Development of Probabilistic Socio-Economic Emissions Scenarios

Final Report

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1 Introduction

In support of assessment for policy development, the Administration recently developed a range of values to use in regulatory analysis for quantifying the social costs of adding (or social benefits of removing) one ton of carbon dioxide from the atmosphere. This value is referred to as the “social cost of carbon” (SCC). As a monetary measure of the incremental damage resulting from carbon emissions, the SCC is intended to include the global economic impacts of climate change, including but not limited to effects on agricultural productivity, human health, coastal property, and ecosystem services.

Most SCC estimates have been derived from one of three simulation or dynamic optimization models commonly referred to as integrated assessment models (IAMs): DICE (by William Nordhaus at Yale University; Nordhaus and Boyer, 2000), FUND (by Richard Tol at the Economic Social Research Institute in Dublin, Ireland; Tol, 2002), and PAGE (by Chris Hope at the University of Cambridge; Hope, 2006). These IAMs combine reduced-form representations of climate processes, economic growth, and feedbacks between the two in a single modeling framework. Ongoing work seeks to update these models by incorporating more of these complex interactions and improving the representation of physical and economic processes.

In the summer of 2009, an interagency group developed a set of interim SCC values based on existing estimates in the literature for use in Federal regulatory analysis until a more comprehensive analysis could be conducted. Subsequently, the interagency group convened to discuss key inputs and assumptions that were then used to generate SCC estimates based on DICE, PAGE, and FUND. An extensive review of the literature was conducted to select three sets of input parameters for these models: climate sensitivity, socio-economic parameters, and the discount rate. Since each IAM takes a different approach to modeling damages, all other model features were left unchanged, relying on the model developers' best estimates. The Federal government has set a preliminary goal of revisiting the SCC values within two years. In the meantime, the participating agencies, including EPA, are interested in determining how these modeling frameworks can be improved so the latest scientific and economic research are better represented in policy and regulatory analyses.

Reference socio-economic scenarios are closely tied to climate damages because, all else equal, more and wealthier people tend to emit more greenhouse gases and also have a higher (absolute) willingness to pay to avoid climate disruptions. However, there exists significant uncertainty in key parameters that underlie such projections. In the 2009-2010 U.S. Interagency Workgroup on the Social Cost of Carbon this uncertainty was not directly addressed. Instead, a scenario approach was undertaken in which four business-as-usual scenarios were considered along with a fifth "international policy" scenario represented by averaging across four model runs constrained not to exceed atmospheric concentrations of 550 ppm CO_2 by 2100. In the final analysis the five scenarios were given equal weight, implicitly assuming a 20% probability for each.

Without explicit probabilities depicting the likelihood of each scenario the interagency workgroup applied equal weights, implicitly assuming each outcome to be equally likely. Schneider (2001) and Webster et al. (2003) have suggested that treating scenarios as equally likely, even when they are not in reality, can be expected if they are not attached specific probabilities by the scenario developers.

The purpose of this analysis is to help overcome these limitations through the development of a publically available library of socio-economic-emissions projections derived from a systematic examination of uncertainty in key underlying model parameters, which may then be used in probabilistic damage assessments.

2 Overview of Methodology and Data Sources

The primary methodology consists in uncertainty propagation Monte Carlo simulation techniques within the MIT Emissions Prediction and Policy Analysis (EPPA) model, version 4 (Paltsev *et al*., 2005). EPPA is a computable general equilibrium (CGE) model which is solved in a recursive dynamic mode, and represents the world as 16 distinct economic regions with trade among them. The Monte Carlo-based uncertainty analysis of the EPPA model will generate the socio-economic scenarios that constitute the product to be delivered.

Key steps in performing the uncertainty analysis include:

1. Perform local sensitivity analysis to identify the critical uncertain parameters in the model;
2. Develop probability distributions for each parameter identified using on expert elicitation or secondary data sources; and,
3. Perform the Monte Carlo simulation, drawing random samples from the parameter distributions, and simulating the model for each set of parameter values.

In addition, two steps are required to compile the ultimate deliverable product for this activity:

1. Extrapolate key results from the 100 year simulation results from EPPA into 300 year scenarios; and,
2. Organize all scenarios into a data library for easy access and usage.

Sensitivity analyses of the EPPA model (step 1 above) have previously been performed and documented in the literature (Webster et al., 2008; Webster et al., 2002). As a result of these analyses, numerous parameters in EPPA have been identified as critical uncertainties, including:

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

Initial probability distributions for these parameters were developed prior to this effort (Webster et al., 2008). As described in Section 3, some of the prior distributions are updated to incorporate more recent data. We also add a set of probability distributions parameters that reflect future emissions reduction policies in non-U.S. regions, as described in Section 4.

The Monte Carlo methodology, including the methods for sampling parameters and extrapolating the results to 300-year scenarios, is described in Section 5. Section 6 describes the resulting library of socio-economic emission scenarios. Below, we summarize the EPPA model, through which uncertainty will be propagated to form the scenarios.

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 2-1.

Much of the sector 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 2-1: 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*. (2005b); 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).

3 Probability Distributions for Key Non-Policy Parameters

In this section we describe previously developed probability distributions for the non-policy the EPPA model parameters that were used to create the library of socio-economic emission scenarios. As described below, some parameter distributions were developed based on empirical data, while others were derived from prior expert elicitation efforts.

Sensitivity analyses of the EPPA model to determine the parameters that contribute most to uncertainty in greenhouse gas and criteria pollutant emissions and costs of abatement was previously conducted by Webster *et al*. (2002) and 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, 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 required the use of expert elicitation as the basis for input distributions.

3.1 Distributions Based on Empirical Analyses

3.1.1 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 3-1.[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.

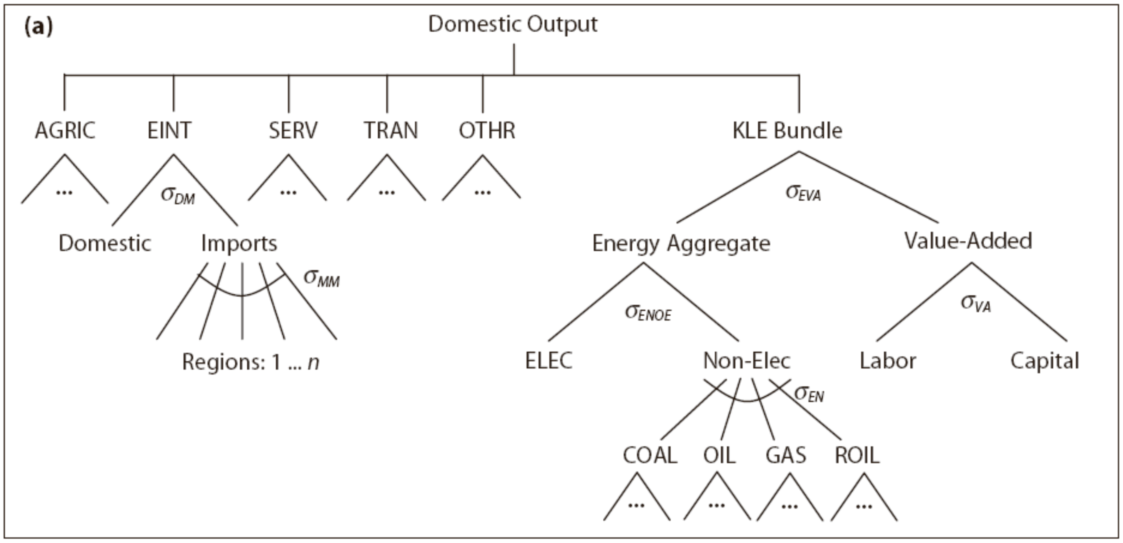

Figure 3-1: Example of the nest structure for production sectors in EPPA: parameters that govern energy demand (and abatement costs) are substitution elasticities for energy—non-energy, σ_{EVA}; labor-capital, σ_{VA}; electricity-fuels, σ_{ENOE}; and that among fuels, σ_{EN}.

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 Figure 3-1, 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 3-1). 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 3-2). We calculate the relative standard errors of the cross-price elasticities, which are proportional to the substitution elasticities. While the Figure 3-1 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 3-2) 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 3-2). 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 3-3) 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 3-1: 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 3-2: Inter-Fuel 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 3-3: 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

3.1.2 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 3-4). We estimate the standard deviation based on GDP per capita annual growth rates from 1950-2009 for all regions.[2] Specifically, the change in the growth rate in GDP per capita is

[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 1950-2009. Using data from

$$\frac{dGDPPC}{dt} = \mu\, dt + \sigma$$

Where μ is the drift term or average growth rate, and σ is the volatility.

Forward projections of EPPA are conducted by applying the estimated uncertainty in growth rates to labor productivity growth (LPG) rates in the EPPA model, and we do not apply the average growth rates from the historical data. The reason for this choice is that future economic growth rates will not necessarily be the same as in the past, and in fact for many regions are like.ly to change. Some countries in the past experienced rapid economic growth during an industrialization phase but will likely slow in the future, while others may enter the rapid growth phase in the next several decades. Instead, we assume that the median trend for each region is the original productivity growth rate in the EPPA reference simulation, which have been carefully calibrated to near-term economic projections for each region (see Paltsev *et al.*, 2005). In other words, the drift term (μ) 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 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.

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 3-4: 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 1950-2009 (%)		Projected Annual Average Growth Rate (%) 2000-2100		
Region	***Mean***	***Std Dev***	***0.05***	***0.5***	***0.95***
USA	2.2	2.0%	1.7	2.2	2.6
CAN	2.3	2.6%	1.6	2.2	2.7
MEX	2.2	4.4%	1.5	2.2	3.0
JPN	4.9	2.4%	1.6	2.1	2.6
ANZ	2.0	2.2%	1.9	2.4	2.8
EUR	2.8	2.4%	1.5	2.0	2.6
EET	1.1	2.3%	2.2	2.7	3.2
FSU	1.1	6.3%	1.8	2.8	3.7
ASI	4.3	3.1%	1.9	2.6	3.3
CHN	4.3	2.9%	2.6	3.1	3.7
IND	2.3	2.7%	2.1	2.8	3.6
IDZ	2.7	4.2%	1.6	2.6	3.5
AFR	1.0	2.3%	1.8	2.5	3.1
MES	2.3	3.1%	1.4	2.2	3.2
LAM	1.7	2.3%	2.1	2.7	3.4
ROW	2.2	2.0%	1.8	2.4	3.0
GLOBAL			2.1	2.3	2.6

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 2009 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 3-2. 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 3-2 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 3.4 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.

