Emissions Projections

EPPA projects emissions of greenhouse gases (CO_2, CH_4, N_2O, HFC, PFC, SF_6) and of urban pollutants (NO_x, SO_2, CO, VOC, NH_3, black carbon, organic carbon). **Figure 10** shows the uncertainty in anthropogenic global CO_2 emissions under the no policy scenario, represented by the shaded regions on the graph. The lighter shaded region is higher above the median than below, indicating that the uncertainty is skewed towards higher emissions. This pattern results from the fact that there are many more ways of obtaining higher than modal emissions, but less likely to obtain lower than modal emissions. Higher emissions can result from any one of several parameters with values that cause high emissions; *e.g.,* high GDP growth *or* low AEEI *or* large amounts of coal and shale, etc. This results in the long upper tail. Conversely, there are far fewer ways (thus lower probability) to obtain low emissions, because most or all of several critical parameters must take on values that constrain emissions; *e.g.,* low growth *and* high AEEI *and* less coal and shale available.

In Figure 10, we also reproduce the six IPCC SRES marker scenarios (Nakicenovic and Swart, 2000) and the four stabilization scenarios from Clarke *et al*. (2007). Only two of the SRES scenarios are fully within the 90% probability bounds of no policy emissions from EPPA.

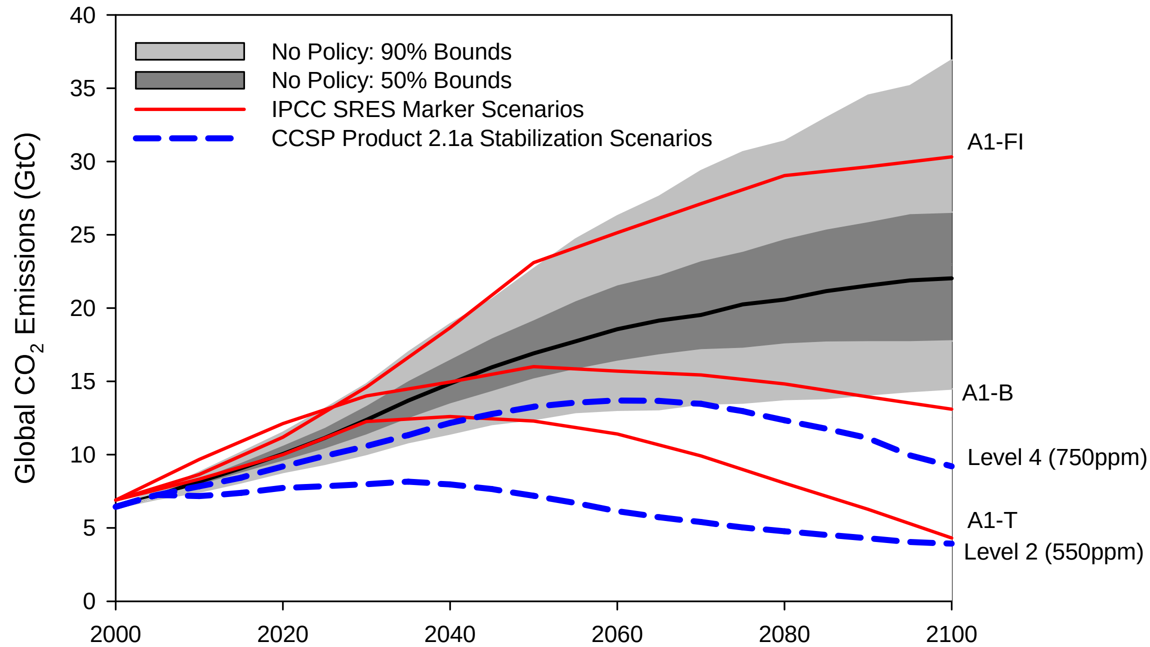


Figure 10. Global anthropogenic emissions over time. Shaded regions show the 50% (darker shading) and 90% (lighter shading) probability bounds on EPPA emissions in the no policy case. The red lines indicate the IPCC SRES marker scenarios, with scenario label to right of graph. The blue dashed lines indicate the Level 4 (750ppm) and Level 2 (550ppm) stabilization scenarios from Clarke *et al*. (2007).

The other four fall mostly outside the 90% bounds. Thus, by our analysis the lower SRES scenarios seem very unlikely to occur without a climate policy. They are, however, easily within the range of the CCSP stabilization scenarios and so our modeling exercise does not dispute the idea that they are achievable. Formulating our exercise differently—to include likelihoods on different levels of policy action or if we were to consider an endogenous policy response to the evolving climate scenarios—would lead to SRES-like scenarios emerging as much more likely or as central estimates. Thus, while these different results might in part reflect fundamental differences about the drivers of future emissions, they may also simply reflect the fact that the exercises were conducted for different purposes with different expectations about how the scenarios would be used.

Figure 11 shows the median, 50% bounds, and 90% bounds on global emissions of CH_4 (Fig. 4b), N_2O (Fig. 4c), SO_2 (Fig. 4d), and NO_x (Fig. 4e) in the absence of climate policy. Numerical values of these projections and for emissions of other GHGs and urban pollutants are given for selected years in Appendix B. Greenhouse gas emissions absent climate policy are all increasing, with uncertainty ranges that grow wider over time. In contrast, median projections of SO_2 emissions are decreasing after 2010, with a low but not negligible probability that global SO_2 emissions will continue to increase over most of the 21st century. Median emissions of NO_x grow slowly in the first half of the century and stabilize in the second half. Half of the samples

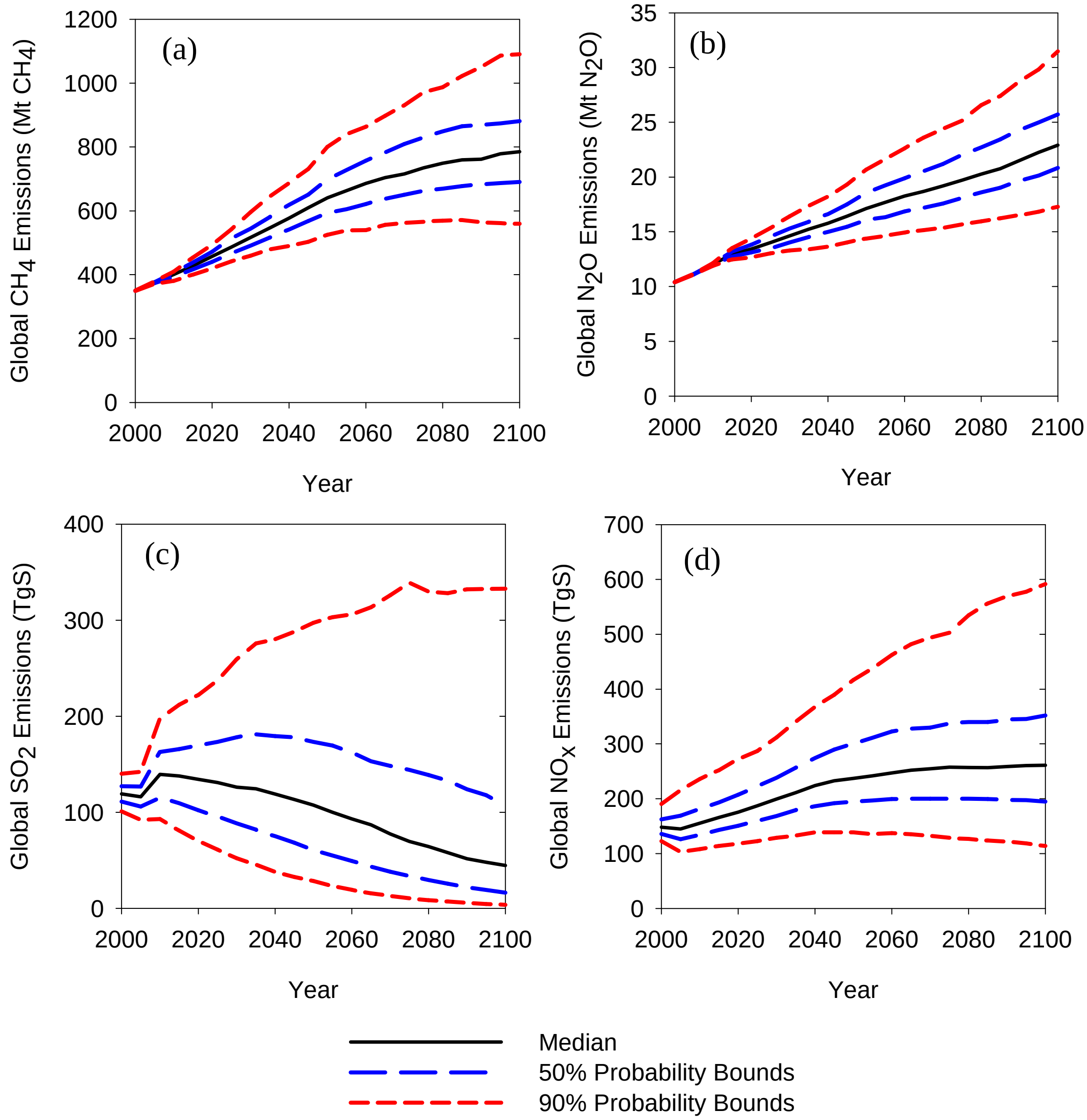


Figure 11. Global emissions under No Policy case of (a) CH_4, (b) N_2O, (c) SO_2, and (d) NO_x.

have NO_x emissions that increase over the century. Unlike SO_2, there is little likelihood that global NO_x emissions will fall significantly below current levels.

The uncertainty in emissions projections under the four CCSP scenarios with emissions constraints are given for selected years in Appendix A. Because the stabilization scenarios are modeled as emissions constraints, there is very little or no variance in greenhouse gas emissions within each scenario. The only exception is in the Level 4 (750ppm) scenario in the early decades where up to 5% of the samples are unconstrained because global emissions are below the emissions cap for that period, albeit only very slightly below. Given that the emissions caps are generally binding, uncertainty in emissions in the constrained cases is minimal. Instead the uncertainty appears in the cost of meeting the target (see Section 3.2 below). In contrast, emissions of the urban pollutants are affected by the stabilization policies and are not subject to specific constraints in the exercise and so continue to vary in all scenarios. In general, the more stringent the greenhouse gas emissions cap, the lower the urban pollutant emissions are, as a result of substituting lower-emitting activities for those with higher emissions. Uncertainty in emissions under all policy scenarios are given in Appendix B (Tables B1-B5).

3.2 Uncertainty in Costs of Emissions Reductions

We present the resulting uncertainty in the costs of the four stabilization targets described in Section 2.3. In this study we only present global aggregate costs, as weighted by market exchange rates (MER).[5] These estimates represent uncertainty in costs related to fundamental characteristics of the economy in terms of growth and technological and resource factors that affect emissions and abatement costs. There is no explicit consideration of the effect on cost of uncertainty in how policies are implemented—in all cases all countries participate starting in 2012 and in all cases the policy is achieved through a cap and trade system that equates marginal cost of reductions across regions and gases.[6] Uncertainty in regional costs is obviously important as it is individual countries involved in negotiations that must ultimately bear these costs. However, how the global cost burden might be shared depends on the outcome of these negotiations, which are beyond the scope of this study. We have made no attempt to consider factors that would affect that allocation and so the specific regional costs that underlie the global total are not particularly informative. Here, therefore, we present global aggregate costs, which under emissions trading are largely independent of the initial allowance allocation. For a study, under certainty, that examines the allocation of the burden see Jacoby, *et al*. (2008).

We present two measures of effort required to meet the assumed atmospheric targets. One measure is carbon price, which reflects the marginal cost of abatement for a specified emissions cap. Because we assume globally traded greenhouse gas emissions allowances, there is a single world carbon price in each period for these simulations. The global emissions caps are held constant in each scenario at the level assumed in Clarke *et al*. (2007), so uncertainty in the underlying parameters will be reflected not in emissions but in the CO_2 prices and other economic impacts. **Figure 12** presents the resulting probability distributions of carbon prices for model periods 2020, 2060, and 2100. We choose these years as representative of near-, medium-, and long-term costs to illustrate CO_2 prices (and welfare losses below) to facilitate comparison to Clarke *et al*. (2007) which gave numerical results for these years. Numerical values for the mean, standard deviation, and several fractiles for the CO_2 price are given in Appendix A (Table A6) for selected years. The mean CO_2 price increases as the global target becomes more stringent (from Level 4 to Level 1), as do the fractiles (*e.g.,* 95th percentile). However, as shown in the Figure 12 and Table A6, there is considerable uncertainty around the mean and the point

[5] For a discussion of purchasing power parity as an alternative approach and the choice of MER weights for this analysis, see Clarke *et al.* (2007), p. 65.

[6] "When flexibility"—simulating conditions that would lead to optimal allocation of abatement over time—is not necessarily assured in the uncertainty runs. The CCSP emissions paths were developed to ensure optimal reductions over time. Here, we use the emissions paths defined in the CCSP as a quantity constraint. However, as parameters vary across samples, the emissions paths will no longer be intertemporally optimal.

estimates given in the CCSP (Clarke *et al*., 2007). For example, under the Level 4 (750 ppm) scenario constraint, the carbon price in 2020 given in the CCSP for the EPPA model is $5 per ton CO_2 and the mean of the distribution is $6.8 per ton CO_2, but the 50% probability range is $1.7 to $9.8 per ton, and the 90% probability range is $0.0 to $28.5 per ton. The CCSP analysis included other modeling groups, and in most cases their estimates of carbon prices fall easily within our uncertainty range[7]. Similarly, the carbon price in 2020 under the Level 1 (450 ppm) scenario is $71 per ton in the CCSP report, but has a 50% probability range of $58 to $80 per ton, and a 90% probability range of $44 to $111 per ton.

A better measure of emissions-reductions effort is the change in global welfare which is measured in EPPA as the change in macroeconomic consumption. The uncertainty in global consumption losses are shown as probability density functions in **Figure 13** for the four stabilization targets in the years 2020, 2060, and 2100. The numbers in the figure indicate the values given in the CCSP report for the EPPA/IGSM. Table B7 (Appendix A) gives the mean, standard deviation, and selected fractiles for welfare loss in selected years, as a % of the reference (No Policy) case. Similar to the CO_2 price results, the consumption losses increase with the stringency of the emissions constraint for point estimates, means, and 95% fractiles. Again, there is considerable uncertainty in the economic impacts from reducing emissions. In 2020, the point estimate of global losses under the 750ppm constraint is 0.1%, the 50% probability range is 0.1% to 0.3%, and the 90% range is 0% to 0.6%. The global loss in 2020 under the 450ppm constraint is 2.1% as a point estimate, the 50% range is 0.9% to 2.1%, and the 90% range is 0% to 3.8%. Again, these ranges easily contain the range of cost estimates of other groups represented in the CCSP exercise. Too much should not be made of differences in point estimates of cost studies using different models, as those differences likely reflect plausible judgments about a future where costs that are either fairly high or fairly low cannot easily be ruled out.

Another distinct feature of the uncertainty, in both carbon prices and global consumption losses, is that they are highly skewed, much more so than any of the input distributions or than the resulting uncertainty in emissions. This skewness indicates that the most likely cost will be in the low end of the range for that scenario, but that there is a small probability of extremely high costs under each constraint. This feature is the result of the fact that there are many more combinations of input assumptions that can make an emissions constraint relatively low-cost; for example slower growth or more rapid increases in energy efficiency or ease of substituting away from carbon-emitting energy inputs to production or relatively cheap low-carbon energy technologies. There are far fewer combinations of parameters that can lead to very high costs of abatement, but these cannot be ruled out based on the uncertainty in input assumptions used here.

[7] The only exception is the Level 1 (450) path in the initial period, where MiniCAM has a carbon price below our 90% range. For other time periods and other emissions paths, the ranges in this study encompass MiniCAM and MERGE results from Clarke *et al*. (2007).

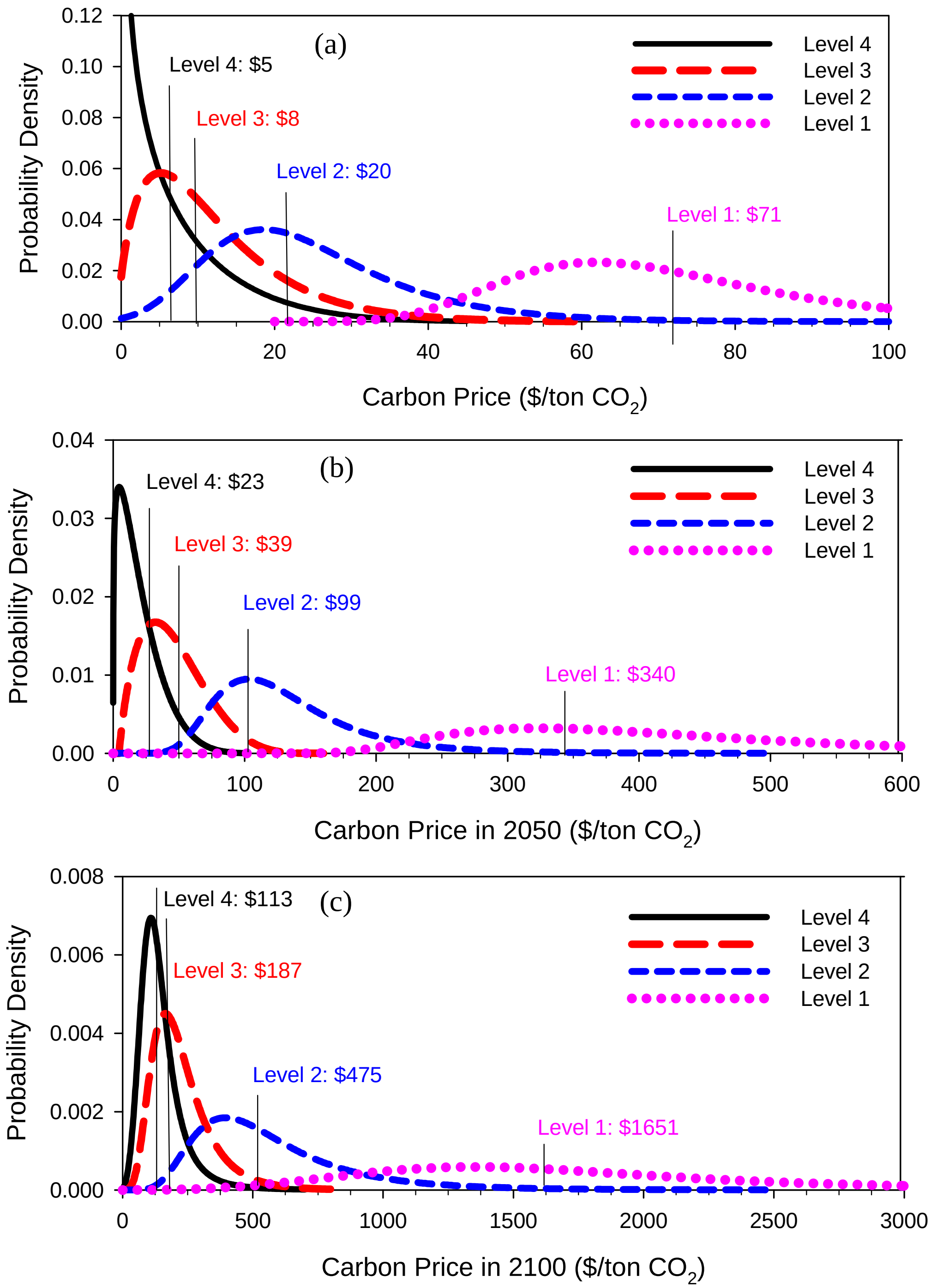


Figure 12. Probability density functions of carbon prices in (a) 2020, (b) 2060, and (c) 2100. The numbers shown indicate the values given as EPPA results in Clarke *et al*. (2007).

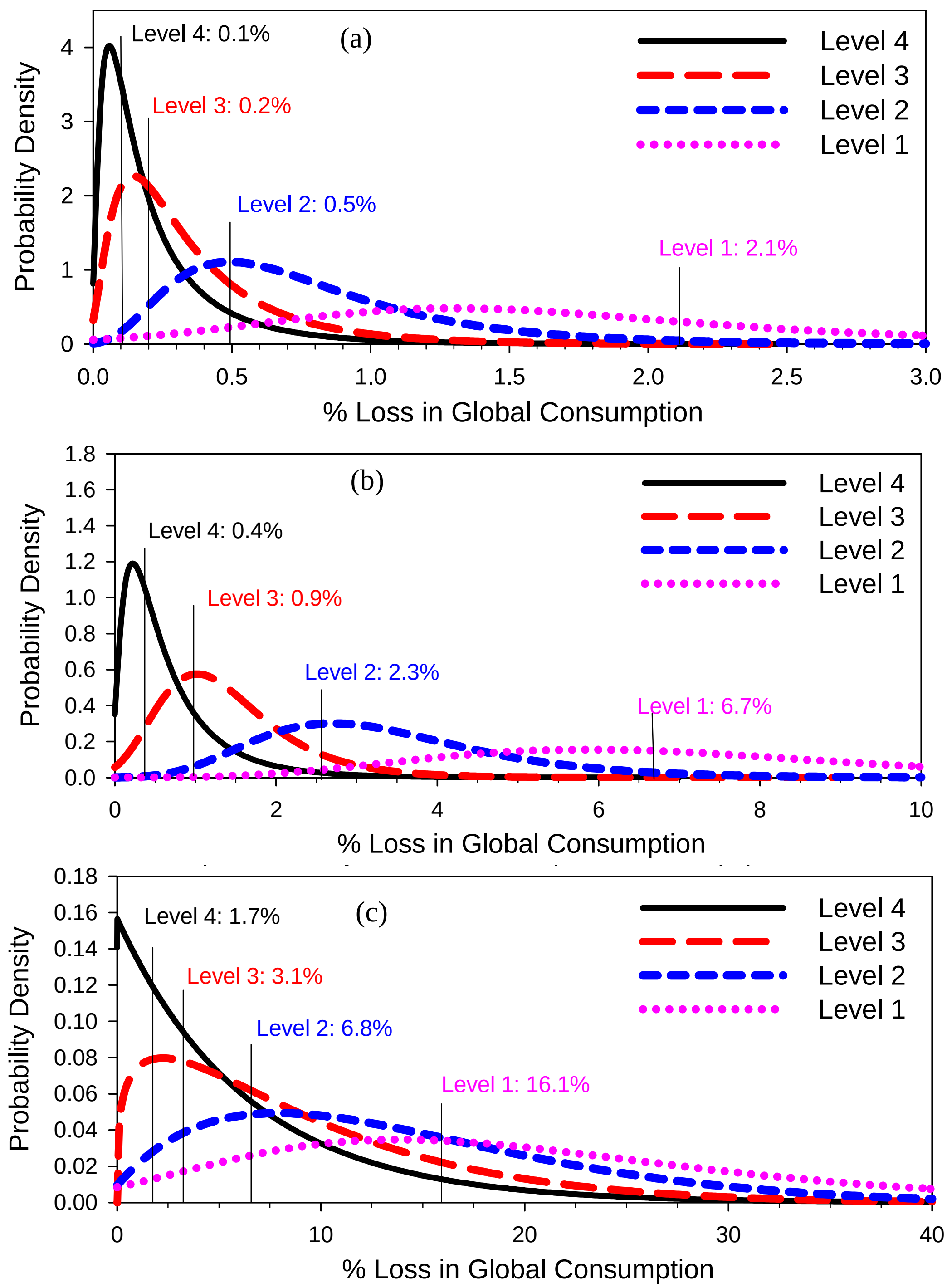


Figure 13. Probability density functions of global economic losses due to emissions reductions, measured as % change in consumption for the years (a) 2020, (b) 2060, and (c) 2100. The numbers indicate the values given as EPPA results in Clarke *et al*. (2007).

Finally, the spread of possibilities is very broad in the distant future especially under the tightest policy constraint case. Those looking for a precise projection of future costs, or to resolve whether a tight constraint is either clearly impractical or necessarily easily achievable, are likely to be disappointed that we can shed no more light on the issue. Indeed, we would recommend that any analysis giving a narrow range of future costs should be treated with great skepticism because of the severe limits to our ability to know or describe technology or other determinants of abatement cost over the long term.

3.3 Energy Consumption by Fuel and Technology

In addition to emissions (Section 3.1) and abatement costs (Section 3.2), the uncertainty in other projected quantities under reference and policy scenarios provide some insight into the possible future. One such set of quantities is the shares of different fuels and technologies in global energy consumption. In this section, we compare the uncertainty in energy consumption under two scenarios: the reference and the Level 2 (~550ppm) constraint.

Reductions of carbon dioxide are achieved both by switching to lower carbon sources of energy and by reducing the amount of energy consumed (both in production and final consumption). For example, in 2050, the global total of primary energy across all fuel sources had a mean of 910 exajoules (EJ) in the reference scenario and 671 EJ under the Level 2 scenario (see **Figure 14**), a 26% reduction. However, the total primary energy under both scenarios has a wide uncertainty range; the 90% probability bounds are 600-1300 EJ under the reference and 470-970 EJ under the Level 2 scenario. In addition, the amount of energy consumption reduced under the Level 2 constraint is uncertain, driven by the uncertainty in the ease of substituting energy for non-energy inputs to production and consumption as compared with the ease of substituting low- or non-carbon energy for carbon-based fuels. Thus the 90% probability range in the reduction in total primary energy in 2050 under the Level 2 constraint is 13% to 37%.

The remainder of the carbon reductions results from switching to lower carbon-emitting energy sources or from capturing and storing carbon. The sources of primary energy in EPPA are coal, conventional (crude) oil, natural gas, shale oil, nuclear, hydro, biofuels, and a composite of solar and wind energy[8]. The amount of primary energy from each of these sources is uncertain under both the reference and the Level 2 scenarios. **Figure 15** presents these uncertainties in the form of Tukey box plots, in which the box indicates the 50% probability range, the line within the box indicates the median value and the whiskers indicate the 95% range. There are notable shifts in the distributions of some fuels between the no policy and policy cases. For example, there is a dramatic reduction in primary energy from coal, falling from a 95% range of 190-500 EJ in the reference to a range of 80-250 EJ in the Level 2 case. In fact, the Level 2 constraints result in a reduction in primary energy from all fossil fuels: coal, oil, natural gas, and shale, as one would expect. The non-carbon sources all increase. However, only the increase in biofuels constitutes a significant increase in the share of total energy. The other increases in nuclear,

[8] EPPA does not distinguish between solar and wind (See Table 1), and uses a single production technology to represent total electricity from both sources.

hydro, and solar/wind are only a small increase in total share. Although natural gas and crude oil decrease under the Level 2 scenario in terms of physical energy units, their shares of the total energy actually increase. For example, the share of natural gas as a percentage of total primary energy in the reference case has a mean of 17% and a 90% range of 11-25%; its share under the Level 2 case is a mean of 20% and a 90% range of 14-28%. This is due to the much larger increases in coal and shale consumption over time in a no-policy economy. Coal is able to remain viable because of carbon capture and storage.

A related question is what is the uncertainty in the generation of electricity from different technology types, and how do these shares change under a policy constraint? The distinct electricity generation technologies in EPPA are conventional coal, refined oil, conventional natural gas, natural gas combined cycle (NGCC), natural gas combined cycle with carbon capture and sequestration (NGCAP), advanced coal-fired electricity generation with carbon capture and sequestration (IGCAP), nuclear, hydro, bioelectric, and composite solar/wind generation. The uncertainty range in the global electricity production from each technology in 2050 under the reference and Level 2 scenarios are shown in **Figure 16** as Tukey box plots. The Level 2 scenario results in dramatic reductions in conventional coal, oil, and natural gas generation. Most of this electricity is replaced with generation from coal and gas-fired generation with carbon capture and sequestration (NGCAP and IGCAP). There is also an increase in NGCC generation, but the uncertainty range is large in both scenarios, driven by uncertainty in the availability and therefore the price of natural gas, as well as the stringency of the emissions cap which is a function of economic growth rates. The Level 2 scenario also results in small increases in generation from nuclear, hydro, bio, and solar/wind, but these are not significant shifts. The precise mix of fuels and technology within each region, not shown here, will vary, and many regions have larger uncertainty ranges than the global aggregate shown in Figures 15 and 16.

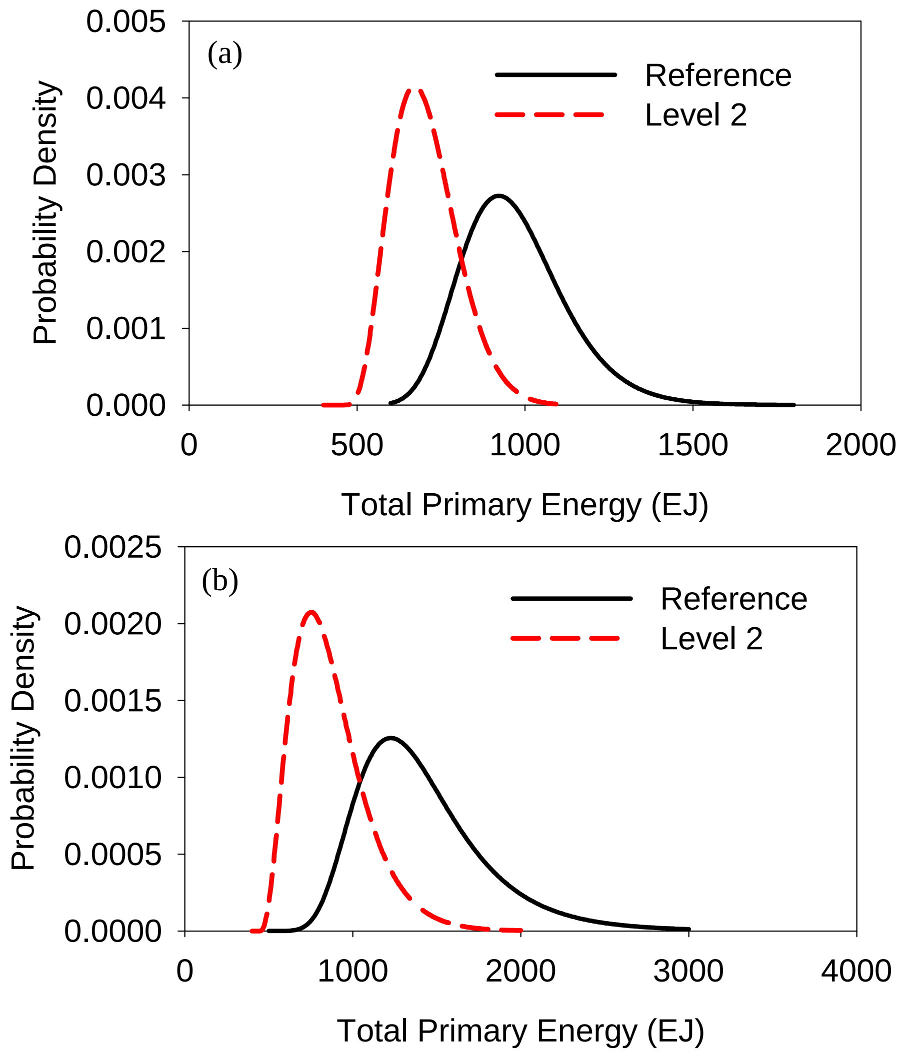


Figure 14. Probability density functions of global total primary energy (sum across all fuel types) in (a) 2050 and (b) 2100 under no policy and Level 2 stabilization.

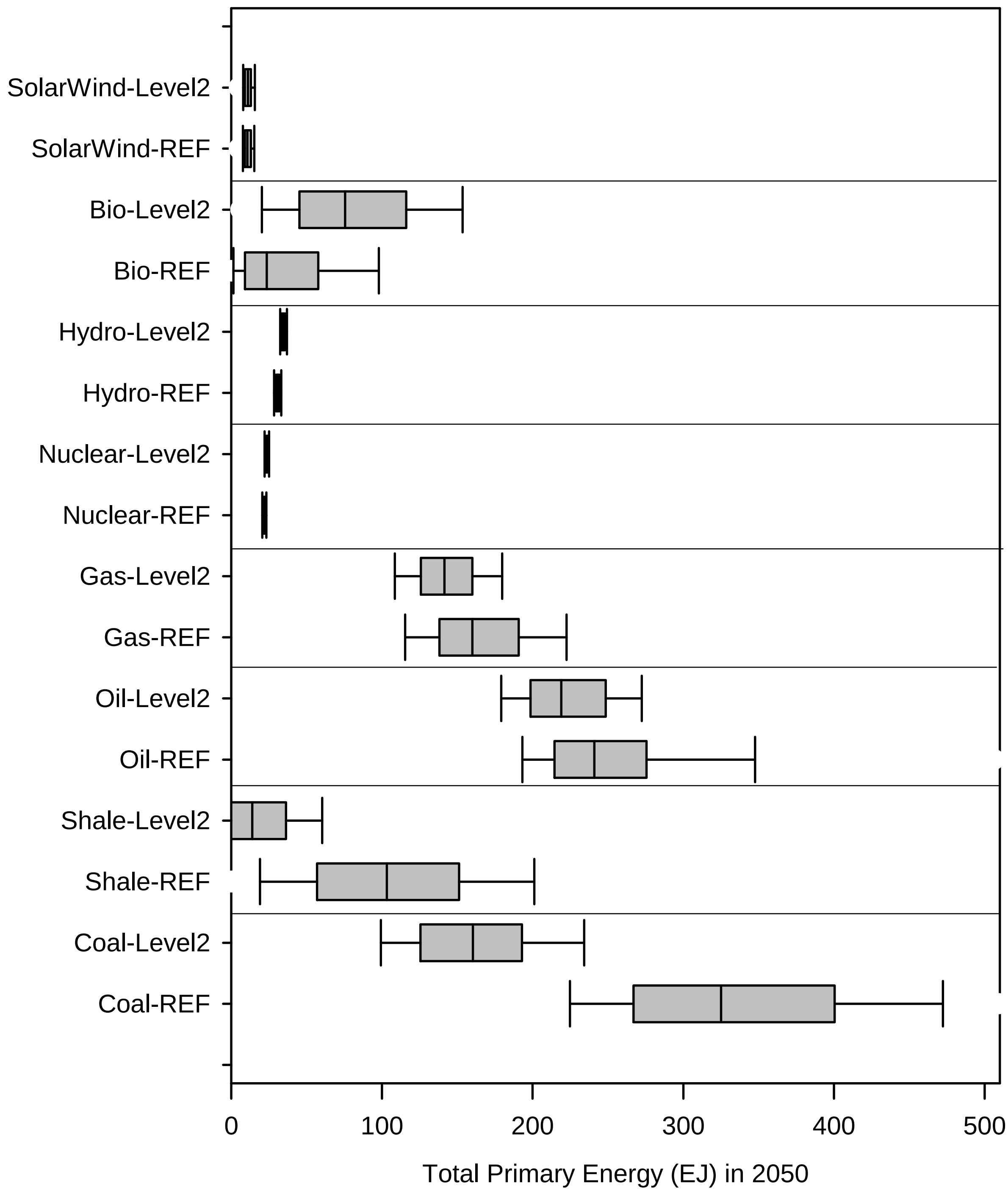


Figure 15. Uncertainty in global primary energy consumption by fuel in 2050. Each box indicates the 50% probability interval, the line inside the box indicates the median, and the whiskers indicate the 95% probability interval. Ranges are shown for energy consumption under No Policy (REF) and under the CCSP Level 2 (550ppm CO_2) policy case.