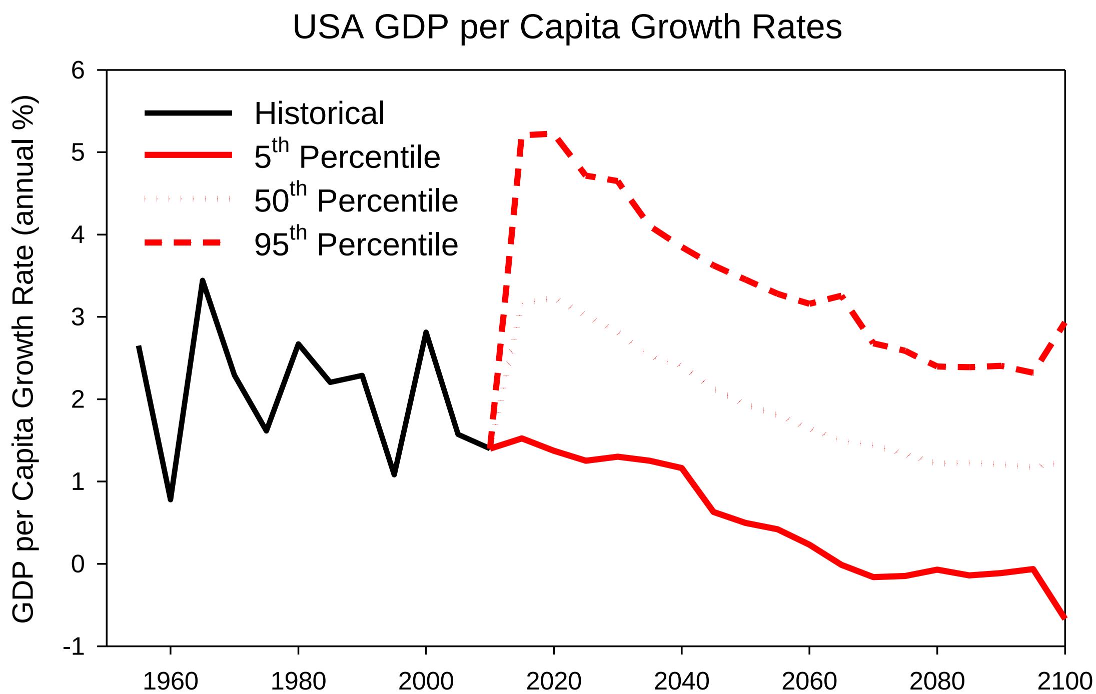

Figure 3-2: Historical and projected GDP per capita growth rates for the United States. Projections are shown for the 5th, 50th, and 95th percentiles in each period.

3.1.3 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:

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

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 3-5) and equation (2) (Table 3-6) 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)). 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 3-6) 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 indicate 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 2½ to 4½ times) than without the lag.

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. The correlation between regions is assumed to be 0.9, or highly correlated (see 3.2.5 below). The application of the uncertainty range based on analysis of the US to other regions is an assumption. The data required to replicate the analysis for other regions was not available. However, there is no clear rationale for different ranges of uncertainty across regions.

3.1.4 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 3-5: 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	-0.23**	0.30	0.0013	-0.13	0.90
	(6.1)	(0.040)	(0.21)	(0.0066)	(0.66)	
2. Const, Pr, GDP	9.2**	-0.23**	0.34**	-	-	0.90
	(0.58)	(0.040)	(0.021)			
3. (θ=1)	-9.8**	-0.24**	1	-0.0206**	2.0	-
	(0.21)	(0.047)		(0.00080)	(0.08)	

** Significant at p<0.05 level

Table 3-6: Energy Consumption as Function of Price, GDP, and Time with Lagged Effects

	Estimated Parameters (Standard errors)					Calculated Values		
Specification (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-runGDP 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. (θ=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 3-7). 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 3-3, and the distributions with mean and standard deviation for each fuel are given in Table 3.8.

For natural gas only, we use the more recent probabilistic assessment of supply in the *MIT Future of Natural Gas* study (Moniz et al., 2011). This study assessed the uncertainty in natural gas from both conventional and unconventional (shale) sources, and provided estimates for the EPPA regional aggregation (see Table 2A.1, Appendix 2A). Because of the EPPA model structure, shale oil is a separate resource, but shale gas is included within the natural gas sector.

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 3-3, ranging from 0.5 to 2.0. Each fuel is sampled independently from this distribution (*i.e.* no correlation).

Table 3-7: 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.

Table 3-8: Distributions for Fossil Fuel Availability (Uncertainty Factor)

Fossil Fuel	**Distribution Type**	**Mean**	**Standard Deviation**
Oil	Lognormal	1.05	0.39
Natural Gas	Lognormal	1.01	0.20
Coal	Lognormal	1.05	0.39
Shale Oil	Beta	1.2	0.82

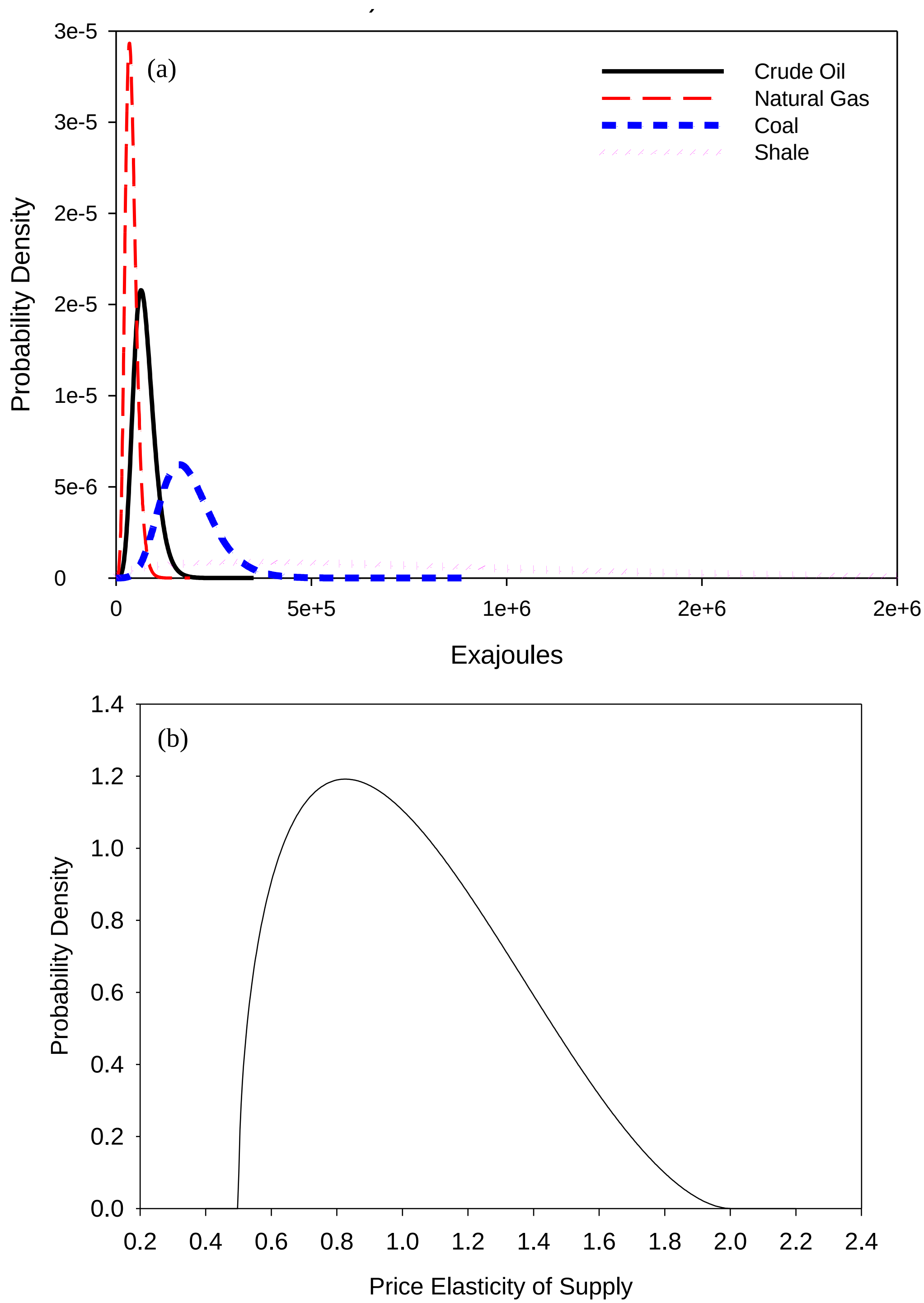

Figure 3-3: PDFs for (a) total fossil resources available for depletion, and (b) price elasticity of supply for fossil fuels.

3.1.5 Population Growth

The uncertainty in population growth is taken from World Population Prospects: the 2010 Revision (UN, 2011). 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 3-4) represent one standard deviation about the medium case, which is taken to be the median. Because the UN only provides these three scenarios, no data is available to assess correlation across regions. We therefore assume perfect correlation to be consistent with the UN projections, a strong assumption. We fit distributions to the global population projection for 2020, 2040, 2060, 2080, and 2100. To construct each scenario, we sample these distributions (perfectly correlated over time), and linearly interpolate between the 20 year steps, to construct a global population scenario. We then scale the regional population in each of that scenario by the ratio of global population of the sample to the reference global population. Figure 3-4 below shows the resulting 50% and 90% ranges in global population that result from this procedure, and compare to the UN reference, high, and low projections.