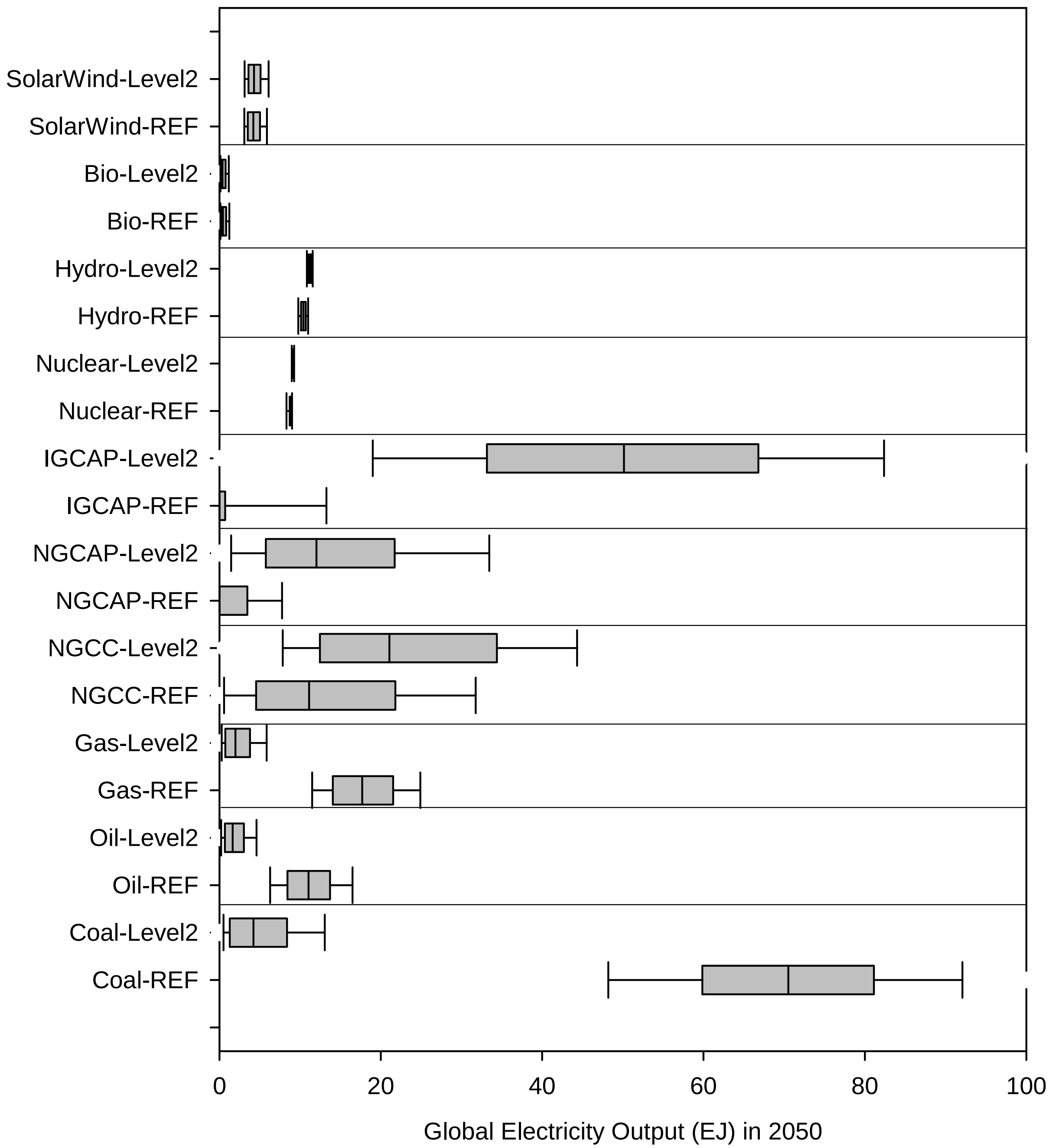


Figure 16. Uncertainty in global electricity production by technology type in 2050. Each box indicates the 50% probability interval, the line inside the box indicates the median, and the whiskers indicate the 95% probability interval. Ranges are shown for energy consumption under No Policy (REF) and under the CCSP Level 2 policy case. Coal, oil, and gas refer to conventional technologies, NGCC refers to natural gas combined cycle, NGCAP refers to natural gas combined cycle with carbon capture and storage, IGCAP refers to coal-fired integrated gasification combined cycle with carbon capture and storage, and Bio refers to bio-electric generation. Different technologies for generating electricity from solar and wind are not distinguished in EPPA.

3.4 Relative Contributions to Uncertainty

Uncertainty analysis can provide several types of useful information. In addition to quantifying the uncertainty in projections, as presented in sections 3.1-3.3, uncertainty analysis can also indicate which parameters are the primary drivers for uncertainty in projected outcomes. This information can be used to in setting priorities for research by identifying those inputs where a reduction in uncertainty would have the greatest impact on outcome uncertainty.

To calculate the percentage variance explained for each outcome, we perform analysis of variance (ANOVA) with the uncertain outcome (*e.g.,* CO_2 emissions) as the dependent variable and the samples of each parameter as the independent variables. The partial sum of squared errors (SSE) for each parameter is then divided by the total SSE to obtain the percentage. To simplify reporting, we sum the partial SSEs within the following groups of parameters:

- AEEI: all regions summed,
- Elasticity of substitution between fuels: all sectors summed,
- Elasticity of substitution between capital and labor: all sectors summed,
- Methane abatement elasticities: all regions summed,
- Nitrous oxide abatement elasticities: all regions summed,
- Oil and natural gas resource availability summed,
- Urban pollutant trends summed across gases,
- Urban pollutant initial emissions summed across gases,

In addition, the labor productivity growth rate samples vary by region and time, so to create a single measure of the aggregate input uncertainty, we calculate the ratio of global aggregate GDP in 2100 to the GDP in 2000. This ratio is the independent variable representing GDP growth uncertainty.

We also present the results in a more aggregated form. We combine the sum-squared-errors explained by parameters into four groups: "Energy Supply" sums the effects of all parameters related to advanced technology costs, penetration rates, and fossil resource availability and supply price elasticities. "Energy Demand" sums the effects of all substitution elasticities, AEEI in all regions, and vintaging. "Scale of Economy" sums the effects of GDP and population growth. All other parameter effects are aggregated in "Other".

The results for cumulative global CO_2 emissions (2000-2100) under the reference case are shown in **Figures 17** and **19**, and the results for the carbon price under the Level 2 (550ppm) stabilization case in 2020, 2060, and 2100 are shown in **Figures 18** and **20**. Which parameters most influence uncertainty in outcomes depends on the outcomes of interest. One important outcome is cumulative emissions in the absence of policy. The variance in long-run emissions absent climate policy is mainly explained by energy supply uncertainties (38%) and energy demand uncertainties (14%) (Figure 17). In terms of individual parameters, the five most important drivers of long-run uncertainty in emissions are 1) the supply elasticity of coal, which determines coal prices, 2) AEEI, which over the century significantly determines the total energy demand, 3) the elasticity of substitution between energy and non-energy (labor and capital) inputs to production, 4) the markup cost of shale, which determines when it is cost-competitive with conventional fuels, and 5) GDP growth over the century (Figure 19). These five account for 53% of the total variance explained.

One of the key differences in this result compared with past studies (*e.g.,* Webster *et al*., 2002; Nordhaus and Yohe, 1983, Reilly *et al*., 1987) is that GDP growth, while still more important than many other parameters, is not the primary driver of uncertainty in emissions (only 6% of variance in emissions explained). This change is a result of the new approach of generating GDP growth paths using a random walk, and of the assumption that growth shocks are not correlated across countries. As we noted earlier, our new approach uses evidence on variations in actual GDP growth as a basis for our projections about uncertainty and obtains from that the implications for global growth over the century as this is what matters for GHG concentrations. It doesn't matter much for the atmosphere whether it is China that grows rapidly or the US, or if neither grow rapidly but instead growth occurs in Russia, Latin America, or the Middle East. We would argue that previous estimates of variation in global rates of growth over the century were based on expert judgment that assessed growth rates over a similar period but failed to fully account for how swings from year to year or decade to decade or balancing of varying prospects among countries leads to a relatively smaller range in global growth. Our findings do not show that GDP is a less important driver of emissions growth than others have suggested but rather that, at the global level, past work may have overestimated the range of uncertainty.

With GDP uncertainty less important in explaining the range of future emissions other variables more closely related to the energy sector emerge as the primary drivers of uncertainty in no-policy carbon emissions. These include technological change, both price driven (*e.g.,* elasticity of substitution) and non-price driven (*e.g.,* AEEI), and the total fossil resources available, particularly coal and shale.

The result that the elasticity of coal supply with respect to price is an important driver of uncertainty in no-policy carbon emissions also is somewhat surprising as the general presumption has been that coal is widely available and so supply factors are not important. The elasticity range is supported in the literature and is based on econometric evidence as we earlier discussed. In fact, with all other EPPA parameters at reference/median levels, varying only this supply elasticity has only a weak effect on global CO_2 emissions. That result embodies the conventional wisdom for coal supply. Knowing this, the emergence of this parameter as important in the uncertainty analysis was initially a puzzle. Further investigation showed that the significant contribution to uncertainty of this parameter comes through its interaction with other uncertainties. As any of several other parameters — including AEEI, elasticities of substitution between energy and non-energy, and interfuel substitution elasticities — take on values that lead to higher-carbon emitting economies, the coal supply elasticity parameter becomes influential in determining how much of the abundant coal resources are used, relative to alternative energy sources. Thus, within the range of supply elasticities in the literature there is a question of whether coal supply would easily keep up with demand (under admittedly somewhat extreme demand conditions but ones that cannot be easily ruled out.) The broader implication of this finding is the need for caution in ruling out some parameters are not important based on sensitivity tests around median values of other parameters as the importance may only show up when other values are outside what is considered their normal values.

Different subsets of assumptions drive the uncertainties in the costs of policies, and the parameters that matter most depend on whether one considers effects in the near-term (*e.g.,* 2020), medium-term (*e.g.,* 2050) or long-term (*e.g.,* 2100). One interesting result that is consistent across time horizons is that despite significant uncertainty over future technologies for energy supply, demand determinants dominate the uncertainty in carbon prices (Figure 18). In fact, by 2100, the uncertainty in carbon prices are almost entirely driven by energy demand and economic scale uncertainties, with energy supply accounting for only 1% of the variance in carbon prices. In this regard, it is important to remember that this result does should be interpreted to mean that supply considerations are not important but rather that they contribute less to explaining uncertainty. In part, this may reflect a model structure that is more disaggregated on the supply side so that while any one supply technology is uncertain, this result indicates that there are enough different options such that even if some end up more costly there are others that can fill in.

In terms of specific parameters that drive the results, CO_2 prices over all time horizons depend most strongly on the elasticity of substitution between energy and non-energy inputs to production. The uncertainty in carbon prices in 2020 also is sensitive to uncertainty in the cost markup factors for natural gas combined cycle and liquid fuels from biomass, AEEI, and the supply elasticity of oil. GDP growth is not as important as a driver of near-term carbon prices. The markup costs of liquid fuels from biomass and of liquid fuels from shale, GDP growth, and the oil supply elasticity are the additional critical drivers of uncertainty in carbon prices over longer time horizons (2060 and 2100).

Some of the uncertainties are likely to remain so and others may be resolved with time. GDP growth, for example, likely will always remain uncertain from whatever point one makes new projections; in 2050 we will know what economic growth was from 2008-2050, but will still have considerable uncertainty about what the rates will be for 2051-2150. Others, such as the costs of alternative technologies, may be better resolved through additional research and demonstration and eventually if they become commercial. They may still be subject to price shocks and changes in resource and technology but the large uncertainties with technologies that have not operated at commercial scale will be resolved. Still other assumptions may experience a shift over time in the mean or median estimate as technologies change, such as the ease of substituting inputs in production. A complete analysis of the value of information for reducing uncertainty would require, in addition to the results here, information on the supply side of uncertainty reduction, *i.e.* how much uncertainty can be reduced at what cost. Such an analysis is beyond the scope of this study.

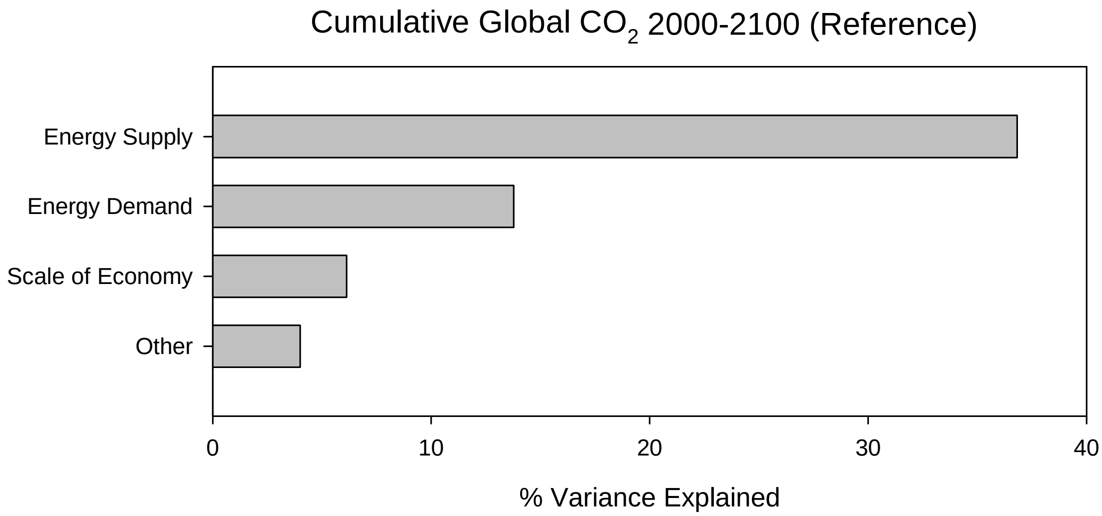


Figure 17. Percentage of variance in cumulative global CO_2 emissions under the reference case explained by each group of uncertain parameters. The percentage variance is calculated as the ratio of the partial sum of squared errors to the total sum of squared errors from the results of an Analysis of Variance (ANOVA). "Energy Supply" sums the effects of all parameters related to advanced technology costs, penetration rates, and fossil resource availability and supply price elasticities. "Energy Demand" sums the effects of all substitution elasticities, AEEI in all regions, and vintaging. "Scale of Economy" sums the effects of GDP and population growth. All other parameter effects are aggregated in "Other".

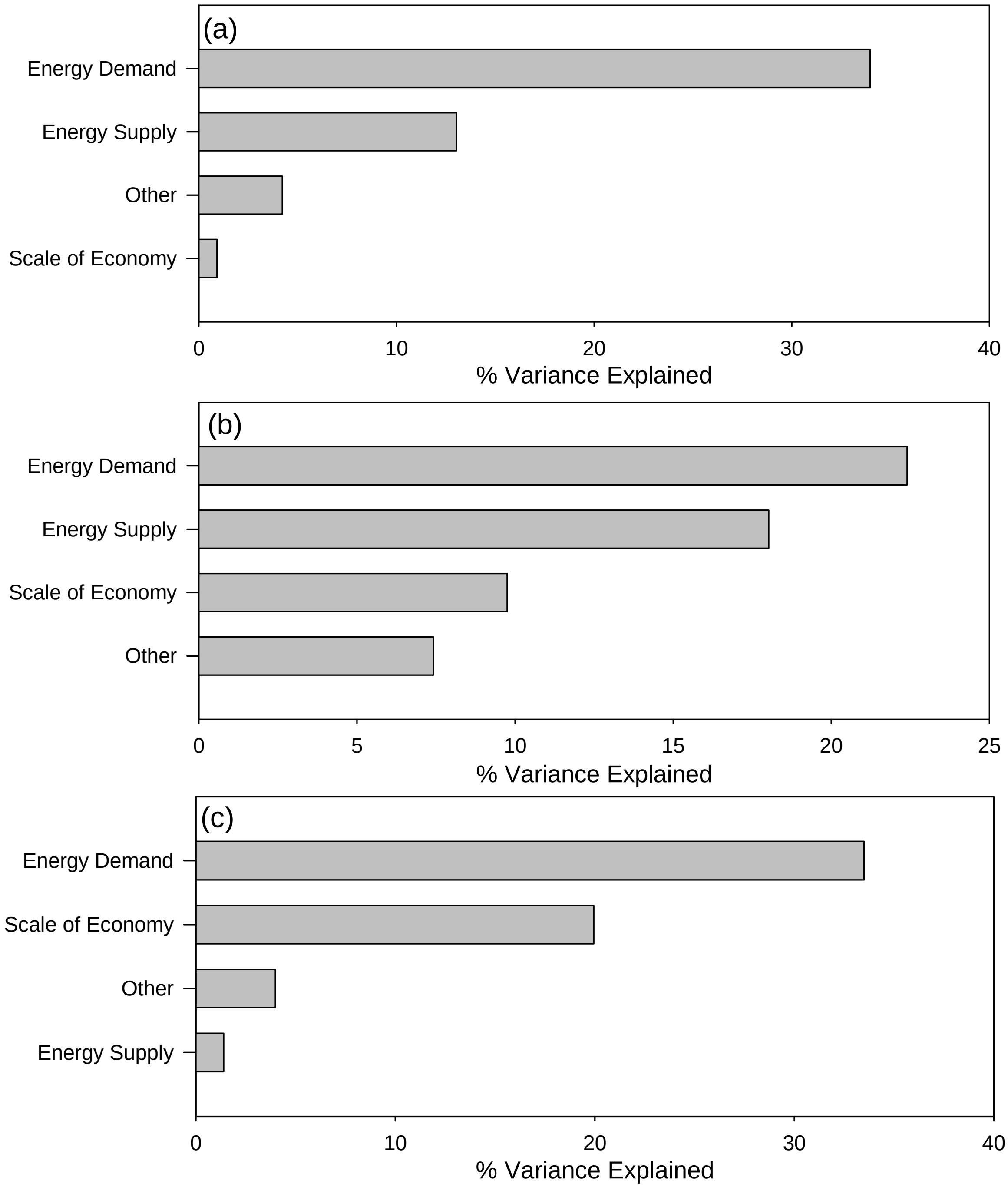


Figure 18. Percentage of variance in carbon prices under the Level 2 (550ppm) scenario explained by each group of uncertain parameters. The percentage variance is calculated as the ratio of the partial sum of squared errors to the total sum of squared errors from the results of an Analysis of Variance (ANOVA). "Energy Supply" sums the effects of all parameters related to advanced technology costs, penetration rates, and fossil resource availability and supply price elasticities. "Energy Demand" sums the effects of all substitution elasticities, AEEI in all regions, and vintaging. "Scale of Economy" sums the effects of GDP and population growth. All other parameter effects are aggregated in "Other".

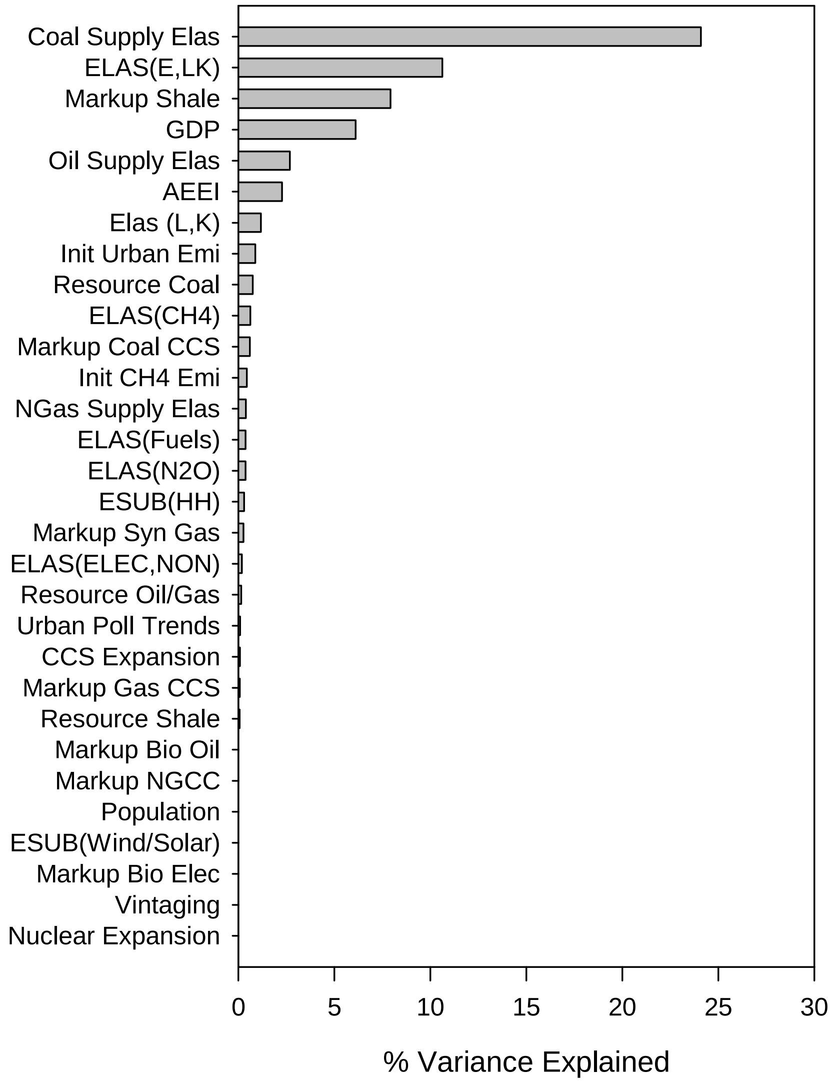
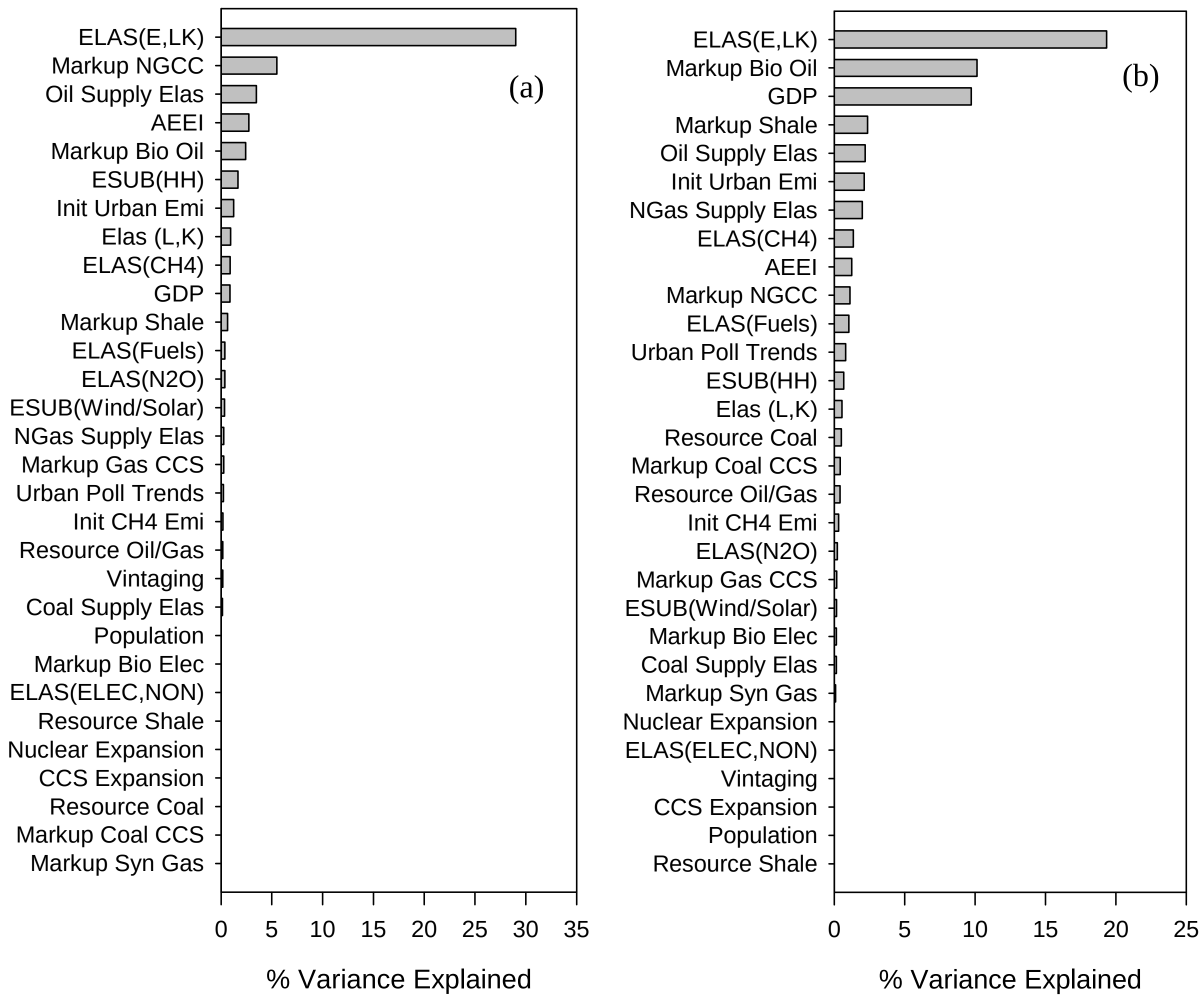


Figure 19. Percentage of variance in cumulative global CO_2 emissions under the reference case explained by each uncertain parameter. The percentage variance is calculated as the ratio of the partial sum of squared errors to the total sum of squared errors from the results of an Analysis of Variance (ANOVA).


(a)
ELAS(E,LK)
Markup NGCC
Oil Supply Elas
AEEI
Markup Bio Oil
ESUB(HH)
Init Urban Emi
Elas (L,K)
ELAS(CH4)
GDP
Markup Shale
ELAS(Fuels)
ELAS(N2O)
ESUB(Wind/Solar)
NGas Supply Elas
Markup Gas CCS
Urban Poll Trends
Init CH4 Emi
Resource Oil/Gas
Vintaging
Coal Supply Elas
Population
Markup Bio Elec
ELAS(ELEC,NON)
Resource Shale
Nuclear Expansion
CCS Expansion
Resource Coal
Markup Coal CCS
Markup Syn Gas
0 5 10 15 20 25 30 35
% Variance Explained
(b)
ELAS(E,LK)
Markup Bio Oil
GDP
Markup Shale
Oil Supply Elas
Init Urban Emi
NGas Supply Elas
ELAS(CH4)
AEEI
Markup NGCC
ELAS(Fuels)
Urban Poll Trends
ESUB(HH)
Elas (L,K)
Resource Coal
Markup Coal CCS
Resource Oil/Gas
Init CH4 Emi
ELAS(N2O)
Markup Gas CCS
ESUB(Wind/Solar)
Markup Bio Elec
Coal Supply Elas
Markup Syn Gas
Nuclear Expansion
ELAS(ELEC,NON)
Vintaging
CCS Expansion
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Resource Shale
0 5 10 15 20 25
% Variance Explained

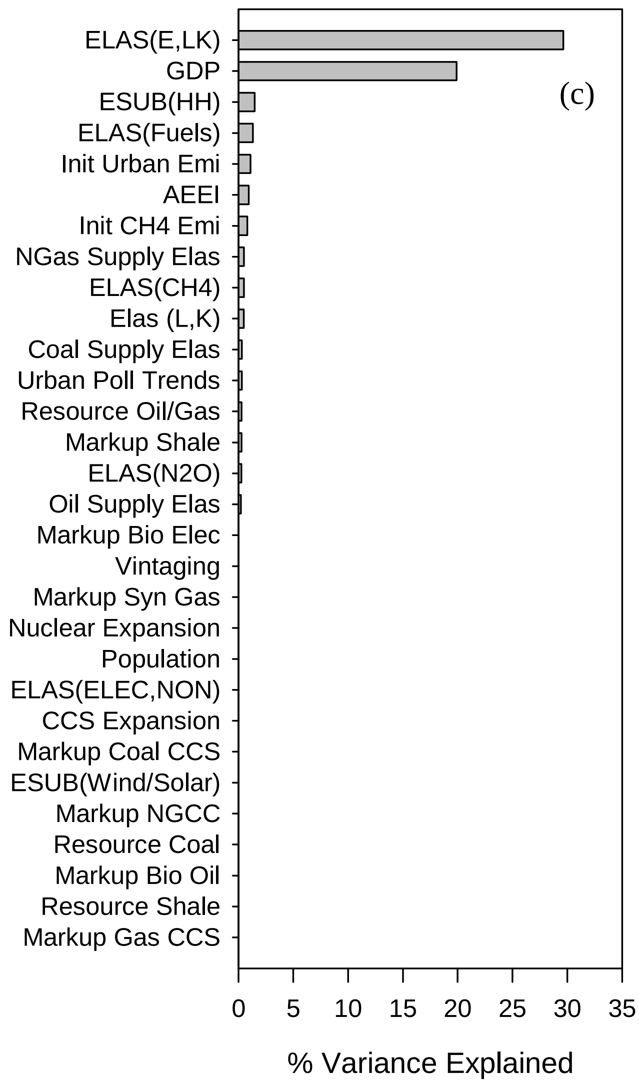

Figure 20. Percentage of variance in carbon prices in (a) 2020, (b) 2060, and (c) 2100 under the Level 2 (550ppm) stabilization case explained by each uncertain parameter. The percentage variance is calculated as the ratio of the partial sum of squared errors to the total sum of squared errors from the results of an Analysis of Variance (ANOVA).

3.5 Comparison with Previous Uncertainty Analysis Results

It is useful to compare the results of this study with those of an exercise conducted using an earlier version of the EPPA model as reported in Webster *et al*. (2002). The differences between Webster *et al*. (2002) and the present study include (1) added detail and improvements to the EPPA model (Paltsev *et al*., 2005), (2) additional uncertain parameters treated, and (3) new probability distributions for many uncertain parameters, including the treatment of GDP growth and of future trends for non-greenhouse gas pollutants (*e.g.,* SO_2).

In **Figure 21**, we compare the 90% probability bounds on global CO_2 emissions under the no policy scenario between the current and previous studies. The upper bounds are very similar between the two studies: 36.9GtC in 2100 here vs. 35.8GtC in 2100 in Webster *et al*. (2002). The largest difference between the results is that the lower 90% bound in the new study (14.5GtC in 2100) is significantly higher than the previous lower bound (6.5GtC in 2100), and the median emissions level is now also higher (22.0GtC vs. 18.0GtC in 2100). There are two causes of this difference in the CO_2 emissions uncertainty results. First, the previous work was not normalized to its reference and had a median in the uncertainty analysis that was significantly lower than its reference. The reference CO_2 emissions in EPPA v3 is 22.9GtC in 2100, and the reference emissions in EPPA v4 is 22.4GtC in 2100. Second, the range of GDP growth at the global level is far narrower because of the new approach of representing stochastic growth at the regional/country level. It appears that the main effect of this is to pull in the lower tail, with energy supply and demand factors continuing to provide uncertainty on the high side. This study has a 90% range of global GDP growth over 2000-2100 of 2.2%-2.6% (Table 5), while the previous study had a range of 1.7%-2.5%. The impact of the improvement in methodology is to significantly reduce the likelihood of very low-growth samples, resulting in fewer low-emissions samples. The elimination of very low-emissions samples also has the effect of raising the mean and median CO_2 emissions, which are now close to the EPPA reference case emissions.

Uncertainty in sulfur emissions are compared in **Figure 22**. For SO_2, the biggest change is also to the lower bound and median cases, while the upper 90% bounds are very similar. In this case, we believe the change is largely due to the new approach to long-run emissions trends in non-greenhouse gas emissions. The methodology in Webster *et al*. (2002) led to no cases where global SO_2 emissions decreased over the 21st century. The new approach (see Section 2) builds on recent work showing that a median projection would have global SO_2 emissions falling by the second half of the next century. Our new range reflects uncertainty around the new expected trend. The result is a significantly higher likelihood of very low sulfur emissions by the end of the century—overall the uncertainty range is much wider so it does not rule out higher scenarios present in the previous analysis but the new median is by 2100 actually somewhat lower than the previous lower 90% probability bound.

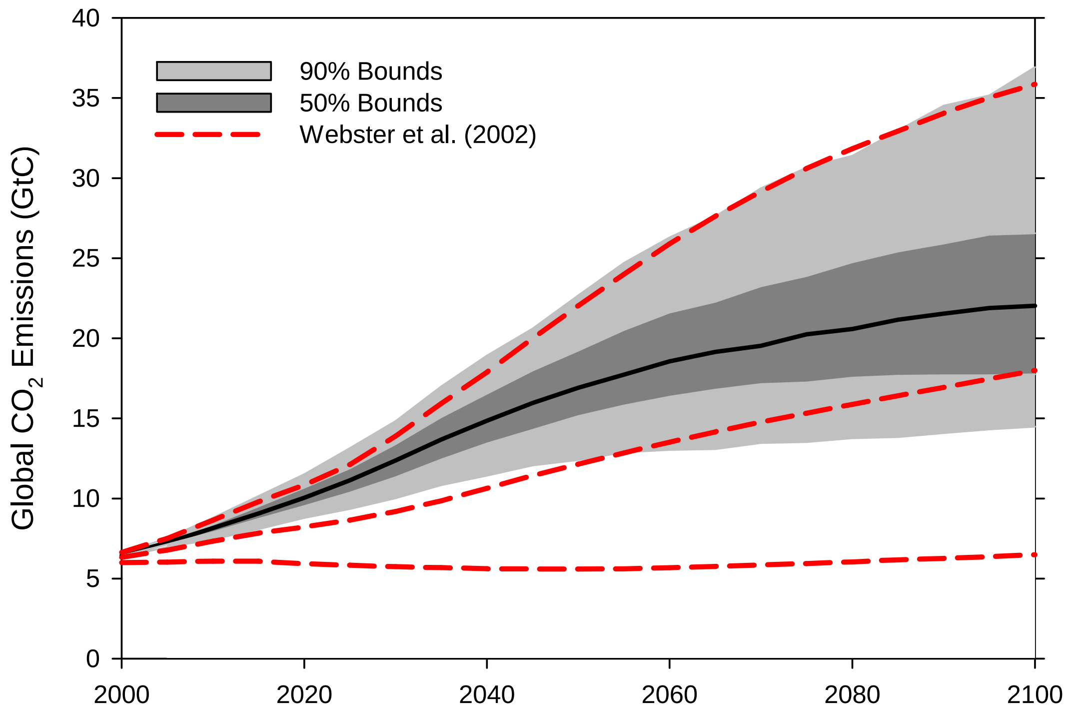

Figure 21. Comparison of 90% bounds on global CO_2 no-policy emissions between current study (shaded area) and Webster *et al*. (2002) (red dashed line).