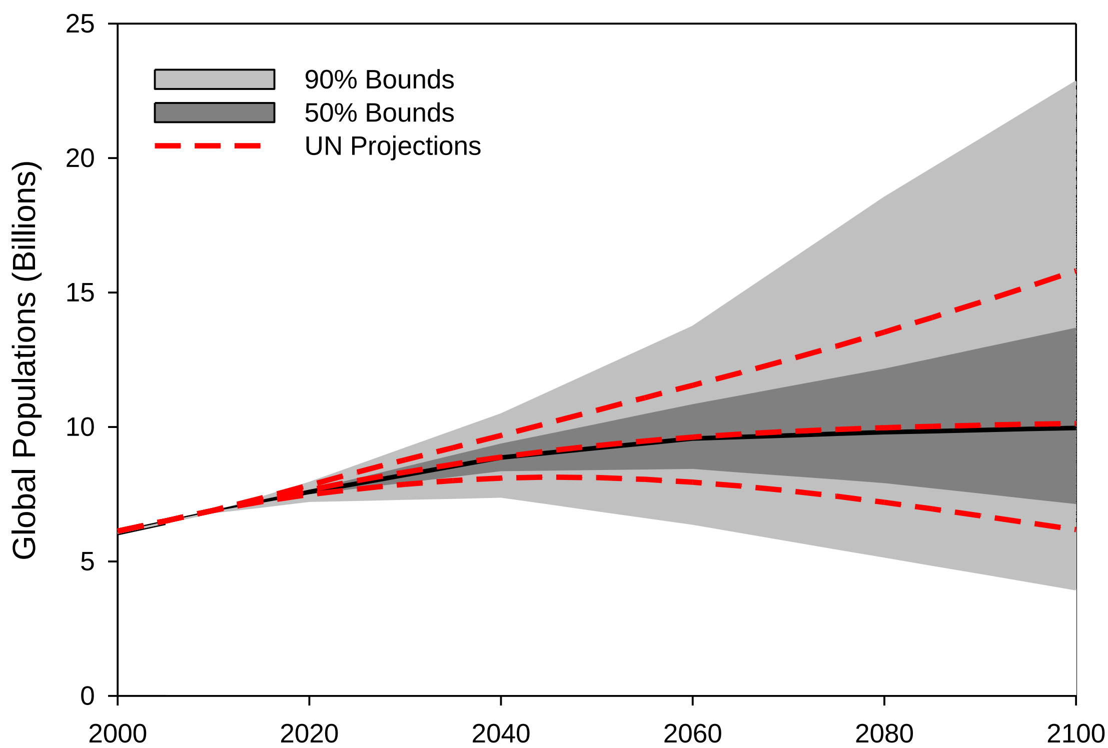

Figure 3-4: Shaded regions show the 50% (darker) and 90% (lighter) ranges of the EPPA population projections to 2100, and lines show the UN population projections to 2050 (source: UN, 2007).

3.1.6 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:

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

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 3-.

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 3-.

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.

Note that these pollutant trends are assumed to reflect both technological and policy changes over time, as both are included in the estimates by Stern.

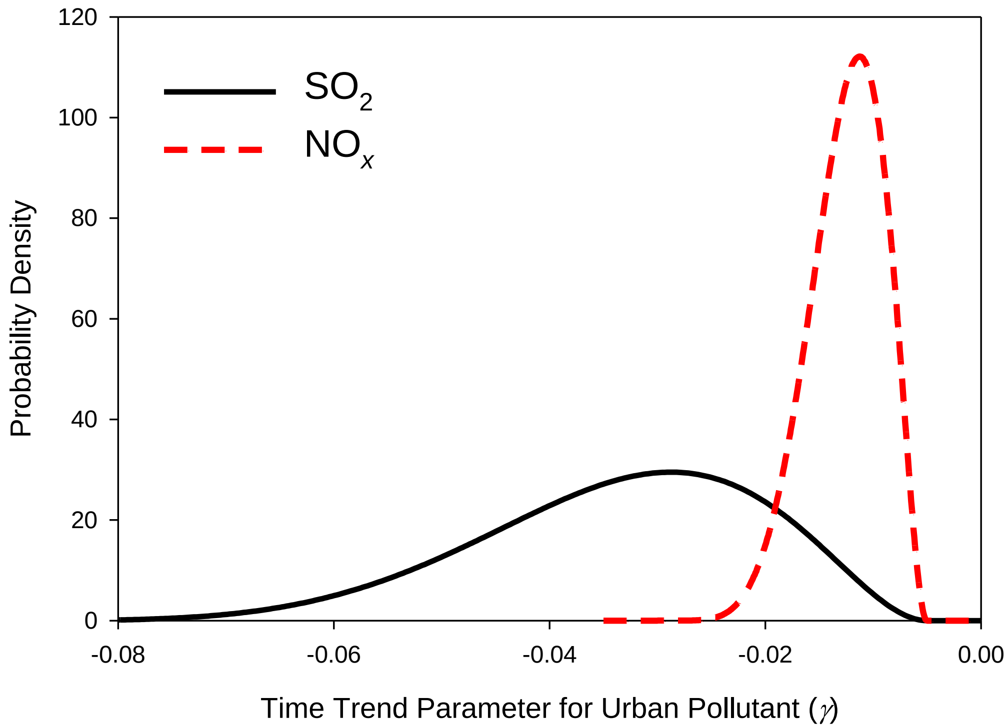

Figure 3-5: Probability density functions assumed for the time trend parameters for urban pollutants.

3.2 Non-Policy Parameter Distributions Based on Expert Elicitation

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

3.2.1 Expert Elicitation Methodology

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 our experts with a simple protocol that tries to gather all the phases. The protocol used consists 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 expert was given a chart similar to Figure 3-, 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).

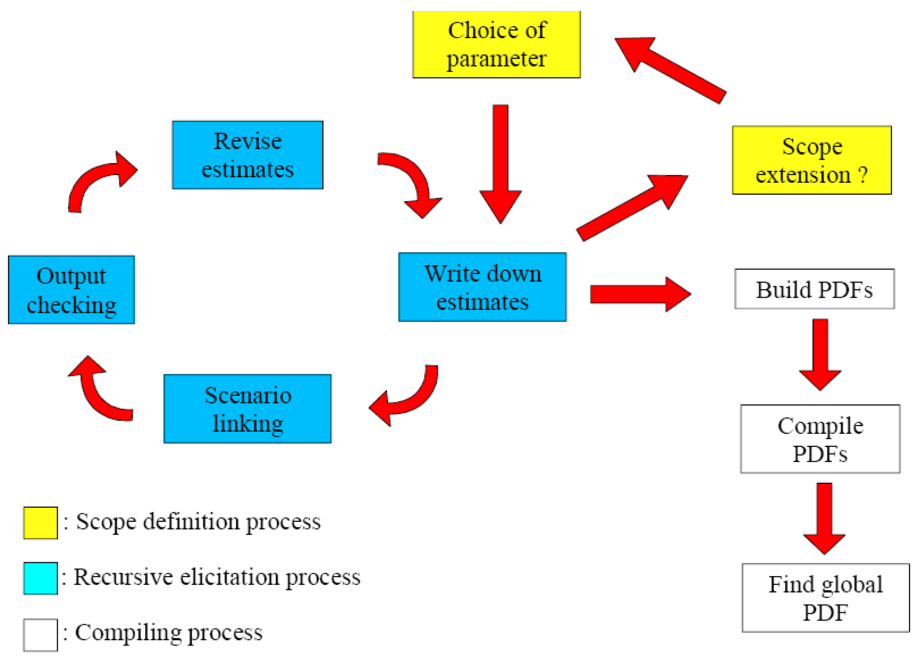

Figure 3-6: Diagram of Expert Elicitation Process for Uncertainty Judgments.

3.2.2 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 3-8. 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). We use the same markup factor applied to both labor and capital input requirements.

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 (IGCC) 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 3-9. 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 3-10.

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 3-10.

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 3-10, and is based on Cheng (2005).

Table 3-9: 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 3-10: 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 3-11: 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 3-12: 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

3.2.3 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 Table 3- and Table 3-2. These fractiles are used to develop probability density functions for these parameters.

3.2.4 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 that was allocated in that period is frozen to become part of the non-malleable portion. In other words, a fraction of the capital investment made in nuclear energy in 2020 will continue to be allocated to nuclear in the following periods, even if relative prices make this use of capital less desirable. 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 3-3. The probability density function is constructed using the average of these fractiles, and is shown graphically as a probability density function in **7**.

Table 3-13: 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%

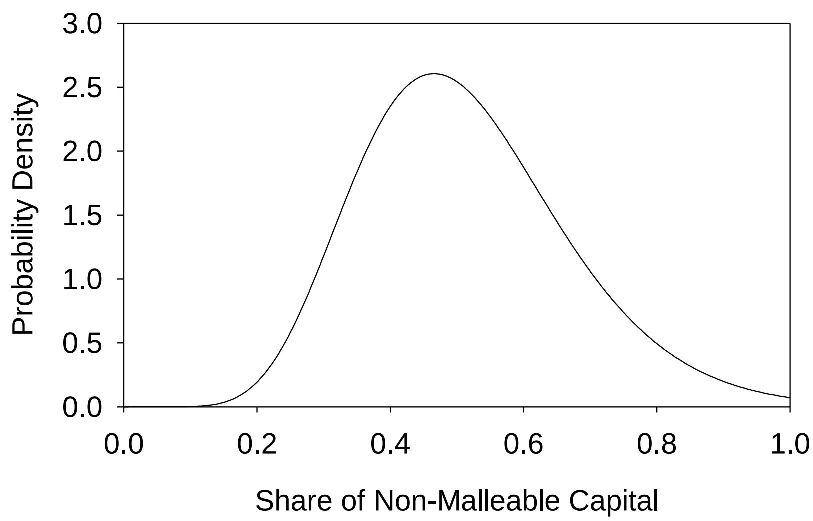

Figure 3-7: Probability density function for share of vintaged capital.

3.2.5 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 3-84. 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 3-84: 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

4 Non-US GHG Policy Probability Distributions

In addition to the parameters described above, an additional set of parameters required a joint probability distribution. All socio-economic scenarios in this project assume no constraints on greenhouse gas emissions from the U.S. However, the policy decisions of other nations are considered to be uncertain. We therefore have developed a set of distributions to describe the range of possible greenhouse gas constraints in non-U.S. regions.

As shown in Table 2-1, there are 15 regions in the EPPA model in addition to the U.S., including some regions based on an individual nation (e.g., China, India, Canada, Japan) and others consisting of aggregate groups of nations (e.g., European Union, Central and South America, and Africa). For each of these regions, we require a set of parameters to describe their constraints on greenhouse gas emissions (if any), which for any region is a vector of emissions or emissions prices over time. Below, we describe the elicitation process, and how the elicited distributions were used in generating emissions scenarios from the EPPA model.

4.1 Expert Elicitation Methodology for GHG Constraints in Non-U.S. Regions

Because the policy decisions by national governments about greenhouse gas emissions cannot be characterized as independent and identically distributed with large numbers of observations, frequentist methods do not apply. Only a Bayesian perspective is relevant for such quantities, and the only possible source for data regarding the uncertainty is expert elicitation, despite all its known flaws as described in Section **Error! Reference source not found.**. We use expert elicitation to construct the probability istributions for non-U.S. greenhouse gas policies.

The general elements of an expert elicitation were described above in Section 3.2.1. Here we outline the specific steps involved in eliciting the uncertainty in non-U.S. emissions policies to be carried out. These steps follow the general methods described above, and as documented in, e.g., Morgan and Keith (1995), Spetzler and Stael von Holstein (1975), and von Winterfeldt and Edwards (1986).

The main tasks in carrying out the assessment were:

- Identifying the (potential) experts to be invited to participate;
- Designing the detailed elicitation protocol (see Appendix B);
- Performing the elicitation with each expert that agrees to participate;
- Combining results from experts into a single composite distribution to be used in simulations.

The first step was to establish criteria for experts to invite to participate. For the concept being assessed (i.e., future non-U.S. GHG constraints), there are multiple disciplines that could have an informed opinion and credibility, including academics who study global climate change in terms of economics, political science, negotiation, law, and even the earth sciences if they are engaged in international policy processes. In addition, practitioners in international governance, such as diplomats, bureaucrats in foreign ministries / State Department, and advisors to international negotiation processes could have credible expertise as well.

Key criteria used to select experts for the elicitation included:

- Expert should have documented expertise in climate change policy, international negotiation, and/or political science, where possible including a record of peer-reviewed publications on one of these topics;
- Expert should have a record of analyzing non-U.S. governments' approach to climate change or similar policies; and,
- Expert should be in a professional setting in which there is no obvious motivation for giving biased responses.

The nine experts who participated are listed below in Table 4-1, in alphabetical order. Note that this order has no relationship to the expert ID codes (A-I) used in the results.

Table 4-1: List of Expert Participants in Eliciation of Future non-U.S. GHG Policy

Name	Institution
Prof. Henry Jacoby	MIT
Prof. David Victor	University of California at San Diego
Dr. Valentina Bosetti	FEEM
Prof. Eugene Skolnikoff	MIT
Dr. David Reiner	Cambridge University (UK)
Prof. Joe Aldy	Harvard University
Prof. William Pizer	Duke University
Prof. Ted Parsons	University of Michigan
Dr. Michael Levi	Council on Foreign Relations

The second task included designing the questionnaire for the elicitation.[3] The questions in the package addressed all the elements identified as necessary to minimize biases in the responses: 1) An Introduction/Background to frame the expert's understanding of the process; 2) Structuring questions, to define an unambiguous measure for each quantity to be elicited; 3) Conditioning phase to describe the biases that experts should be aware of in their thinking; 4) The encoding questions, a series of questions to elicit the expert's view of uncertainty in each quantity; and 5) Verifying questions, to push the expert to reconsider responses, test for overconfidence, redundant checking to ensure consistency. This is a standard outline, as described in detail in Staël von Holstein and Matheson (1979) and Morgan and Henrion (1990).

1. **Introduction/Background**

   The purpose of this step is to frame the expert's understanding of the process

   - *Description of the expert elicitation process*
   - *Description of this specific exercise*

2. **Structuring Questions**

   The purpose of this step is to define an unambiguous measure for each quantity to be elicited. This should include a set of open-ended questions that attempt to define unambiguous quantities that the expert feels comfortable making statements about, and that represent the concepts we want to elicit.

3 See Appendix B for the formal Expert Elicitation Information Package

- *What actions/policies by a government would constitute a restriction on greenhouse gas emissions?*
- *Can you describe GHG actions in terms of percentage reduction of emissions targets in a given year?*
- *If so, relative to what? A historical year? Baseline/BAU emissions for that year?*
- *How do you think about actions by regional aggregates such as EU, Latin America, Africa, or Southeast Asia?*
- *Are there issues in unambiguously defining a "start-year" for GHG policies?*
- *Over what time horizon are you comfortable providing even probabilistic judgments?*
- *Are there exogenous events that might change your assessed probabilities of policies?*

3. **Conditioning Phase**

   The purpose of this step is to describe the biases that experts should be aware of in their thinking

   - *Overconfidence and Bias*
   - *Heuristics used in judging uncertainty*

     i. Representativeness

     ii. Availability

     iii. Anchoring and Adjustment

4. **Encoding Questions**

   The purpose of this step is to elicit the expert's view of uncertainty in each quantity; to push the expert to reconsider responses, test for overconfidence, redundant checking to ensure consistency. For each quantity and for each region/country as defined above in Step #2, ask the following questions:

   a. *What is value of this quantity such that there are only 1 in 20 odds (5% probability) that the true value turns out to be HIGHER than your value?*

   b. *Suppose the true value were HIGHER. Under what conditions would this be true? Describe this world. Do you now wish to revise your estimate?*

   c. *What is value of this quantity such that there are only 1 in 20 odds (5% probability) that the true value turns out to be LOWER than your value?*

   d. *Suppose the true value were LOWER. Under what conditions would this be true? Describe this world. Do you now wish to revise your estimate?*

   e. *What is value of this quantity such that there is an equal likelihood of being higher or lower (median)? If not clear, elicit a "best-guess" (mode).*

   f. *Sketch PDF for expert by hand. In viewing it, do they have any additional thoughts or revisions to suggest?*

5. **Verifying Questions**

   After eliciting for individual regions/countries, ask the following additional questions about pairs of regions to help elicit the correlation structures:

a. *Given your responses about Country A, would you like to reconsider your responses regarding Country B?*

b. *Suppose Country A is enacts policy X (choose upper 95% value) from your distribution? Does that change what Country B will do? B's 1 in 20 upper bound? B's 1 in 20 lower bound? What if Country A does nothing?*

c. *Engage in open-ended discussion about the quantities elicited, and further thoughts form the experts about what conditions might change their responses.*

Results from the above-described elicitation process are summarized below in Section 4.2.

Once the elicitations were performed, we combined the results into a single composite probability distribution that can be used in the Monte Carlo simulation. Several methods of combining experts, who will almost surely give differing responses, can be appropriate, including equal weighting (Clemen and Winkler, 1999) and weighting by performance assessment (French et al., 1991). Given that data for performance assessment is unlikely to exist, we equally weigh each expert in generating a single distribution from the responses. The development of the composite distributions is described in Section 4.3.

4.2 Expert Elicitation Results for Non-US GHG Constraints

This section summarizes findings from our efforts to elicit expert input to support the development of a joint probability distribution of possible greenhouse gas constraints in non-U.S. regions.

The synthesis of expert results points to a few general observations:

- With respect to timeframe, the experts are unanimous and vigorous in their refusal to consider the conditional scenario beyond a time frame of 2050 for some, and beyond 2035 for others. The reason for this is that they assess "U.S. no further action" as having zero probability because one or more of the following are likely to occur:
  - breakthrough technological change leading to low-cost emissions reductions; or
  - climate-change related catastrophe; or
  - related breakthrough in the science of climate that increases the consensus that anthropogenic climate change warrant serious emissions reductions.

  Given this prior of zero probability, experts were unable/unwilling to assess the conditional probability of policies in other countries beyond 2050.
- The reference point for elicited quantities varies widely across experts and across regions for a given expert, and include reductions below a base year (e.g., 1990 or 2005), reductions below "reference" or no-policy emissions for the target year, and reductions in carbon intensity of GDP relative to a base year. In addition, most ranges include the net effect of economic growth and further policies, which means that post-processing with the exogenous GDP growth assumptions will be required to back out the independent policy uncertainties implied by the given judgments.
- The de-identified results are relatively consistent, and many appear to be anchored roughly on stated policy objectives in the international negotiation process for a median, with uncertainty ranges that typically go only slightly further on the low emissions side to easily including no-policy outcomes (BAU) on the high emissions side. The constraints on these ranges are typically observed to be 1) the assumed U.S. non-participation, and 2) the likely high costs and the lack of major technological improvements to non-carbon energy within the time-frame.

4.2.1 Raw Results (De-Identified and Order Randomized)

In Tables4-2through 4-12, the range of emissions increases/reductions are relative to different baselines, as noted along with the year that the reductions occur. OECD countries and Russia are in terms of emissions, but China and India are either specified in terms of carbon intensity (CI) or emissions (EMI). The probabilistic spread between the "low" and "high" values vary; for some it is an 80% range (from 10^{th} percentile to 90^{th} percentile) and for others it is a 90% range (5th percentile to 95^{th} percentile). We have randomly assigned a letter code "A" – "I" to each of the experts, to indicate in the tables which ranges come from the same expert. We also indicate which experts explicitly included economic growth as a driver in their assessed range.

Table 4-2: European Union (Emissions Reduction)

Year	Low	Median	High	Low-High Range	Expert	Includes Growth?
2020 (Rel. to 1990)	-14%	-18%	-22%	80%	E	
2020 (Rel. to 1990)	-10%	-20%	-25%	80%	D	
2025 (Rel. to 2005)	-10%	-20%	-30%	80%	F	Y
2025 (Rel. to 1990)	0%	-15%	-30%	90%	G	Y
2025 (Rel. to 1990)	20%	-10%	-25%	80%	I	Y
2025 (Carbon Price)	$20	$25	$30	50%	C	
2030 (Rel. to 1990)	-12%	-22%	-30%	80%	E	
2030 (Rel. to 1990)	-20%	-30%	-35%	90%	A	Y
2030 (Rel. to 1990)	-15%	-22%	-30%	80%	B	
2030 (Rel. to 1990)	-10%	-30%	-40%	30%	D	
2035 (Rel. to Ref.)	-5%	-15%	-20%	90%	H	
2050 (Rel. to 2005)	-20%	-30%	-50%	80%	F	Y
2050 (Rel. to 1990)	10%	-45%	-90%	90%	G	Y
2050 (Rel. to 1990)	60%	-25%	-60%	80%	I	Y

Table 4-3: Japan (Emissions)

Year	Low	Median	High	Low-High Range	Expert	Includes Growth?
2020 (Rel. to 1990)	-20%	5%	10%	80%	E	
2020 (Rel. to 2005)	-5%	0%	10%	80%	D	
2025 (Rel. to 2005)	-20%	-10%	20%	90%	F	Y
2025 (Carbon Price)	$5	$10	$15	50%	C	
2030 (Rel. to 2005)	-10%	-10%	0%	90%	B	
2030 (Rel. to 1990)	-25%	5%	15%	80%	E	
2035 (Rel. to Ref)	-10%	-5%	0%	80%	H	
2050 (Rel. to 2005)	-50%	-5%	40%	90%	F	Y