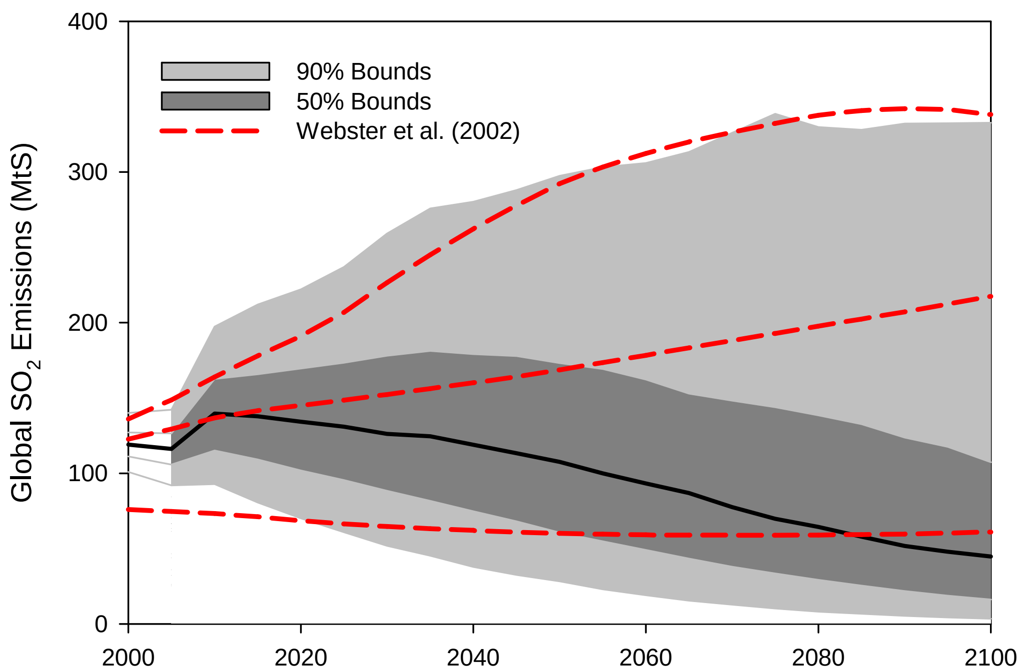

Figure 22. Comparison of 90% bounds on global SO_2 no-policy emissions between current study (shaded area) and Webster *et al*. (2002) (red dashed line).

Although it is beyond the scope of this analysis to study the effects of the uncertain emissions on the physical earth system, it is worth noting that these two major changes in our uncertainty in no-policy emissions are to shift the distribution of global mean surface temperatures upward. The changes in the distribution of CO_2 emissions are likely to contribute to a lower likelihood of relatively small increases in temperature and to shift the median upward. Similarly, because SO_2 has a negative radiative forcing effect, a higher likelihood of low SO_2 emissions samples is likely to shift the overall distribution toward larger temperature increases. The quantification of these effects requires a similarly rigorous uncertainty analysis of an earth system model, which is a companion analysis (Sokolov *et al*., 2008)).

4. DISCUSSION

This paper has presented an analysis of uncertainty in projections of emissions and costs under no climate policy and under four GHG concentration stabilization targets. Such quantitative descriptions of uncertainty are a useful input into the consideration of alternative stabilization targets. Projections differ in their purpose and it is important to be clear about their design and the uses intended for the results. Unfortunately the results of scenario exercises are often used for other than their intended purpose. For example, the IPCC SRES scenarios were not intended to be interpreted in terms of likelihood, but they have nonetheless come to be viewed in these terms.

The study reported here was designed to be interpreted in terms of likelihood, where the likelihoods are conditioned on specific policy assumptions. In particular, the exercise asks the question: If the world proceeds along an industrial, agricultural, and energy development path *without consideration of the climate consequences* what level of GHG and related pollutant emissions are likely over the next century? Taking these reference, *i.e.* “no policy”, scenarios and running them through a climate modeling system we can then answer the question of how much climate change we might expect in the absence of climate policy. Given that the risks imposed by proceeding in that way may be unacceptable we then suppose four different policy scenarios, assuming they can be implemented with certainty, to explore the range of costs associated with meeting each of the associated emissions targets, *given more or less ideal implementation*. Running these scenarios through an earth system model, taking account of uncertainty in the response of that system, we can then assess how these constrained emissions scenarios will reduce the risks of exceeding critical thresholds. In this way, we hope to contribute to the debate about what level of emissions control is desirable or feasible — providing information on mitigation to be weighed against the benefits in terms of reduced climate change risk.

As constructed, none of the five ensemble sets are an unconditional projection of what will happen nor are any of them a “business-as-usual” path. An unconditional projection would include some estimate of how, as climate change proceeded, the world would respond to that information and (likely) abate emissions. Some analyses assume an optimal weighing of costs and benefits to reflect a behavioral response. Given the problems of negotiating a solution (or evaluating economic damages) the optimal response is extremely uncertain and even if we could know what it was it seems unlikely that the world could agree to the necessary policy. Other, more *ad hoc* behavioral assumptions are obviously possible — perhaps with a weighting by an expert judgment of the likelihood of different levels of abatement. For example, experts might attach a 10% likelihood of no policy, a 20% likelihood of the tightest policy, etc. If the question is how much climate damage should one prepare for, then an exercise that includes an estimate of how much abatement we might undertake should be included.

Regarding "business-as-usual" there are now various climate policies and mitigation goals that have been adopted and many business decisions are being made on the expectation of implementation of additional policies. A true business-as-usual scenario would need to include a continuation of such policies. Just how to deal with the wide variety of policies measures some of which are very precise—e.g. the European Trading Scheme—others less so or as yet not fully specified such as the California emissions goals is a further design decision in a uncertainty or scenario exercise. Still another exercise might be to ask, given a particular emission goal how might political considerations lead to less than ideal implementation and, in so doing, raise the cost of implementation. This would require a set of judgments about how real policies might diverge from the idealized policies we have implemented as well as judgment about how failure to engage important parties would be reconciled with the emissions target.

All of these different approaches to scenario analysis and uncertainty analysis are useful in answering particular questions. We raise them here to make clear that the design of our exercise is useful for answering some specific questions, but much work remains to answer other questions.

Given the design of our exercise several key findings emerge. In terms of global CO_2 emissions our no-policy ensemble suggests that most of the lower IPCC SRES scenarios are unlikely unless there are specific climate policies. The SRES scenarios were not designed to represent a particular probability space but to span the range of scenarios in the literature, some of which likely included, at least implicitly, specific concerns about climate change. Despite warnings to the contrary in the SRES documentation, a popular interpretation of the scenarios often appears to be that they span a likely range in the absence of policy and that the middle of the range is what one might expect to be a median case. The interpretation is informal but has perhaps been encouraged by some uses of these scenarios (*e.g.,* Wigley and Raper, 2001). Recent debate about the fact that they are too low (*e.g.,* Pielke Jr. *et al*., 2008) is a further attempt to suggest they are unrepresentative of the most likely evolution of global emissions, but since they were not designed to represent explicitly a likely range that charge should be leveled against the design criteria rather than the scenarios themselves.

A major reason for our higher range of global CO_2 emissions compared to earlier work with the EPPA model (Webster *et al*., 2002) is an improved treatment of GDP growth uncertainty. Another consequence of this improvement is that GDP growth is a less important driver in emissions uncertainty than had been concluded by our previous studies. We have also presented the uncertainty in carbon prices and welfare losses due to atmospheric stabilization targets.

Despite concerns over the significant uncertainty in future supply technologies, we find that the uncertainty in carbon prices are far more sensitive to parameters that determine energy demand, primarily through price-driven (elasticities of substitution) and non-price driven (AEEI) technological change. In particular, the single most influential parameter on carbon price uncertainty is the elasticity of substitution between energy and non-energy (labor and capital) inputs to production. This suggests that research aiming to reduce the uncertainty in the costs of greenhouse gas mitigation should include efforts to better characterize demand side processes.

Acknowledgments

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APPENDICES

APPENDIX A. HISTORICAL AND PROJECTED GDP PER CAPITA GROWTH RATES BY REGION

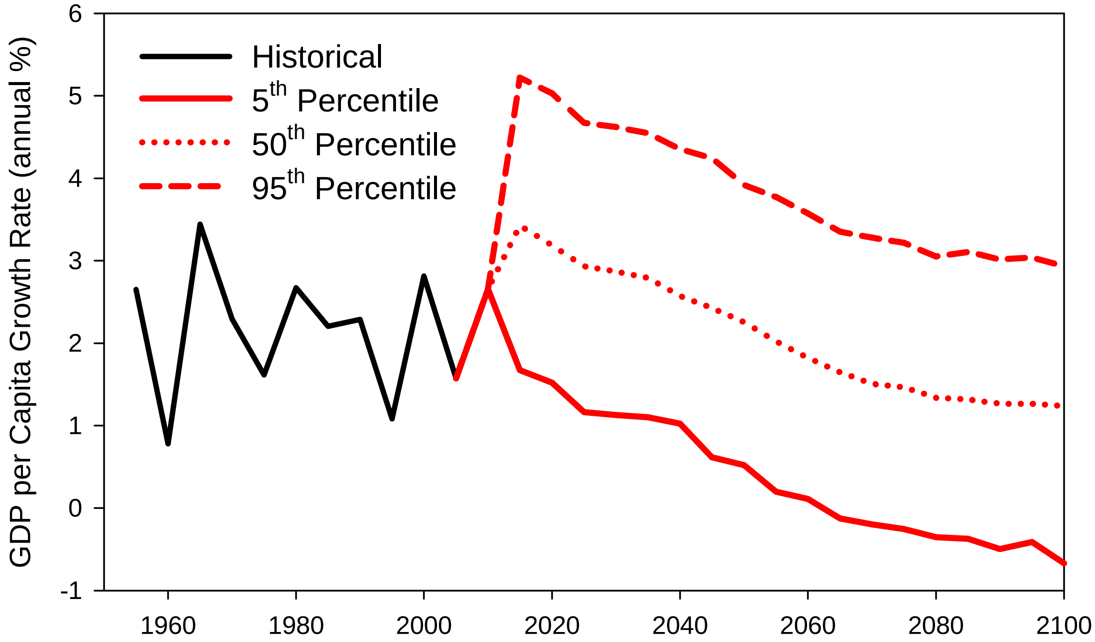

Figure A1. GDP per capita growth rates for U.S.

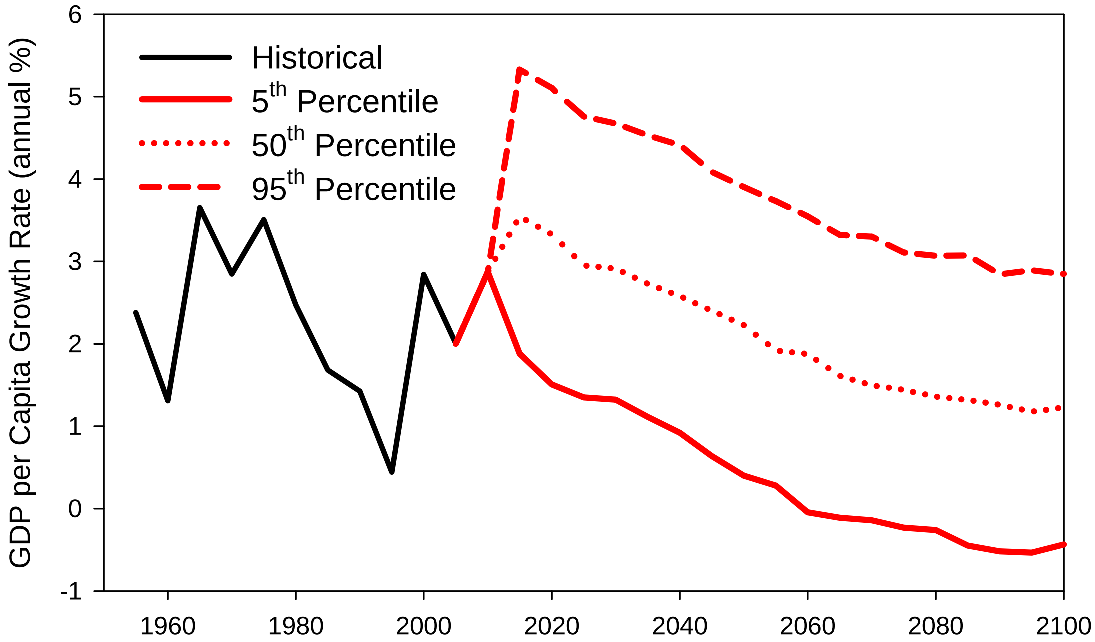

Figure A2. GDP per capita growth rates for Canada (CAN).

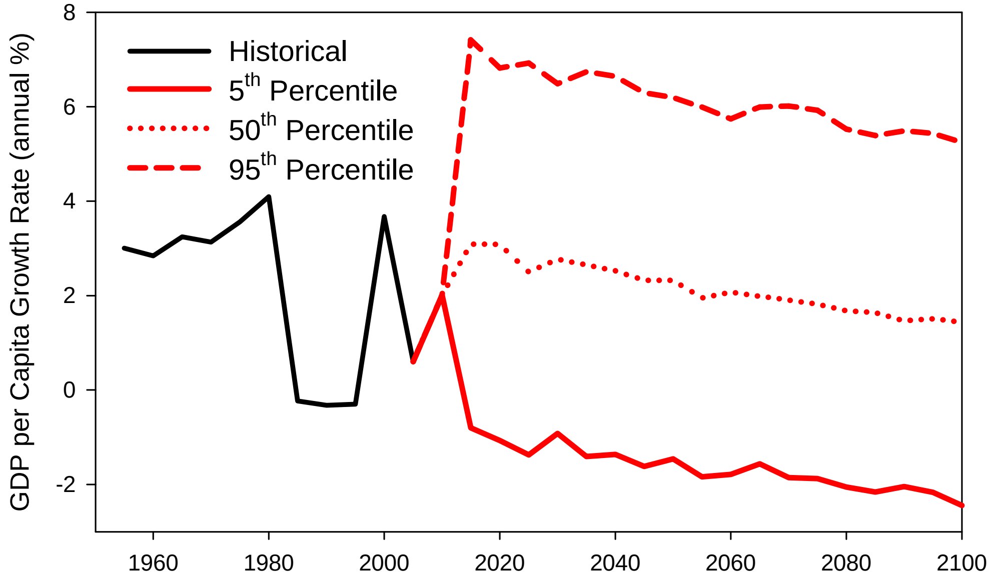

Figure A3. GDP per capita growth rates for Mexico (MEX).

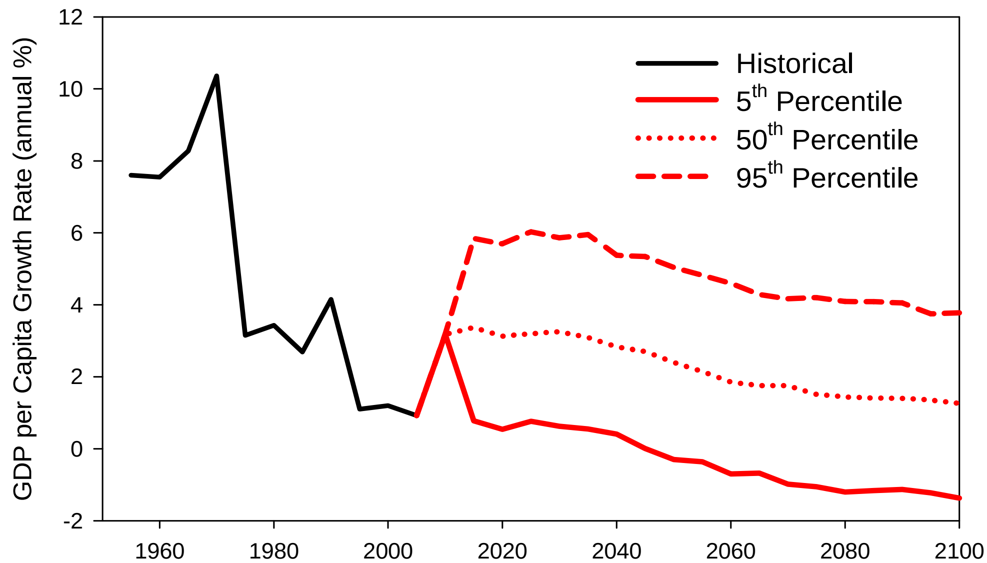

Figure A4. GDP per capita growth rates for Japan (JPN).

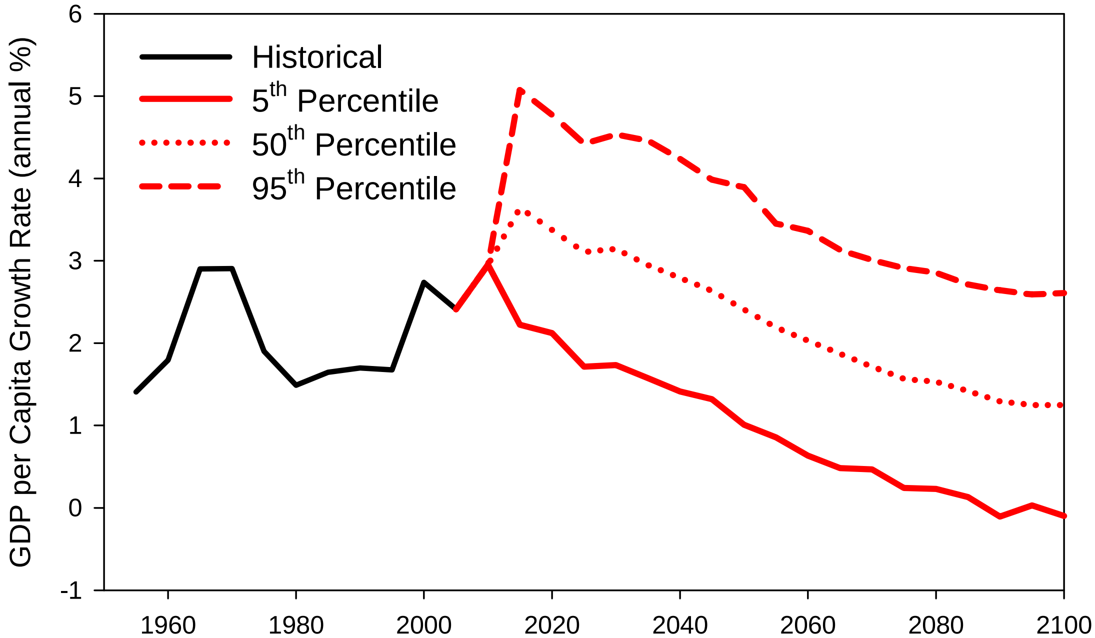

Figure A5. GDP per capita growth rates for Australia/New Zealand (ANZ).