Table 4-4: Russia (Emissions)						
Year	**Low**	**Median**	**High**	**Low-High Range**	**Expert**	**Includes Growth?**
2025 (Rel. to 2005)	-20%	10%	50%	90%	G	Y
2025 (Rel. to 2005)	-20%	0%	20%	80%	F	Y
2025 (Rel. to 2010)	0%	20%	30%	80%	I	Y
2025 (Carbon Price)	$0	$0	$5	50%	C	
2050 (Rel. to 2005)	-20%	10%	40%	80%	F	Y
2050 (Rel. to 2005)	-30%	20%	80%	90%	G	Y
2050 (Rel. to 2010)	-30%	40%	80%	80%	I	Y

Table 4-5: Canada (Emissions)						
Year	**Low**	**Median**	**High**	**Low-High Range**	**Expert**	**Includes Growth?**
2020 (Rel. to 1990)	-35%	-22%	-15%	80%	E	
2025 (Rel. to 2005)	-20%	10%	25%	80%	I	Y
2025 (Rel. to 2005)	-10%	5%	15%	80%	F	Y
2025 (Carbon Price)	$5	$10	$15	80%	C	
2030 (Rel. to 1990)	-15%	26%	50%	80%	E	
2035 (Rel. to 2005)	-15%	-10%	-5%	90%	H	
2050 (Rel. to 2010)	-80%	-35%	70%	80%	I	Y
2050 (Rel. to 2005)	-15%	5%	20%	80%	F	Y

Table 4-6: Australia (Emissions)						
Year	**Low**	**Median**	**High**	**Low-High Range**	**Expert**	**Includes Growth?**
2025 (Carbon Price)	$20	$25	$30	50%	C	
2025 (Rel. to 2005)	-10%	0%	10%	80%	F	Y
2035 (Rel. to Ref)	-20%	-10%	-5%	90%	H	
2050 (Rel. to 2005)	-30%	0%	20%	80%	F	Y

Table 4-7: China (Emissions or Carbon Intensity)						
Year	**Low**	**Median**	**High**	**Low-High Range**	**Expert**	**Includes Growth?**
2020 (CI: Rel. to 2005)	-35%	-48%	-60%	80%	E	
2020 (CI: Rel. to 2005)	-15%	-25%	-35%	65%	D	
2025 (EMI: Rel. to 2005)	50%	75%	150%	80%	F	Y
2025 (EMI: Rel. to 2005)	140%	200%	280%	90%	G	Y
2025 (EMI: Rel. to 2010)	10%	30%	60%	80%	I	Y
2025 (Carbon Price)	$0	$0	$10	90%	C	
2030 (CI: Rel. to 2005)	-40%	-55%	-70%	80%	E	
2030 (Emi. Gr. %/yr)	2%	2.5%	3%	90%	A	Y
2030 (CI: Rel. to 2005)	-50%	-40%	-35%	80%	B	
2035 (EMI: Rel. to REF)	30%	20%	0%	80%	H	
2050 (EMI: Rel. to 2010)	-10%	60%	140%	80%	I	Y
2050 (EMI: Rel. to 2005)	150%	200%	250%	80%	F	Y
2050 (EMI: Rel. to 2005)	-10%	260%	450%	90%	G	Y

Table 4-8: India(Emissions or Carbon Intensity)						
Year	**Low**	**Median**	**High**	**Low-High Range**	**Expert**	**Includes Growth?**
2020 (CI: Rel. to 2005)	-20%	-10%	20%	80%	D	
2025 (Emi: Rel. to 2005)	50%	75%	100%	80%	F	Y
2025 (Emi: Rel. to 2005)	150%	200%	320%	90%	G	Y
2025 (Emi: Rel. to 2010)	25%	50%	70%	80%	I	Y
2025 (Carbon Price)	$0	$0	$5	90%	C	
2030 (CI: Rel. to 2005)	-30%	-20%	0%	80%	B	
2030 (Emi Gr. %/Yr)	2%	5%	7%	90%	A	
2035 (Emi: Rel. to Ref)	-10%	0%	0%	90%	H	
2050 (Emi: Rel. to 2005)	100%	150%	225%	90%	F	Y
2050 (Emi: Rel. to 2010)	35%	100%	160%	80%	I	Y
2050 (Emi: Rel. to 2005)	150%	250%	450%	90%	G	Y

Table 4-9: Brazil (Emissions)						
Year	**Low**	**Median**	**High**	**Low-High Range**	**Expert**	**Includes Growth?**
2025 (Rel. to 2005)	-5%	-75%	250%	90%	G	Y
2025 (Rel. to 2005)	-10%	5%	15%	80%	F	Y
2025 (Carbon Price)	$0	$0	$5	90%	C	
2030 (Rel. to Ref)	-20%	-16%	-15%	80%	B	
2035 (Rel. to Ref)	-5%	-2%	0%	90%	H	
2050 (Rel. to 2005)	-15%	10%	25%	80%	F	Y
2050 (Rel. to 2005)	0%	260%	400%	90%	G	Y

Table 4-10: Africa (Emissions)						
Year	**Low**	**Median**	**High**	**Low-High Range**	**Expert**	**Includes Growth?**
2025 (Rel. to 2005)	-20%	10%	30%	90%	F	Y
2025 (Carbon Price) (SA only)	$0	$10	$15	50%	C	
2050 (Rel. to 2005)	-30%	50%	200%	90%	F	Y

Table 4-11: Latin America (Emissions)						
Year	**Low**	**Median**	**High**	**Low-High Range**	**Expert**	**Includes Growth?**
2025 (Rel. to 2005)	-20%	10%	25%	80%	F	Y
2050 (Rel. to 2005)	-25%	30%	70%	80%	F	Y

Table 4-12: Middle East (Emissions)						
Year	**Low**	**Median**	**High**	**Low-High Range**	**Expert**	**Includes Growth?**
2030 (Rel. to 2009)	-30%	30%	200%	90%	A	Y

4.2.2 Correlation Considerations

There are three major possible correlations that need to be considered in using the expert data:

1. Correlations between regions
2. Correlation between economic growth and emissions reductions, and
3. Correlation for a given country between time periods (when two time periods were assessed).

Correlation between Regions

Views vary widely on which regions would be more highly correlation, usually as a result of a linkage between policy mechanisms and/or tighter coupling between economies. In general, correlation between countries is thought to be weak, because the nature of this "No U.S. Actions" scenario leads to regions pursuing what is in their own self-interest, and therefore, relatively unaffected by others' actions. Pairings where higher correlations were possible (as posited by different experts) included EU-China; EU-Other OECD; EU-Russia; Japan-China; EU-Brazil-LAM; India-China, but these views were not consistent across experts. Therefore, in our subsequent processing of the expert-based information, we assumed that there were no correlations across regions.

Correlation with Economic Growth

Here the responses are very consistent, with a view that emissions reductions are negatively correlated with income/GDP growth at a "moderate" strength. Note that many responses included economic growth uncertainty as part of the scenario reasoning, and need to be disaggregated for analysis.

Correlation over Time for One Region:

For those experts providing judgments for more than one year (e.g., 2025 and 2050), the outcomes in the later period are highly (but not perfectly) correlated with the earlier period.

4.3 Developing Composite Region-Specific Distributions for Non-US GHG Constraints

This section describes our approach for aggregating policy uncertainty from the expert elicitation and developing region-specific probability distributions. There are four key issues to consider with respect to using expert elicitation results in the analysis:

1. Decomposing economic growth from policy impacts for four of the experts who provided distributions that explicitly included economic growth,
2. Interpolating expert-specific distributions across model years,
3. Aggregating distributions from different experts for each region, and
4. Extrapolating the pooled distributions from 2050 to 2100.

Below, we describe the approach for each step. The approach is demonstrated using results from the European Union as an example.

4.3.1 Decomposing Economic Growth from Policy

The modeling framework includes an assumed marginal distribution for economic growth, which is based on historical growth rates. All the experts indicated that economic growth is positively correlated with emissions. However, the experts provided two types of probability distributions for policy-related emissions reductions:

- The majority of the experts described only the effects from policy for a reference economic growth scenario. That is, probability distributions provided by these experts are conditional distributions of emissions reductions at time t for a specified economic growth rate: $P(ER_t|G = g_r)$. Therefore, assumptions are needed to extrapolate these effects to economic growth paths other than the reference path, i.e., obtain $P(ER_t|G = g)$ for an arbitrary g.

- Other experts explicitly conflated growth-related effects with policy-related effects as a major driver in the range of emissions reductions they described for each region. They effectively provided *partial* information on the joint distribution of policy-related reductions in emissions and economic growth rate: $P(ER_t, G)$. The growth-conflated distributions need to be decoupled from growth prior to their use in EPPA, so that $P(ER_t|G = g)$ for an arbitrary g can again be obtained.

To address this potential source of bias/uncertainty in the distributions, we made the following assumptions:

1. The marginal distribution for economic growth, $P(G)$, in EPPA adequately represents what the marginal distribution for economic growth that experts had envisioned.
2. The median growth in EPPA can represent the reference growth that some experts had in mind.
3. There is a perfect correlation between growth and emissions. This assumption is justified because the experts view this correlation closer to unity than to zero.
4. Although magnitude of policy-related emissions reductions are dependent on economic growth, carbon prices are not: $P(CP_t, G) = P(CP_t)P(G)$. In the EPPA modeling framework, policy can be represented by either specifying the emissions reductions or by setting a carbon price. We expressed policy through carbon price (and let emissions adjust accordingly) because this was more in line with experts' thinking.

We used the following procedure to obtain $P(CP_t)$:

1. Perform a Monte Carlo simulation of the EPPA model without any policy, but with uncertainty in GDP growth. The results of these simulations were used to extract several fractiles for the growth paths (e.g., p5, p50, and p95). This is performed using the labor productivity growth uncertainty described above (the other uncertain parameters have only a negligible effect on GDP growth.
2. Then, for each GDP growth scenario, simulate many possible paths of carbon prices over time (e.g., in 2015 $10/ton, $20/ton, etc. and increasing at the rate of interest (4%) for the EPPA model).
3. For each given level of emissions in a target year – for example 20% below 1990 levels in 2025 – determine the level of the carbon price in 2025 that would result in that emission level. Recall that we assume perfect correlation for this conversion: low growth scenario and lowest emissions judgment, median growth and median emissions, and high growth for high emissions.