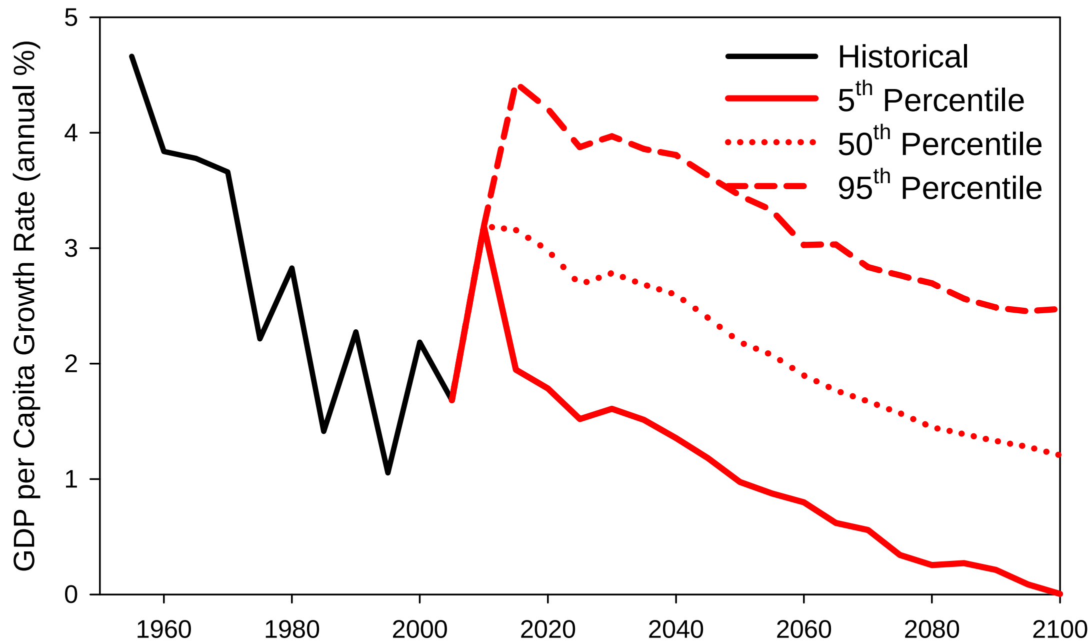

Figure A6. GDP per capita growth rates for Europe (EUR).

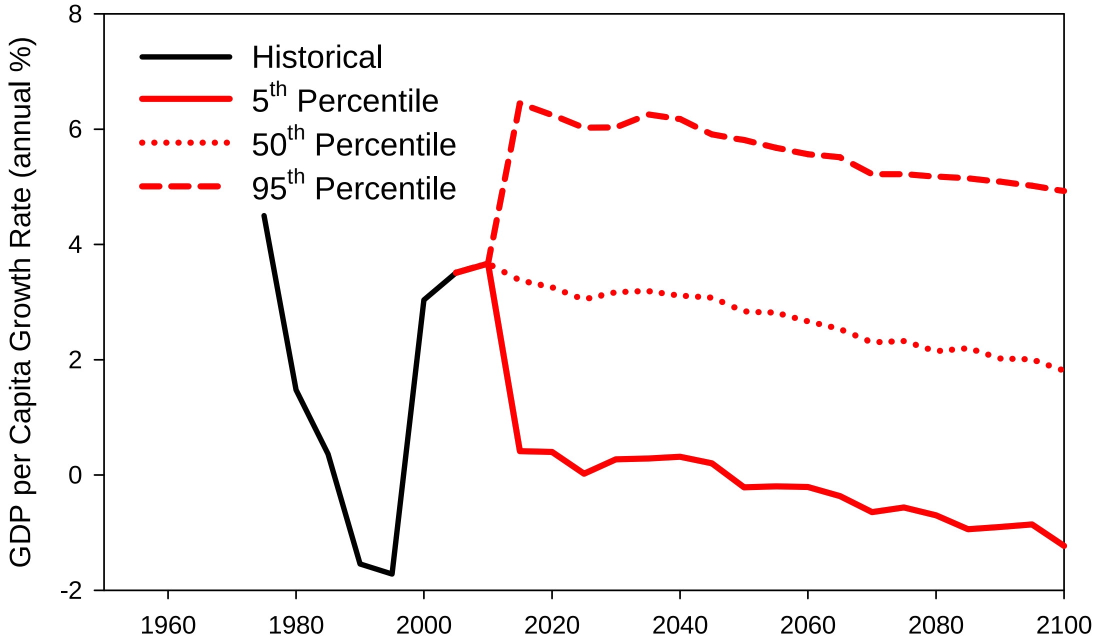

Figure A7. GDP per capita growth rates for Eastern Europe (EET).

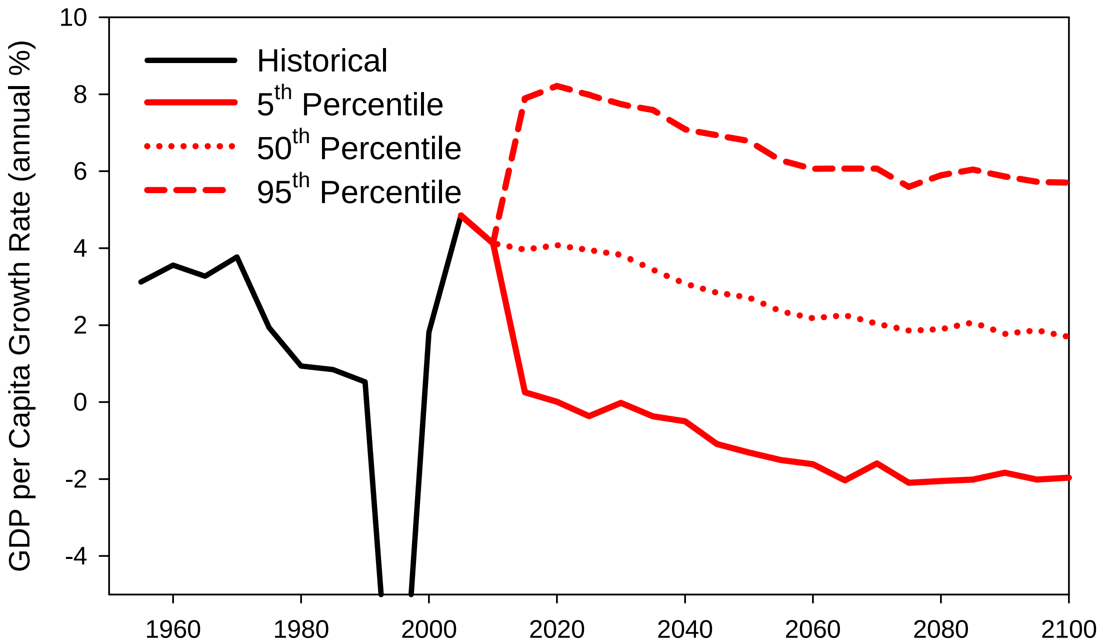

Figure A8. GDP per capita growth rates for Former Soviet Union (FSU).

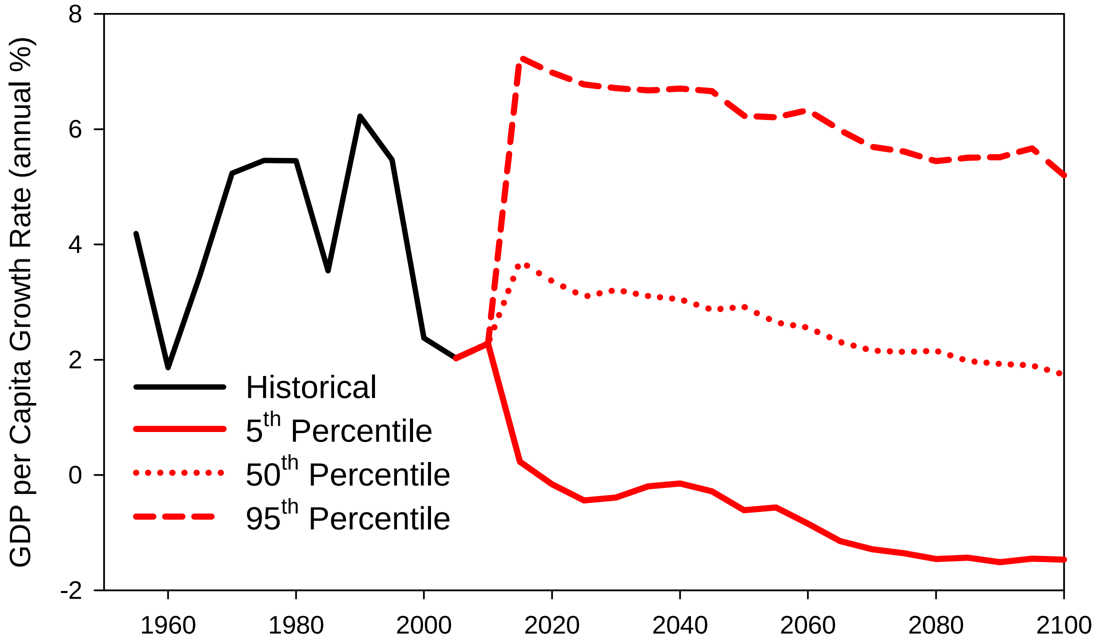

Figure A9. GDP per capita growth rates for East Asia (ASI).

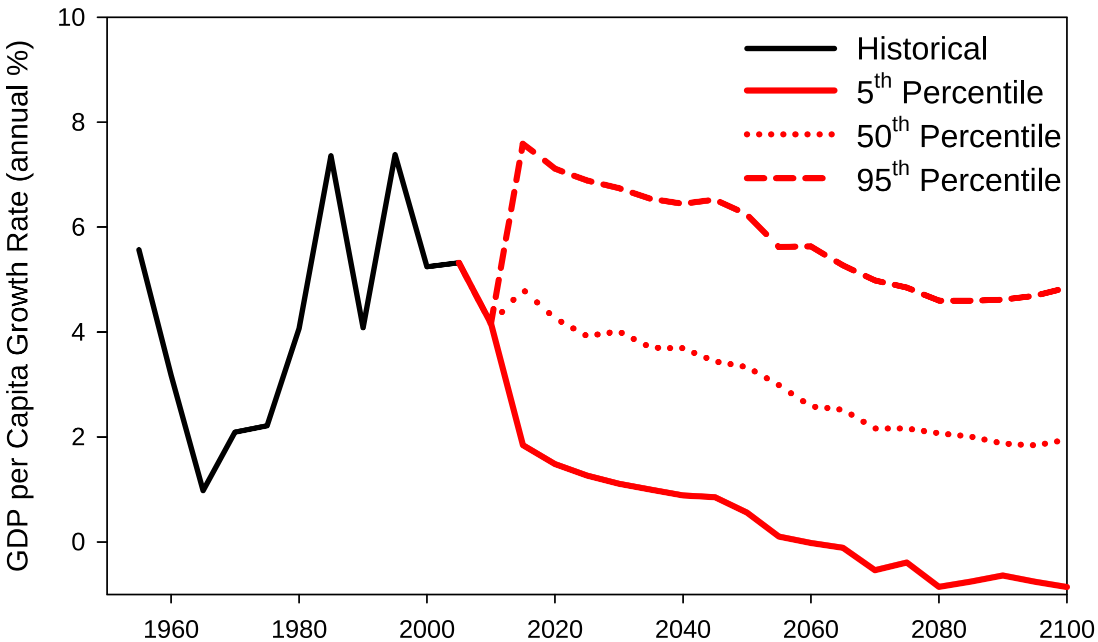

Figure A10. GDP per capita growth rates for China (CHN).

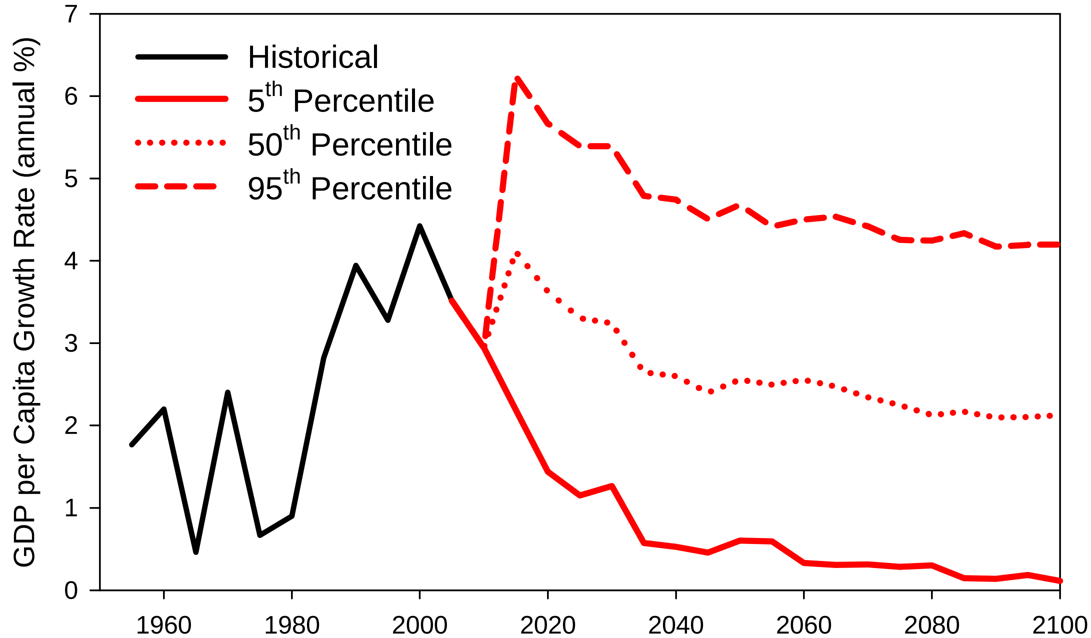

Figure A11. GDP per capita growth rates for India (IND).

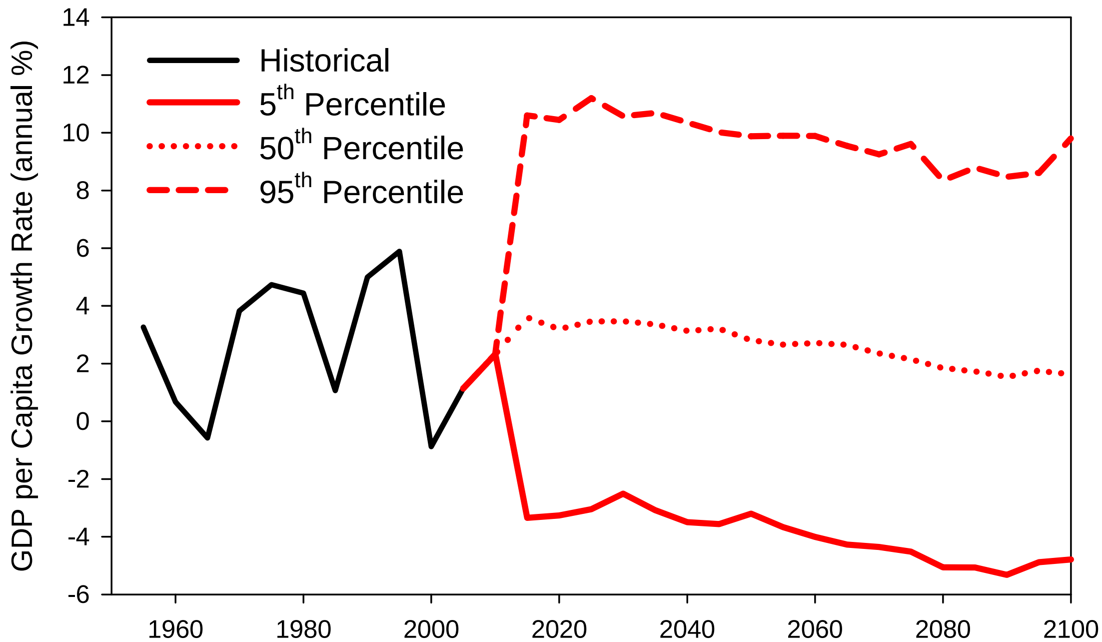

Figure A12. GDP per capita growth rates for Indonesia (IDZ).