This procedure converts partially known $P(ER_t, G)$ to marginal probability distributions of carbon prices in 2025 and 2050 that can be aggregated across experts, such that correlation between emissions and GDP growth are preserved.

For all remaining distributions, which are conditional on a reference GDP growth scenario, we use a similar procedure to the above to convert emissions to equivalent carbon prices. In this case, we only use the results of carbon prices in the median growth scenario to convert to carbon price.

4.3.2 Interpolating Expert-Specific Policy Uncertainty over Time

Experts provided uncertainty distributions for at most two years between 2020 and 2050. Therefore, in addition to conversion of expert elicitation data to the year-specific distributions over carbon price (in $ per ton C), modeling the policy uncertainty obtained from the experts required interpolation of these distributions over time.

To create time profiles of carbon price distributions we made the following assumptions:

1. The fractile of the carbon price at time t is dependent only on the past history of values for the same fractile. This assumption is not unreasonable, because all the experts expressed the belief that their distributions are strongly correlated over time: a higher carbon price in 2025 implies a high probability of a high carbon price in 2050.

2. For experts who provided data for only one time period, we assumed that their carbon price probability distribution does not change over time (in years that follow the time period for which the data were provided). In the absence of information on carbon price for at least two points in time, it is not possible to make inferences about a trend in carbon price. Thus, the assumption of constant carbon price probability distribution reflects that we are agnostic about the time trend in these cases, and the need to make a transparent and plausible assumption.

The distribution time profile between 2010 and 2050 for each expert was generated using the following procedure:

- For each year elicited from an expert, we solve for the best fitting theoretical probability distribution family for the assessed quantiles;[4]
- For each available year, we estimated 100 fractiles of the carbon price distribution;[5]
- For each fractile path (e.g., at the median path), we linearly interpolated (over time) between the initial carbon price in 2010 (average ETS price of $50/ton C for the EU and $0/ton C for other regions) and the value of this fractile in the first year for which the expert elicitation data were available (e.g., 2025).
- We then continued reconstruction of each fractile path in the following way:
  - If expert had only one year of data available, we kept fractile values in subsequent years constant (see Expert C in Figure 4-1).
  - If the expert had provided information for two years and the second year of data was 2050 then we linearly interpolated fractile values between the first observed year and 2050. See Expert G in Figure 4-1;
  - If the expert had provided information for two years and the second year was not 2050 (see Expert E in Figure 4-1, for whom 2025 and 2030 are available) then we linearly interpolated fractile values between the first observed year and the second observed year. We kept fractile values in years between the second observed year and 2050 constant.

As a result, we obtained year-specific 2010-2050 carbon price distribution profiles for each expert, which were then pooled across experts for use in modeling. The process of re-constructing expert-level distribution time-profiles first and pooling them second, rather than pooling first and interpolating second, was intentional. We wanted to preserve expert-level carbon price growth information (when available) and to ensure that pooled distribution in any given year was not based on a single expert. We describe the pooling process in the next section.

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4 We used distribution fitting software within the @Risk commercial package. This fitting routine finds the best fit parameters for each of a large set of distribution families, and then ranks these distributions to minimize the error in the cumulative distribution function.

5 Note that the carbon price floor was set to $0. That is, whenever a negative carbon price value was generated from the expert- and year- specific distribution, it was set to zero, and the fractiles were estimated for the resulting censored distribution. Negative carbon price draws were an artifact of fitting analytical probability distributions to the expert-provided percentiles prior to aggregation. For example, for Japan in 2035 expert H provided 1st, 50th, and 90th percentiles, which were equal to 0, 20, and 130, respectively. The @Risk software fit a lognormal distribution with mean, standard deviation, and shift parameter equal to 59.213, 130.64, and –4.4444, respectively. A negative shift parameter implies that the support of this lognormal distribution includes values of carbon price below zero. This issue was addressed by censoring the distribution at zero.

4.3.3 Aggregating Expert Distributions: Same Model Year

For each model year from 2010 to 2050, we obtained actual or interpolated distributions from each expert. Another important step was the development of a pooled carbon price distribution for each of these years. The academic literature is mixed on how to combine elicitations from multiple experts, but in the absence of any information to rank or score experts in terms of their relative calibration most analyses weight all experts equally. We used an equal weight approach here, given the lack of data to justify any other weighting scheme.

The procedure for the convolution of distributions is simple. The individual expert distributions for each year (e.g., 2025) are represented by sets of equal-sized draws. The samples from all distributions are then pooled into a single dataset, and then fractiles of the pooled distribution are estimated based on the combined sample set.

The implied density distributions for select model years for the EU are presented in Figure 4-2. To enable visualization of the multiple density functions on the same figure, violin plots were used.[6] We show the violin plots of density functions for the pooled expert distribution for all assessed regions in Appendix C, along with a table of the fitted probability distributions for selected years.

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6 A violin plot combines a box plot with a rotated kernel density plot. The box plot is represented by a black rectangle (the interquartile range) with a white dot (the median) and black whiskers (the range). The rotated kernel densities are the blue portions of the plot on each side of the box. Violin plots in this report were produced by R package <vioplot> available at http://cran.r-project.org/web/packages/vioplot/index.html.

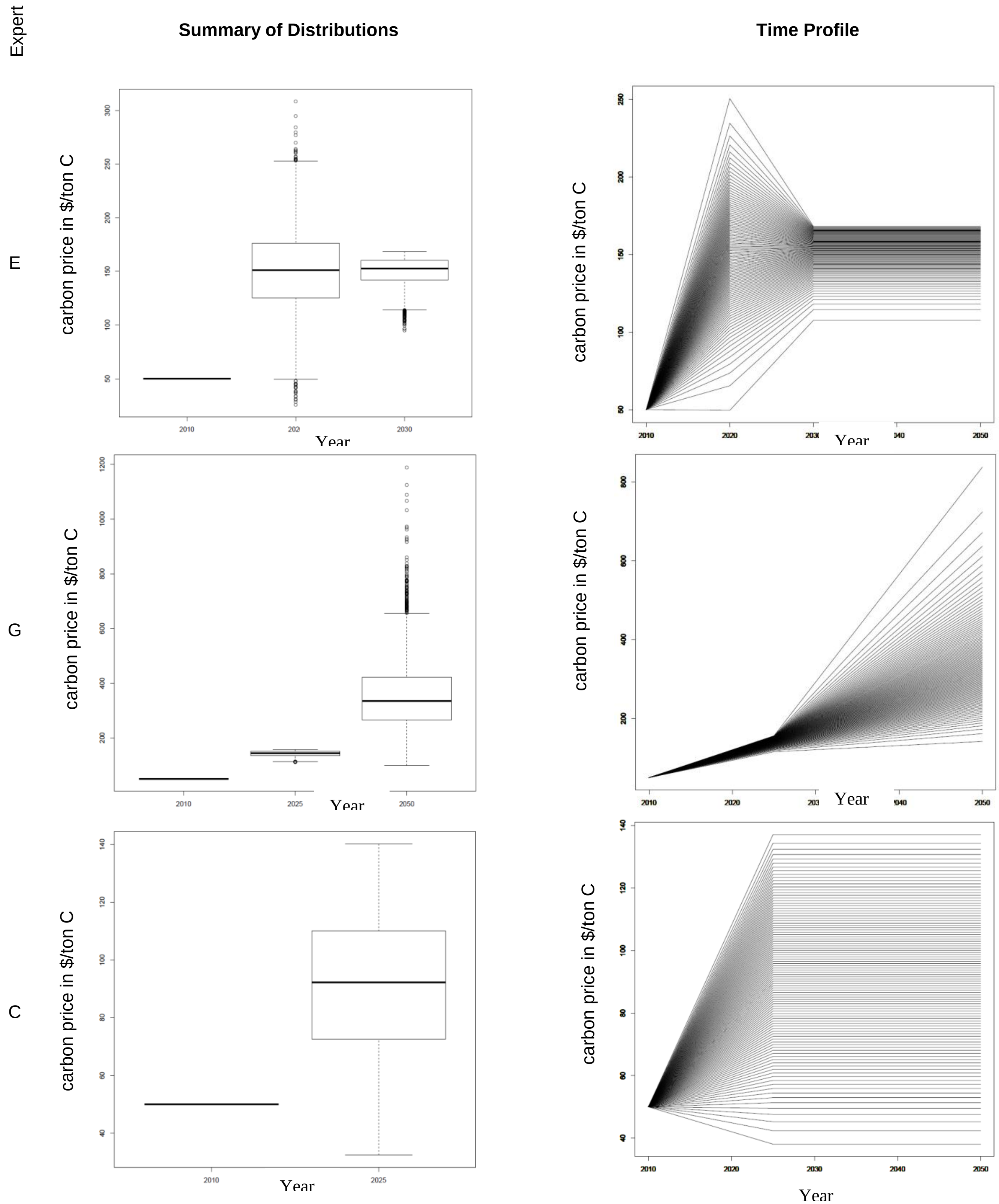

Figure 4-1: Year-Specific Distributions and Interpolated Time Profiles for Select Experts

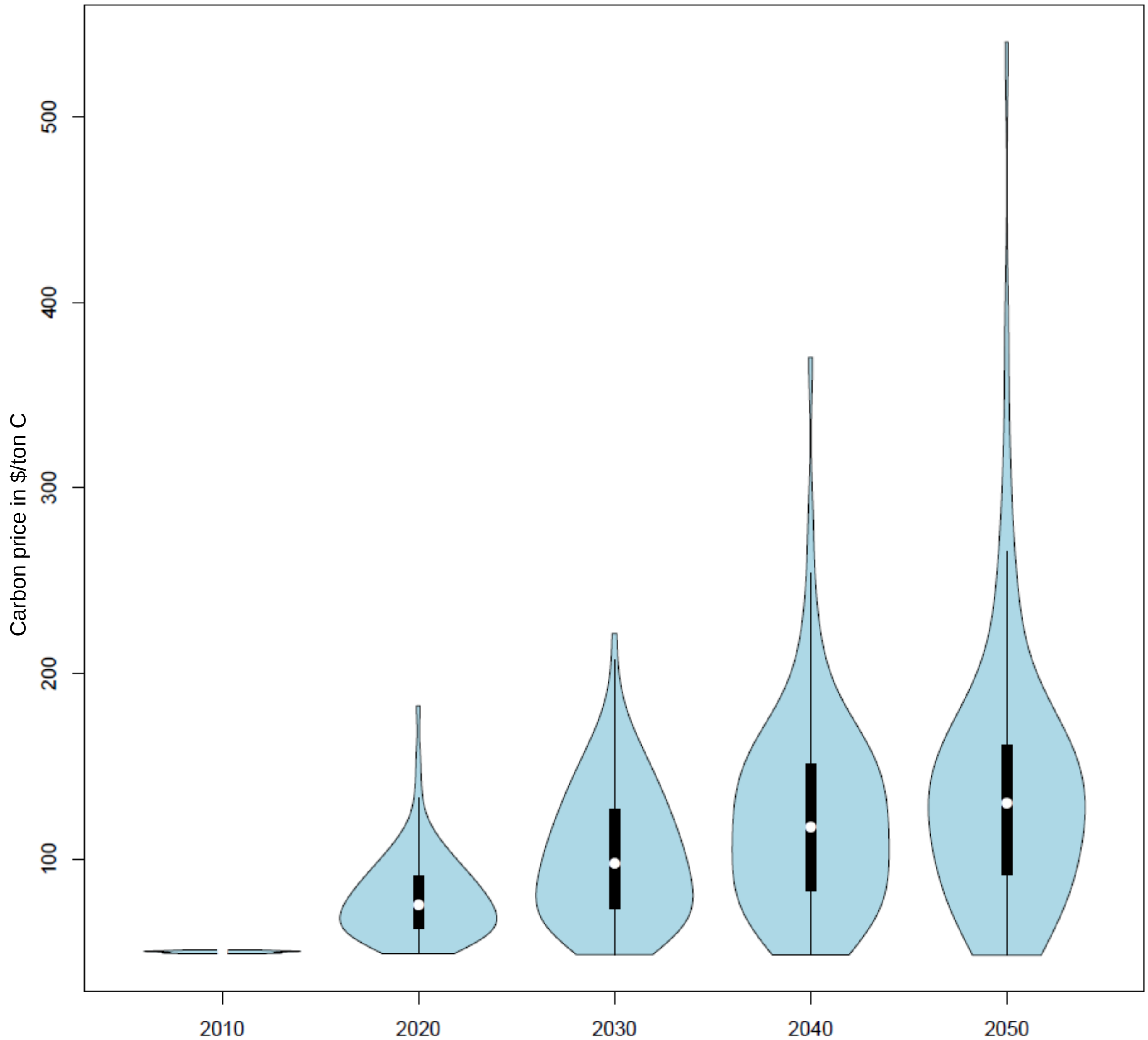

Figure 4-2: Time Profile of the Pooled Carbon Price Distribution for Europe

4.3.4 The Post-2050 Extrapolation

None of the experts provided any information for the post-2050 period. However, in this exercise the region-specific carbon prices were elicited for the future with no U.S. climate policy. Therefore, these region-specific carbon prices would be mainly the result of internal/domestic factors, which would presumably persist after 2050. Therefore, an extrapolation of these prices post-2050, at the rate of growth observed between 2010 and 2050, was carried out.[7]

We used exponential smoothing-based procedure[8] to forecast each fractile of the pooled carbon price distribution for years from 2051 to 2100. For example, an exponential smoothing model was estimated using time series of a pooled median EU carbon price between 2010 and 2050. These parameters were then used to generate forecasted median EU carbon price between 2051 and 2100. This procedure was repeated for all fractiles and regions.

Because forecasting was carried out independently for each fractile, the forecasted fractiles for a given year occasionally failed to exhibit monotonicity. To alleviate this problem, we used isotonic regression to impose monotonicity in each set of year-specific forecasted fractiles. Isotonic regression relies on PAVA algorithm (Robertson et al., 1988), which replaces adjacent violators of monotonicity by their weighted average.[9]

Figure 4-3 shows an extrapolated pooled carbon price distribution for the EU:

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7 An alternative to extrapolation of carbon prices post-2050 was to assume that the carbon prices remain at their 2050 levels between 2051 and 2100. In this case, one could interpret region-specific pre-2050 climate policy actions as being anticipatory of some event (e.g., the imminent U.S. climate policy). After 2050, this event is no longer expected to occur and the regions "freeze" their existing climate policies by maintaining the same stringency level. However, this is not consistent with the regional actors having reasonably accurate expectations (e.g., about policy actions by other regional actors). Therefore, the extrapolation approach taken by this study, which assumes that the regional policy is driven primarily by internal/region-specific factors, appears to be more reasonable. Furthermore, constant carbon prices implies a decreasing level of effort; under economic growth, rising carbon prices are required to even maintain constant emissions. Another alternative assumption would be to assume that after 2050, carbon prices decline linearly to zero. In the absence of any information, these alternatives are at least as strong, if not stronger, assumptions than our approach of extrapolating the growth rate in carbon prices.

8 R Project package <forecast> (available at http://robjhyndman.com/software/forecast/) was used for this purpose. Exponential smoothing model estimates for each carbon price fractile in each region are available upon request.

9 This post-processing was carried out using R Project <isoreg> routine, which is available with the base distribution.

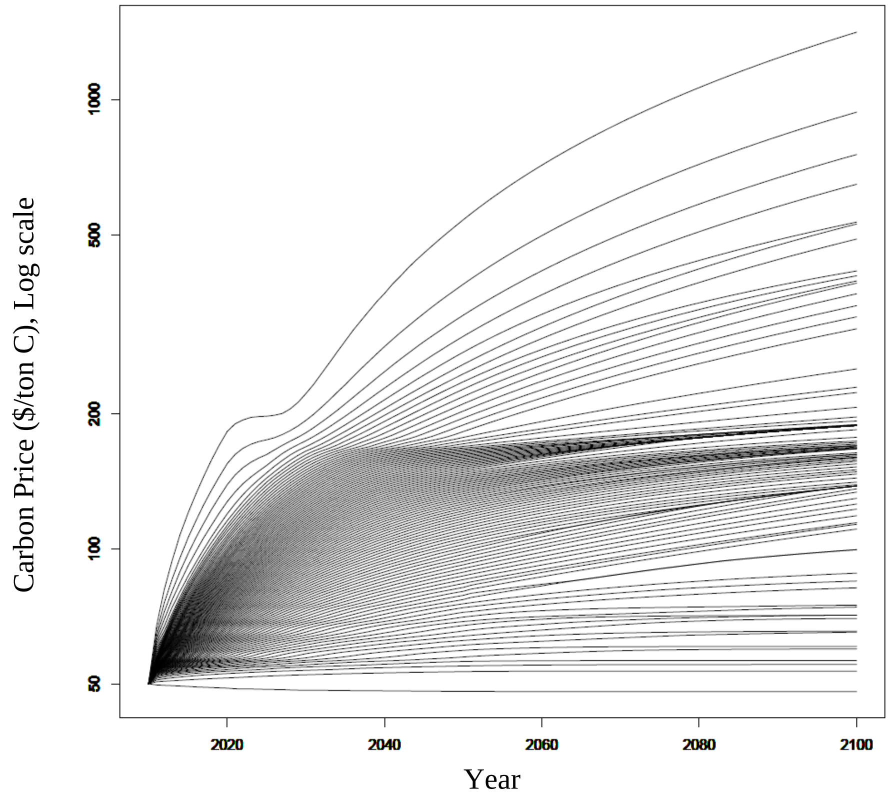

Figure 4-3: Extrapolated pooled carbon price distribution for the EU

5 Uncertainty Analysis using the EPPA Model

The uncertainty analysis to generate the set of socio-economic scenarios is performed by applying Monte Carlo simulation to the EPPA model. This task requires sampling values from the parameter distributions and simulating the EPPA model for each sampled set of parameters. Lastly, the results are extrapolated to the year 2300.

5.1 Uncertainty Parameter Sampling Design

To limit the ensemble size, we employ stratified sampling (see Rubenstein and Kroese 2008, Ch. 5) and, in particular, the Latin Hypercube method for sampling across multiple parameters (McKay et al. 1979). Numerical experiments demonstrate that, compared with pure random sampling, the outcome distributions converge more quickly to the limiting distributions as sample size increases. We propose to use 400 samples, a sample size that, for Latin Hypercube sampling, has been shown to approximate well the limiting distribution for many nonlinear models. In previous Monte Carlo analyses with EPPA, we tested the adequacy of the ensemble size by comparing sample sizes of 100, 200, 300, 400, 500, and 1000. To do this we performed 20 independent ensembles (drawing different sample sets for each) for each ensemble size, and compared the standard deviation of the estimate of median temperature change to the mean estimate of the standard deviation from the 20 ensembles. The standard deviation of the estimate of the median fell from 0.5% with 100 samples, to 0.2% with 400 samples, and had no appreciable improvement with 500 or 1000 samples. Similarly, the standard deviation of the estimate of the 0.95 fractile fell from 1.8% of its mean with 100 samples to 0.8% with 400 samples, and 0.75% with 1000 samples.

As noted previously, there is correlation among some of the input parameters. For the physical climate parameters, correlation is modeled by sampling directly from the joint distribution described in the previous section. For many of the economic parameters, we impose correlation structure on related subsets of parameters (see Webster et al. 2008a for details). The correlation is imposed during the sampling process using the procedure from Iman and Conover (1982). This method chooses the next subinterval for sampling, without replacement, by imposing the specified rank correlation. This procedure generalizes to an N-dimensional joint distribution with a correlation or covariance matrix by applying this technique iteratively as a sample is drawn from each marginal. We propose to apply this technique to sampling from the joint distributions with correlation.

5.2 GHG Emission Scenario Assumptions

The current project is intended to assess a range of scenarios that are conditional on a specific assumption: that the U.S. does not enact any greenhouse gas emissions restrictions over the 21st century. As described above, the actions of other regions/nations were treated as an uncertainty. Because of the implementation of the EPPA model, it was necessary that for every sample with at least one region containing a non-zero price on GHGs, that a first simulation be performed assuming no GHG prices anywhere with the other parameter sample values held constant. Thus, two ensembles will be available at the end of the calculations: *one where no country reduces emissions and another where the emissions reductions are uncertain*. For some economic results, especially costs to the regions with policy, those quantities will be calculated as the difference between results in the two scenarios for the same samples of other parameters.