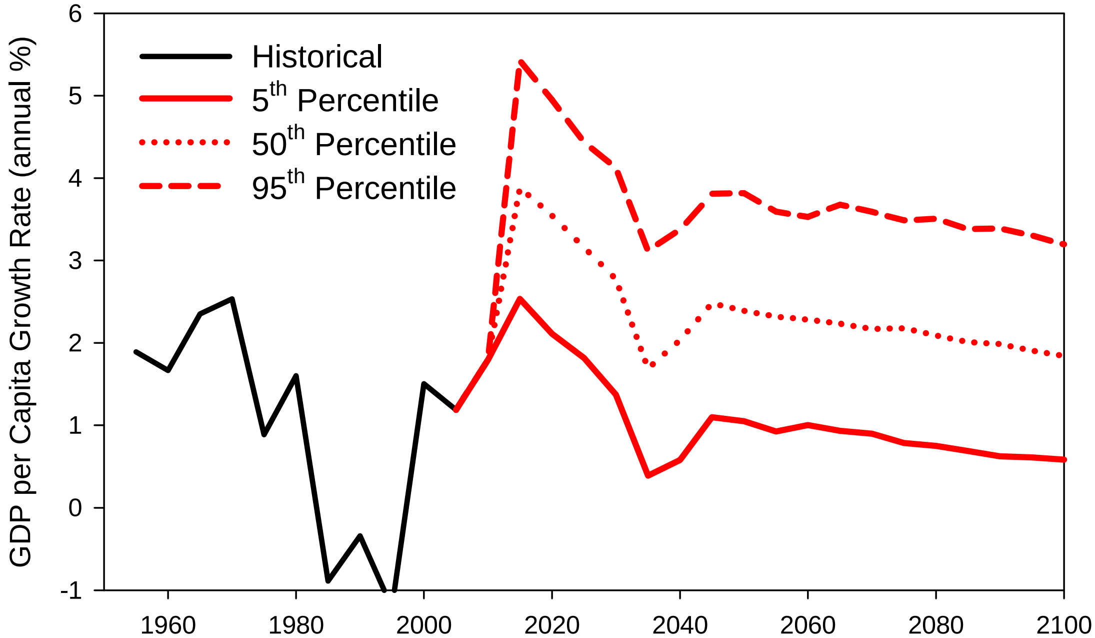

Figure A13. GDP per capita growth rates for Africa (AFR).

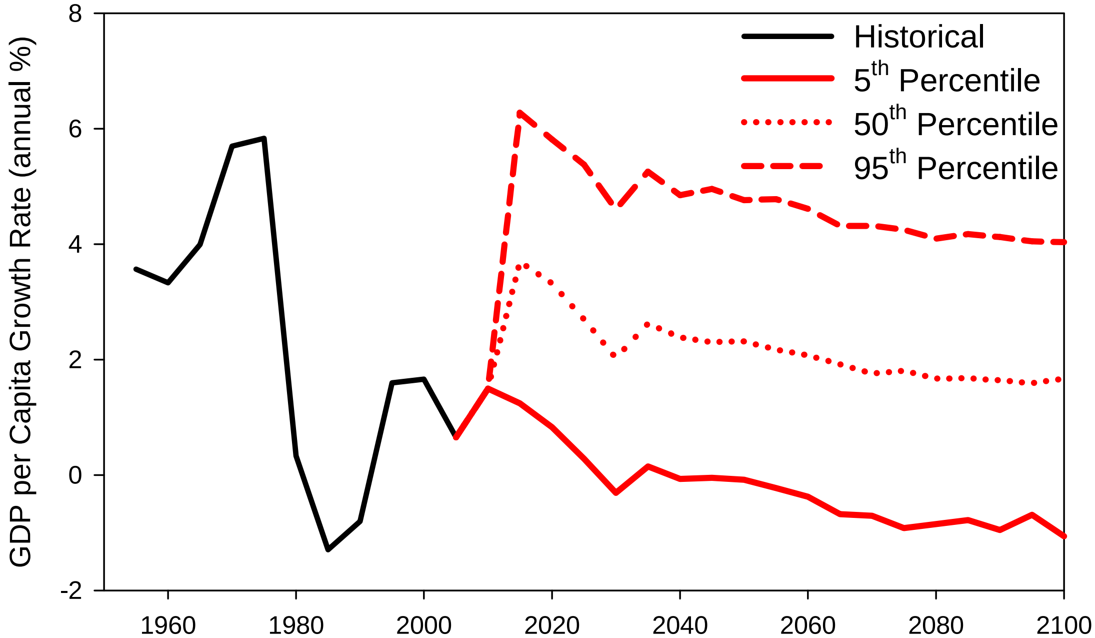

Figure A14. GDP per capita growth rates for Middle East (MES).

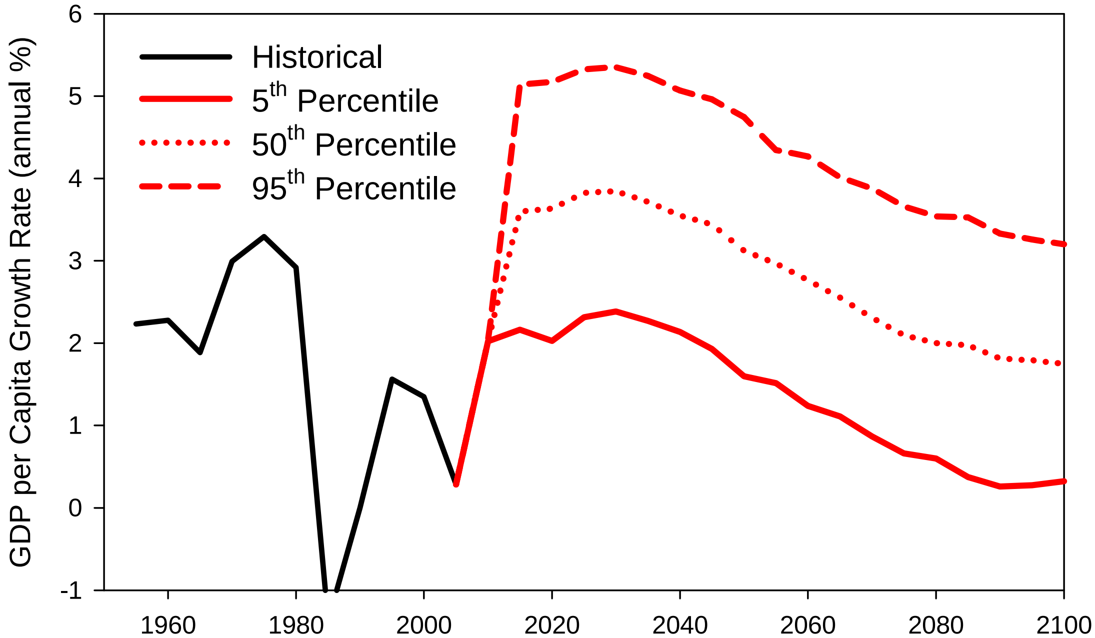

Figure A15. GDP per capita growth rates for Latin America (LAM).

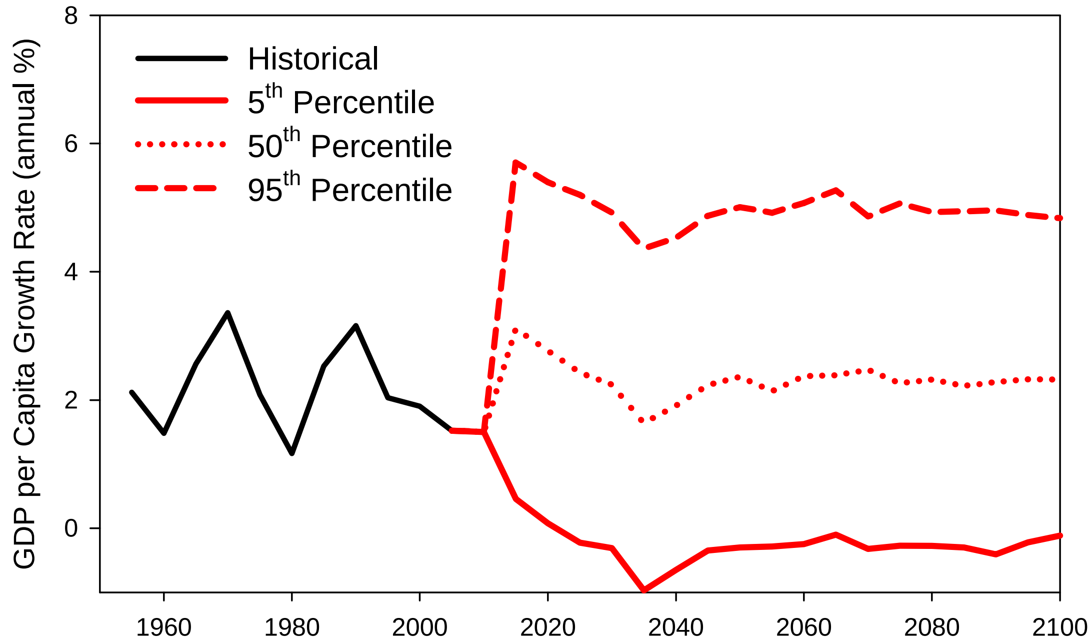

Figure A16. GDP per capita growth rates for Rest of World (ROW).

APPENDIX B. TABLES OF RESULTS

Table B1. Uncertainty in CO_2 Emissions for Selected Years.

		2020	2040	2060	2080	2100
No Policy	Mean	10.1	15.1	19.1	21.4	22.9
	Std Dev	0.8	2.4	4.1	5.3	6.7
	5%	8.8	11.4	13.0	13.8	14.5
	25%	9.5	13.4	16.4	17.6	17.8
	50%	10.0	14.8	18.6	20.6	22.0
	75%	10.7	16.5	21.6	24.8	26.6
	95%	11.5	18.9	26.3	31.4	36.9
CCSP750	Mean	9.2	12.2	13.7	12.4	9.2
	Std Dev	0.0	0.0	0.1	0.1	0.2
	5%	9.2	12.1	13.6	12.3	9.1
	25%	9.2	12.2	13.7	12.3	9.2
	50%	9.2	12.2	13.7	12.4	9.2
	75%	9.2	12.2	13.7	12.4	9.3
	95%	9.2	12.2	13.8	12.5	9.4
ccsp650	Mean	8.7	10.7	10.7	8.7	6.7
	Std Dev	0.0	0.0	0.0	0.1	0.2
	5%	8.6	10.6	10.6	8.6	6.6
	25%	8.6	10.7	10.6	8.7	6.7
	50%	8.7	10.7	10.7	8.7	6.7
	75%	8.7	10.7	10.7	8.7	6.7
	95%	8.7	10.7	10.8	8.8	6.8
ccsp550	Mean	7.7	8.0	6.1	4.8	3.9
	Std Dev	0.0	0.0	0.0	0.1	0.1
	5%	7.7	7.9	6.1	4.7	3.9
	25%	7.7	7.9	6.1	4.8	3.9
	50%	7.7	8.0	6.1	4.8	3.9
	75%	7.7	8.0	6.2	4.8	4.0
	95%	7.7	8.0	6.2	4.8	4.0
ccsp450	Mean	5.8	4.0	2.8	2.5	2.2
	Std Dev	0.0	0.0	0.0	0.0	0.1
	5%	5.7	4.0	2.7	2.4	2.2
	25%	5.8	4.0	2.8	2.5	2.2
	50%	5.8	4.0	2.8	2.5	2.2
	75%	5.8	4.1	2.8	2.5	2.3
	95%	5.8	4.1	2.9	2.6	2.3

Table B2. Uncertainty in Methane Emissions for Selected Years

		2020	2040	2060	2080	2100
No Policy	Mean	456.7	582.0	693.7	762.2	798.8
	Std Dev	23.3	59.9	101.5	131.7	159.8
	5%	419.5	492.5	539.5	568.8	559.1
	25%	440.2	541.4	621.2	669.5	690.3
	50%	457.6	576.9	686.3	748.6	785.2
	75%	471.6	618.9	757.1	849.0	881.0
	95%	493.6	686.7	863.1	987.3	1090.2
CCSP750	Mean	425.0	425.1	426.2	428.4	431.0
	Std Dev	0.1	0.6	3.4	6.2	7.4
	5%	425.0	425.0	425.0	425.0	425.0
	25%	425.0	425.0	425.0	425.0	425.0
	50%	425.0	425.0	425.0	425.0	428.5
	75%	425.0	425.0	425.0	429.6	434.9
	95%	425.0	425.8	433.7	441.4	444.5
ccsp650	Mean	385.0	385.1	387.3	390.0	393.9
	Std Dev	0.2	0.6	4.9	6.3	6.9
	5%	385.0	385.0	385.0	385.0	385.0
	25%	385.0	385.0	385.0	385.0	388.7
	50%	385.0	385.0	385.0	387.9	392.9
	75%	385.0	385.0	386.9	393.0	397.9
	95%	385.0	385.8	397.3	402.2	404.7
ccsp550	Mean	345.0	345.2	347.9	351.8	356.3
	Std Dev	0.2	1.3	5.0	6.3	7.1
	5%	345.0	345.0	345.0	345.0	346.7
	25%	345.0	345.0	345.0	346.4	351.1
	50%	345.0	345.0	345.0	350.4	355.4
	75%	345.0	345.0	349.7	355.6	360.5
	95%	345.2	345.9	357.4	363.2	370.4
ccsp450	Mean	305.1	305.1	306.2	309.3	311.3
	Std Dev	0.2	0.4	2.4	3.6	3.9
	5%	305.0	305.0	305.0	305.0	305.8
	25%	305.0	305.0	305.0	306.4	308.2
	50%	305.0	305.0	305.0	308.4	310.8
	75%	305.0	305.0	306.4	311.7	314.0
	95%	305.4	305.3	312.4	315.8	319.0

Table B3. Uncertainty in Nitrous Oxide Emissions for Selected Years

		2020	2040	2060	2080	2100
No Policy	Mean	13.5	15.9	18.4	20.7	23.5
	Std Dev	0.5	1.4	2.4	3.3	4.2
	5%	12.7	13.6	14.9	15.9	17.3
	25%	13.1	15.0	16.9	18.6	20.8
	50%	13.4	15.8	18.3	20.3	22.9
	75%	13.8	16.6	19.9	22.7	25.7
	95%	14.4	18.2	22.6	26.6	31.5
CCSP750	Mean	12.3	11.9	11.6	11.2	10.9
	Std Dev	0.0	0.0	0.1	0.2	0.3
	5%	12.3	11.9	11.4	11.0	10.6
	25%	12.3	11.9	11.5	11.1	10.8
	50%	12.3	11.9	11.5	11.2	10.9
	75%	12.3	12.0	11.6	11.3	11.1
	95%	12.3	12.0	11.8	11.7	11.5
ccsp650	Mean	12.1	11.3	10.5	9.8	9.1
	Std Dev	0.0	0.0	0.2	0.3	0.3
	5%	12.0	11.2	10.3	9.5	8.7
	25%	12.1	11.2	10.4	9.6	8.9
	50%	12.1	11.3	10.4	9.7	9.1
	75%	12.1	11.3	10.5	9.9	9.3
	95%	12.1	11.3	10.9	10.3	9.6
ccsp550	Mean	11.9	10.6	9.4	8.3	7.3
	Std Dev	0.0	0.1	0.2	0.3	0.3
	5%	11.8	10.5	9.2	8.0	6.9
	25%	11.8	10.6	9.3	8.1	7.1
	50%	11.9	10.6	9.4	8.3	7.2
	75%	11.9	10.6	9.5	8.4	7.5
	95%	11.9	10.7	9.8	8.8	7.8
ccsp450	Mean	11.6	9.9	8.3	6.8	5.2
	Std Dev	0.0	0.0	0.1	0.2	0.3
	5%	11.6	9.9	8.2	6.5	4.9
	25%	11.6	9.9	8.2	6.6	5.0
	50%	11.6	9.9	8.3	6.7	5.2
	75%	11.7	10.0	8.3	6.8	5.3
	95%	11.7	10.0	8.5	7.0	5.5

Table B4. Uncertainty in Sulfur Dioxide Emissions for Selected Years

		2020	2040	2060	2080	2100
No Policy	Mean	138.7	135.2	120.6	101.9	86.4
	Std Dev	48.8	78.1	98.5	107.7	112.3
	5%	70.1	37.9	19.0	8.2	3.5
	25%	101.8	74.8	49.0	29.3	16.2
	50%	134.2	118.9	93.2	64.4	44.8
	75%	169.6	179.1	162.3	138.5	107.4
	95%	222.1	280.2	305.9	329.8	332.6
CCSP750	Mean	124.7	106.8	87.8	70.6	58.2
	Std Dev	42.3	60.9	70.9	74.7	76.8
	5%	65.5	32.9	14.5	6.0	2.4
	25%	92.3	60.2	34.4	19.7	10.8
	50%	120.9	96.0	68.7	44.2	30.4
	75%	150.8	139.2	117.6	94.6	72.0
	95%	203.0	226.1	239.7	233.8	237.6
ccsp650	Mean	117.1	96.0	75.7	62.0	53.7
	Std Dev	39.6	54.7	60.9	65.9	71.5
	5%	61.7	29.3	12.4	5.1	2.3
	25%	87.1	53.6	30.4	17.5	10.0
	50%	113.7	86.6	58.4	39.3	28.2
	75%	141.8	124.1	102.6	82.7	65.6
	95%	189.3	202.5	203.6	211.0	217.5
ccsp550	Mean	104.5	76.1	62.3	55.5	49.4
	Std Dev	35.5	43.4	50.7	59.5	66.2
	5%	55.3	23.6	10.2	4.5	2.0
	25%	77.4	42.6	25.8	15.7	9.3
	50%	101.0	68.8	47.9	35.8	25.6
	75%	126.6	99.0	83.0	73.4	60.9
	95%	169.5	161.7	169.7	191.2	200.8
ccsp450	Mean	79.9	55.7	51.9	47.6	40.4
	Std Dev	27.2	31.7	42.4	51.0	53.5
	5%	42.7	17.1	8.3	3.8	1.5
	25%	59.0	31.7	21.6	13.8	7.6
	50%	77.8	50.3	40.2	30.6	20.3
	75%	96.3	73.1	68.6	62.9	50.3
	95%	129.6	119.1	145.7	164.6	162.9

Table B5. Uncertainty in Nitrogen Oxides Emissions for Selected Years

		2020	2040	2060	2080	2100
No Policy	Mean	183.5	235.6	267.8	282.5	290.0
	Std Dev	49.6	74.7	103.4	127.3	147.5
	5%	118.2	138.5	137.3	126.6	113.6
	25%	150.8	186.4	199.6	199.7	194.3
	50%	175.5	224.3	247.3	257.0	261.4
	75%	207.3	274.2	323.0	340.0	352.0
	95%	272.1	367.4	462.1	534.6	591.7
CCSP750	Mean	175.1	210.9	227.5	229.7	227.1
	Std Dev	45.9	64.3	83.2	99.4	112.5
	5%	112.7	125.8	122.8	109.2	91.9
	25%	144.5	168.5	171.0	165.4	152.9
	50%	167.0	198.8	211.8	209.0	204.2
	75%	197.5	243.0	269.5	274.4	273.8
	95%	258.4	328.0	392.3	418.1	462.2
ccsp650	Mean	169.8	200.3	210.0	211.6	213.0
	Std Dev	44.4	60.6	76.3	91.7	105.7
	5%	109.5	119.9	113.6	99.7	85.4
	25%	139.7	159.6	159.4	152.1	142.6
	50%	161.9	188.8	192.6	192.2	192.0
	75%	191.8	231.2	252.3	253.6	256.5
	95%	252.0	313.8	354.4	386.3	439.8
ccsp550	Mean	160.3	178.1	185.4	192.5	195.4
	Std Dev	41.6	53.0	66.8	82.5	95.7
	5%	102.1	107.6	96.9	87.2	77.5
	25%	131.9	142.2	141.6	138.4	132.0
	50%	152.7	168.9	172.0	175.4	175.4
	75%	181.5	207.8	221.6	231.6	238.3
	95%	236.0	273.3	312.5	351.0	393.9
ccsp450	Mean	137.2	143.8	157.3	165.7	161.9
	Std Dev	33.8	40.9	54.5	68.2	76.3
	5%	87.5	85.9	83.0	76.3	65.6
	25%	114.2	115.9	121.8	121.6	109.6
	50%	132.0	137.0	146.3	152.8	146.5
	75%	155.5	166.4	188.5	197.8	200.4
	95%	200.1	218.5	261.6	296.1	315.7

Table B6. Uncertainty in Carbon Monoxide Emissions for Selected Years

		2020	2040	2060	2080	2100
No Policy	Mean	1293.3	1725.1	2062.3	2300.9	2469.6
	Std Dev	260.5	439.2	652.0	881.5	1108.9
	5%	868.8	1011.2	1128.9	1131.0	1092.1
	25%	1131.7	1428.2	1558.1	1642.8	1673.3
	50%	1280.6	1682.3	1976.1	2128.5	2233.0
	75%	1453.9	1990.7	2409.6	2773.9	3058.6
	95%	1761.3	2548.5	3264.9	3882.0	4467.8
CCSP750	Mean	1270.8	1676.7	1973.3	2132.5	2223.4
	Std Dev	257.1	423.9	613.3	794.5	971.5
	5%	853.1	993.1	1052.6	1023.4	969.2
	25%	1106.7	1387.9	1499.5	1523.7	1496.5
	50%	1261.2	1626.6	1894.5	2000.1	2030.0
	75%	1435.1	1940.1	2311.6	2556.8	2762.3
	95%	1738.5	2456.9	3143.4	3673.9	4023.3
ccsp650	Mean	1260.5	1655.1	1907.9	2037.8	2117.1
	Std Dev	254.2	416.7	591.5	756.8	919.5
	5%	851.8	998.5	1060.2	990.1	909.8
	25%	1099.0	1370.0	1466.2	1471.6	1430.5
	50%	1248.0	1611.1	1824.2	1911.6	1930.6
	75%	1422.3	1916.0	2230.3	2442.0	2628.0
	95%	1721.7	2431.2	3036.7	3464.8	3818.6
ccsp550	Mean	1235.2	1586.3	1774.7	1891.9	1937.8
	Std Dev	253.0	401.9	552.5	705.7	847.3
	5%	827.1	931.0	945.3	901.4	827.6
	25%	1077.1	1316.4	1372.3	1365.2	1286.2
	50%	1222.3	1549.2	1704.0	1782.2	1760.0
	75%	1397.1	1848.6	2095.7	2310.2	2454.7
	95%	1688.5	2350.1	2812.3	3251.4	3455.3
ccsp450	Mean	1153.0	1403.9	1587.2	1697.6	1678.7
	Std Dev	244.9	369.1	507.7	645.1	740.2
	5%	768.3	817.9	829.6	811.6	712.6
	25%	991.0	1146.5	1207.1	1194.7	1108.8
	50%	1141.0	1358.9	1536.4	1579.6	1542.9
	75%	1320.1	1649.1	1899.6	2119.4	2156.6
	95%	1574.7	2069.4	2529.6	2909.6	3077.0

Table B7. Uncertainty in Volatile Organic Compound Emissions for Selected Years

		2020	2040	2060	2080	2100
No Policy	Mean	269.9	354.0	404.1	434.9	456.3
	Std Dev	64.7	99.3	134.1	168.8	205.3
	5%	184.5	217.9	219.6	203.5	191.0
	25%	221.1	278.1	305.4	314.8	310.2
	50%	261.3	340.3	389.9	410.0	419.4
	75%	305.0	413.0	493.0	539.5	571.1
	95%	393.8	543.6	634.2	719.7	822.4
CCSP750	Mean	264.6	344.9	391.5	412.5	419.6
	Std Dev	61.6	94.0	126.3	156.6	185.6
	5%	180.6	213.4	213.6	194.3	174.6
	25%	219.0	271.8	298.5	300.9	290.2
	50%	255.6	334.8	382.1	389.4	391.1
	75%	300.3	403.1	483.1	509.7	525.2
	95%	376.9	523.9	617.6	682.9	753.8
ccsp650	Mean	263.0	341.7	382.7	398.6	404.4
	Std Dev	62.7	95.0	125.1	152.3	178.6
	5%	178.3	211.2	208.9	188.3	167.9
	25%	217.1	268.8	292.3	290.4	280.8
	50%	253.1	331.4	371.3	376.2	376.9
	75%	298.0	398.5	468.1	489.7	495.7
	95%	378.2	520.6	599.2	667.8	727.1
ccsp550	Mean	257.2	328.2	357.8	370.5	373.7
	Std Dev	61.4	90.5	116.3	140.7	164.5
	5%	173.7	200.2	198.0	176.4	157.4
	25%	213.1	260.3	275.1	268.9	261.1
	50%	248.1	318.8	346.9	348.5	350.4
	75%	292.5	383.5	436.7	453.5	456.7
	95%	369.4	493.4	559.5	628.9	680.2
ccsp450	Mean	238.4	288.1	314.1	329.3	325.3
	Std Dev	57.5	80.1	102.9	126.6	143.1
	5%	160.3	173.8	172.7	155.8	134.4
	25%	194.9	229.7	242.4	237.5	223.3
	50%	231.5	279.4	301.8	312.7	302.1
	75%	273.1	338.7	379.8	397.1	394.4
	95%	341.1	434.6	494.3	557.3	591.7

Table B8. Uncertainty in Black Carbon Aerosol Emissions for Selected Years

		2020	2040	2060	2080	2100
No Policy	Mean	7.4	7.2	6.4	5.5	4.7
	Std Dev	4.8	7.2	8.8	9.8	10.2
	5%	3.3	1.8	0.8	0.3	0.1
	25%	5.5	4.2	2.7	1.7	0.9
	50%	7.1	6.3	4.9	3.6	2.5
	75%	9.1	9.3	8.7	7.3	5.9
	95%	12.0	15.6	16.4	16.8	18.3
CCSP750	Mean	7.1	6.4	5.4	4.5	3.7
	Std Dev	4.6	6.5	7.5	7.9	8.0
	5%	3.1	1.6	0.7	0.3	0.1
	25%	5.1	3.7	2.3	1.3	0.7
	50%	6.8	5.6	4.2	2.9	1.9
	75%	8.6	8.7	7.4	5.9	4.7
	95%	11.4	13.5	14.0	14.2	13.3
ccsp650	Mean	6.9	6.2	5.0	4.1	3.4
	Std Dev	4.4	6.2	6.9	7.2	7.3
	5%	3.1	1.6	0.7	0.3	0.1
	25%	5.0	3.6	2.1	1.2	0.7
	50%	6.6	5.4	3.9	2.6	1.8
	75%	8.3	8.2	6.9	5.5	4.3
	95%	11.1	13.0	12.8	13.0	12.1
ccsp550	Mean	6.5	5.6	4.5	3.7	3.0
	Std Dev	4.2	5.6	6.2	6.6	6.5
	5%	2.9	1.4	0.6	0.3	0.1
	25%	4.7	3.2	1.9	1.1	0.6
	50%	6.2	4.8	3.4	2.4	1.6
	75%	7.9	7.3	6.1	5.0	3.8
	95%	10.5	11.6	11.2	11.6	10.5
ccsp450	Mean	5.8	4.8	4.1	3.3	2.5
	Std Dev	3.8	4.9	5.7	6.0	5.6
	5%	2.6	1.2	0.5	0.2	0.1
	25%	4.2	2.8	1.7	1.0	0.5
	50%	5.5	4.2	3.1	2.1	1.4
	75%	7.0	6.2	5.5	4.5	3.3
	95%	9.4	10.2	10.3	10.4	8.8

Table B9. Uncertainty in Organic Carbon Aerosol Emissions for Selected Years

		2020	2040	2060	2080	2100
No Policy	Mean	29.9	28.4	26.1	23.3	20.5
	Std Dev	18.2	26.4	33.4	38.0	40.9
	5%	13.2	7.0	3.6	1.6	0.7
	25%	22.2	16.5	11.4	6.9	4.0
	50%	28.8	25.1	20.5	15.5	11.3
	75%	35.7	36.8	35.4	30.9	25.2
	95%	51.6	59.0	69.2	74.7	78.6
CCSP750	Mean	29.3	27.1	24.0	20.4	17.4
	Std Dev	17.9	25.4	30.6	33.1	34.5
	5%	12.9	6.5	3.2	1.4	0.6
	25%	21.8	15.7	10.2	6.1	3.6
	50%	28.2	23.9	19.1	13.5	9.5
	75%	35.0	35.1	33.2	27.5	21.8
	95%	50.2	57.5	64.5	66.1	66.0
ccsp650	Mean	29.0	26.5	22.8	19.2	16.1
	Std Dev	17.7	24.8	28.9	30.9	31.7
	5%	12.7	6.4	3.1	1.3	0.6
	25%	21.6	15.4	9.7	5.8	3.4
	50%	27.9	23.3	18.1	12.8	8.9
	75%	34.9	34.6	31.7	25.6	20.7
	95%	49.6	56.5	62.1	61.8	61.9
ccsp550	Mean	28.3	25.2	21.2	17.6	14.3
	Std Dev	17.5	23.8	27.1	28.6	28.2
	5%	12.5	6.2	2.8	1.2	0.5
	25%	21.1	14.7	9.2	5.4	3.0
	50%	27.3	22.1	16.8	11.5	7.7
	75%	34.0	32.7	28.4	23.5	17.9
	95%	48.6	54.3	57.5	57.2	56.4
ccsp450	Mean	26.9	23.1	20.0	16.3	12.4
	Std Dev	17.0	22.3	26.0	26.6	24.4
	5%	11.7	5.4	2.6	1.1	0.4
	25%	19.7	12.9	8.3	4.7	2.4
	50%	26.1	20.4	15.8	10.6	6.5
	75%	32.3	30.3	27.6	22.2	15.8
	95%	46.4	50.8	56.0	52.2	49.7

Table B10. Uncertainty in Ammonia Emissions for Selected Years

		2020	2040	2060	2080	2100
No Policy	Mean	53.8	73.9	93.3	109.7	123.8
	Std Dev	16.0	25.1	36.4	49.0	60.9
	5%	31.3	39.5	43.7	48.2	46.9
	25%	42.1	55.4	65.5	72.3	77.5
	50%	52.1	71.9	89.7	105.4	115.7
	75%	62.8	87.1	113.0	134.5	154.9
	95%	83.7	120.0	165.5	202.6	234.6
CCSP750	Mean	53.7	73.2	90.6	103.7	114.1
	Std Dev	16.0	24.8	34.7	45.0	54.6
	5%	31.2	39.0	43.3	46.6	44.7
	25%	41.9	54.6	64.3	69.0	72.2
	50%	52.1	71.1	87.2	97.5	106.3
	75%	62.6	86.5	109.3	126.8	141.4
	95%	83.7	118.4	153.9	193.0	217.2
ccsp650	Mean	53.4	72.4	88.2	99.6	107.5
	Std Dev	15.9	24.5	33.7	43.1	51.5
	5%	31.2	38.8	43.0	44.7	42.4
	25%	41.8	54.0	63.5	66.4	68.6
	50%	51.8	69.7	84.4	94.5	100.5
	75%	62.1	85.1	105.4	122.4	135.1
	95%	83.4	117.6	151.2	184.9	204.9
ccsp550	Mean	53.2	70.9	84.9	93.9	97.9
	Std Dev	15.9	23.8	32.4	40.5	46.9
	5%	31.2	38.0	41.9	41.9	38.8
	25%	41.6	52.8	61.5	63.0	62.5
	50%	51.6	68.4	81.1	89.9	92.2
	75%	62.1	83.7	100.9	116.3	122.9
	95%	82.3	114.7	142.2	168.2	187.7
ccsp450	Mean	52.0	67.7	81.7	88.1	86.3
	Std Dev	15.2	22.6	31.1	38.1	41.2
	5%	31.0	36.8	40.2	38.8	32.0
	25%	40.4	51.0	58.1	58.8	54.5
	50%	50.4	65.3	77.5	83.7	81.7
	75%	60.5	80.6	99.0	109.7	108.5
	95%	79.9	109.1	139.3	158.6	160.1

Table B11. Mean, Standard Deviation, and Fractiles of Carbon Prices in Selected Years

		2020	2040	2060	2080	2100
CCSP750	Mean	6.8	13.3	20.3	52.3	147.9
	Std Dev	6.9	10.5	15.4	34.1	83.1
	5%	0.1	0.9	1.8	10.2	57.0
	25%	1.7	4.6	8.3	29.2	92.1
	50%	4.9	11.7	17.6	45.8	128.4
	75%	9.8	18.8	29.1	66.8	181.0
	95%	19.1	32.6	48.6	111.8	309.3
CCSP650	Mean	11.9	21.1	45.5	104.5	227.9
	Std Dev	9.3	13.0	23.7	54.2	117.1
	5%	1.2	3.3	14.2	39.4	88.3
	25%	5.8	10.7	27.6	67.8	145.1
	50%	9.5	19.7	42.1	92.0	199.3
	75%	16.4	28.5	59.7	129.1	276.0
	95%	28.5	45.0	88.1	200.8	461.4
CCSP550	Mean	24.6	52.4	132.6	271.3	579.7
	Std Dev	13.8	21.8	55.5	130.1	315.0
	5%	8.0	24.3	68.8	119.6	226.5
	25%	14.9	35.1	92.7	184.3	373.3
	50%	21.5	48.9	120.1	244.2	486.9
	75%	32.3	66.9	163.8	324.9	697.3
	95%	49.7	89.6	222.0	509.6	1230.1
CCSP450	Mean	71.0	174.3	425.8	886.1	1819.6
	Std Dev	20.4	47.7	174.6	446.8	948.6
	5%	44.0	113.1	240.7	388.6	684.3
	25%	57.8	140.6	303.6	582.8	1176.7
	50%	66.7	167.8	393.7	785.5	1608.1
	75%	80.0	198.2	493.7	1061.0	2263.3
	95%	111.4	264.4	758.3	1821.9	3722.9

Table B12. Mean, Std. Deviation, and Fractiles of Welfare Losses (%) in Selected Years

		2020	2040	2060	2080	2100
CCSP750	**Mean**	0.4	0.6	0.5	1.0	0.4
	Std Dev	3.3	3.5	1.2	1.7	7.9
	5%	0.0	0.0	0.0	0.0	0.0
	25%	0.0	0.0	0.1	0.3	0.0
	50%	0.1	0.1	0.3	0.7	0.7
	75%	0.2	0.4	0.6	1.2	3.9
	95%	0.9	1.6	1.7	3.3	10.9
CCSP650	**Mean**	0.5	1.0	1.0	2.3	4.4
	Std Dev	8.0	5.9	2.4	2.5	9.0
	5%	0.0	0.0	0.0	0.3	0.0
	25%	0.1	0.1	0.3	1.0	1.6
	50%	0.2	0.3	0.6	1.7	4.7
	75%	0.4	0.6	1.1	2.6	8.5
	95%	1.5	2.4	2.8	6.6	16.3
CCSP550	**Mean**	0.6	1.0	2.3	5.0	9.1
	Std Dev	2.5	1.9	2.3	4.0	10.7
	5%	0.0	0.1	0.5	1.5	0.0
	25%	0.2	0.3	1.2	2.7	4.3
	50%	0.4	0.7	1.8	4.1	8.8
	75%	0.7	1.2	2.9	6.1	14.7
	95%	1.7	3.1	5.6	11.9	25.6
CCSP450	**Mean**	1.4	2.3	5.4	8.8	14.4
	Std Dev	5.6	5.0	6.3	11.5	21.4
	5%	-0.7	-0.6	0.9	2.2	0.0
	25%	0.2	0.6	2.8	4.8	7.5
	50%	1.0	1.8	4.6	7.5	14.5
	75%	1.8	3.2	7.3	12.3	23.0
	95%	4.3	6.5	13.1	21.9	39.4

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