Several minor modifications were required to implement the carbon tax uncertainties from the expert distributions due to model instabilities that result from incorporating these distributions. The failures to generate numerically stable solutions occur when:

- **Sampled carbon tax values are too low**. Low carbon tax values constitute a large percentage of the samples because experts have judged the most likely policy efforts of other regions as minimal, in the absence of U.S. restrictions. We addressed this issue by rounding carbon taxes below some threshold down to zero or up to the lowest stable value. We also note that this procedure introduces a slight bias relative to the original expert distributions. The distributions simulated are a mixed distribution with a carbon tax of either 0 or a carbon tax of greater than some value $*t*. This threshold value is $6/ton C ($1.6ton CO_2) for all regions except for China and India, which have a higher threshold value of $10/ton C ($2.8/ton CO_2).
- **Rates of increase of carbon taxes (sampled above the threshold) are too high**. These instabilities occur because the model was developed and calibrated to be numerically stable for a narrow range of policies. Specifically, in the past EPPA has been used to analyze carbon taxes predominantly imposed on developed (Annex I) regions and with rates of increase of 4% per year. This rate is intertemporally optimal for the model. As an artifact of the rounding procedure, some samples jump suddenly from a carbon tax of zero in one period to a large non-zero carbon tax in the next period. In such cases, the rate of increase from zero must then be smoothed linearly.

A significant portion of the distribution from experts, especially for non-Annex I regions, consisted of extremely low carbon taxes (less than $10/ton C). However, the EPPA model, which has previously been used mainly for harmonized carbon price scenarios and other economically efficient policies, is not numerically stable for very low carbon prices or for widely varying carbon prices across regions (e.g., very high price in the EU but low price in China). As a result, very low carbon prices were assumed to be zero in order to obtain stable solutions. The percentage of samples with $0/ton is given in Appendix D, Table D-1.

In addition, because of the challenges of obtaining numerically stable solutions, the results here focus on the highest emissions regions. We include carbon tax uncertainties only for the following regions:

- European Union
- Japan
- Australia / New Zealand
- China
- India

The remaining regions are assumed to have no policy in the results provided:

- Canada
- Russia
- Middle East
- Latin America
- Africa

The share of global emissions from the latter set of regions is relatively small, only 22% of cumulative global emissions under the reference scenario. The share of US emissions and the regions where policy uncertainty is modeled comprise 64% of cumulative global emissions (See Appendix D, Figure D-1). We also provide in Appendix D tables and figures summarizing the effect of including the policy uncertainty in the five regions listed above. By 2050, the impact on global CO_2 emissions has an interquartile range of 2 to 6% emission reduction relative to samples without the policy uncertainty (but including uncertainty in all other parameters). The expert-provided carbon prices for the regions not modeled consisted of even lower carbon prices than the regions included in this analysis, and therefore, we expect that the impact of omitting the other five regions is minimal. See Appendix D for more details.

5.3 Extrapolating to a 300-Year Time Horizon

The EPPA model only simulates to the year 2100. Because the scenario library should include projections to 2300, we needed to augment the analysis with the EPPA model to extrapolate key quantities.

There are alternative methods that can be used to extrapolate the scenarios from 2100 to 2300. One approach would be to use an existing model with a longer time horizon such as DICE or PAGE, and calibrate the parameters of that model to match those in the EPPA scenarios. The advantage to such an approach is the use of another well-known model to provide the functional forms. One disadvantage of this approach is that the simpler functional form of the equations in models such as DICE may not fit well the empirical results of a detailed model such as EPPA over the period 2000-2100. A second disadvantage is that whatever model is chosen for the extrapolation may not be consistent with models that will be used in the future with these scenarios.

A second, related, approach is to posit simple functional forms, and calibrate those functions to the scenario results to 2100. However, this approach similarly suffers from the disadvantages of simple functional forms not fitting well the scenario results, and may not be consistent with future models. In addition, the calibration of these extrapolations require assumptions about both the function forms and the terminal values of some parameters, such as long-term convergence of growth rates.

Given the disadvantages described above, we employ here a non-parametric approach. This approach only uses assumptions about terminal conditions such as convergence in growth rates (which would be required in the above approaches as well) and the results to 2100 to perform the extrapolation. This approach is the most straightforward and transparent, and can easily be replicated from the results in the scenario library for alternative terminal assumptions. We describe here the quantities extrapolated and the procedure used, and highlight the key assumptions for transparency.

The extrapolated quantities include

- Population
- GDP per capita
- GDP
- CO_2 Emissions

The procedure here, illustrated using global outcomes, is identical for extrapolating regional outcomes as well.

5.3.1 Extrapolation of Population

Population is extrapolated using only the level of population in 2100, the population growth rate in 2100, and the assumption that the growth rate will linearly decline to zero by 2300. Alternative plausible assumptions could be made, but given the deep uncertainty in projecting this far into the future, we provide results based on this assumption. Extrapolations using alternative assumptions can easily be calculated using the provided scenario results to 2100.

Population $L(t)$ is extrapolated beyond 2100 as

$$L(t) = L(t\text{-}1)\,[1 + g_L(t)]$$

where

$$g_L(2100) = L(2100)/L(2095) - 1$$
$$g_L(2300) = 0$$
$$\Delta g_L = [g_L(2100) - g_L(2300)] / 40$$
$$g_L(t) = g_L(t\text{-}1) - \Delta g_L \qquad t = 2105,\ldots,2300$$

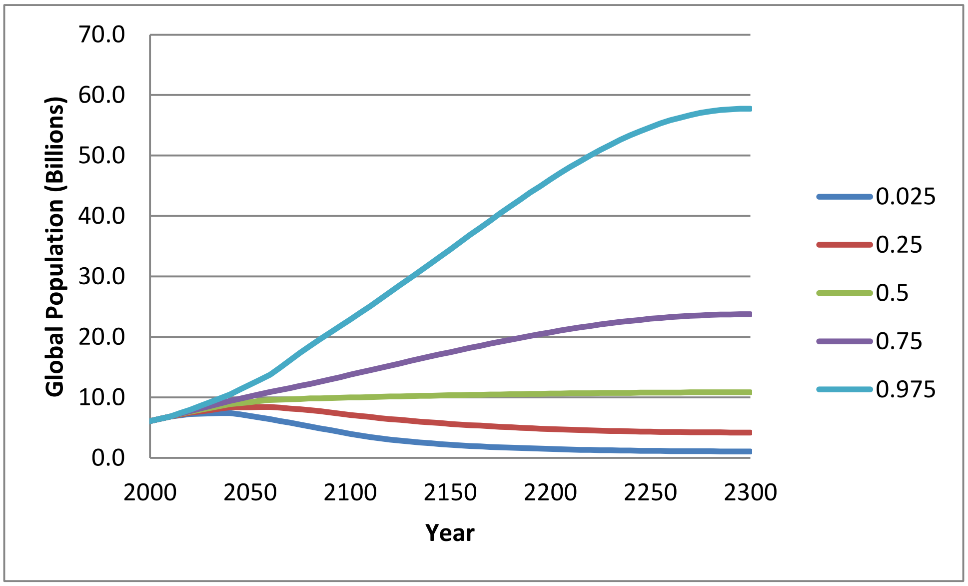

Figure 5-1: Extrapolation of Global Population to 2300

5.3.2 Extrapolation of GDP per Capita and GDP

Similarly to population, we can extrapolate GDP per capita using the level and growth rates in 2100, and an assumption about the terminal growth rate in 2300. Whereas for population a plausible assumption is convergence to zero growth in the long run, for productivity growth, typical long-term convergence assumptions are for a low but non-zero rate of growth. Here, we provide results extrapolated by assuming that the terminal productivity growth rate is 1% per annum (roughly 5% per 5-year period).

The extrapolation procedure is to calculate GDP per capita $\theta(t)$ as

$$\theta(t) = \theta(t\text{-}1)\,[1 + g_\theta(t)]$$

where

$$g_\theta(2100) = \theta(2100)/\,\theta(2095) - 1$$
$$g_\theta(2300) = 0.05$$
$$\Delta g_L = [g_\theta(2100) - g_\theta(2300)] / 40$$
$$g_\theta(t) = g_\theta(t\text{-}1) - \Delta\, g_\theta \qquad t = 2105,\ldots,2300$$

GDP ($Y(t)$) is calculated as

$$Y(t) = L(t)\theta(t) \qquad t = 2105,\ldots,2300$$

Fractiles of extrapolated GDP per capita are given in Figure 5.2 below, assuming non-U.S. policy uncertainties.

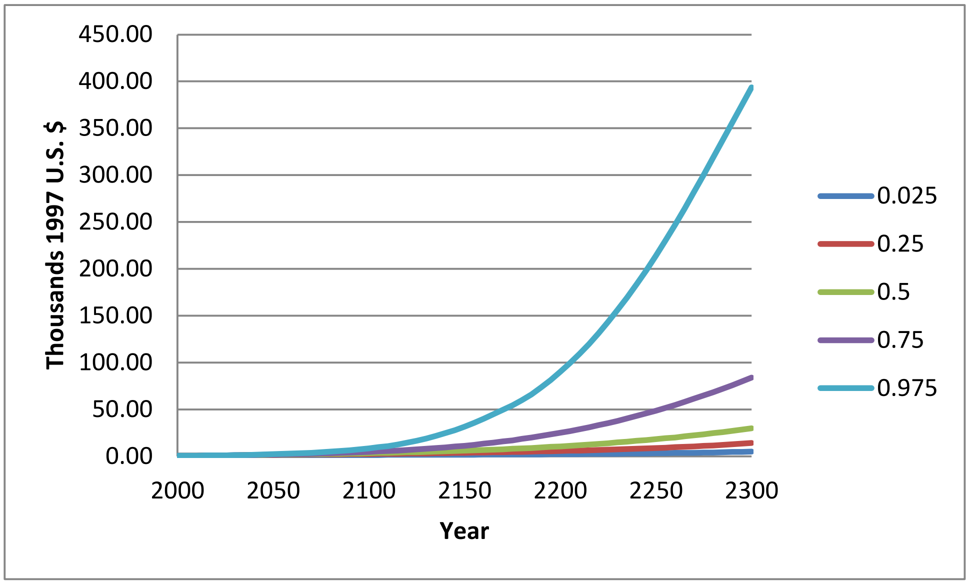

Figure 5-2: Extrapolation of Global GDP per Capita to 2300, Assuming non-U.S. Carbon Policies

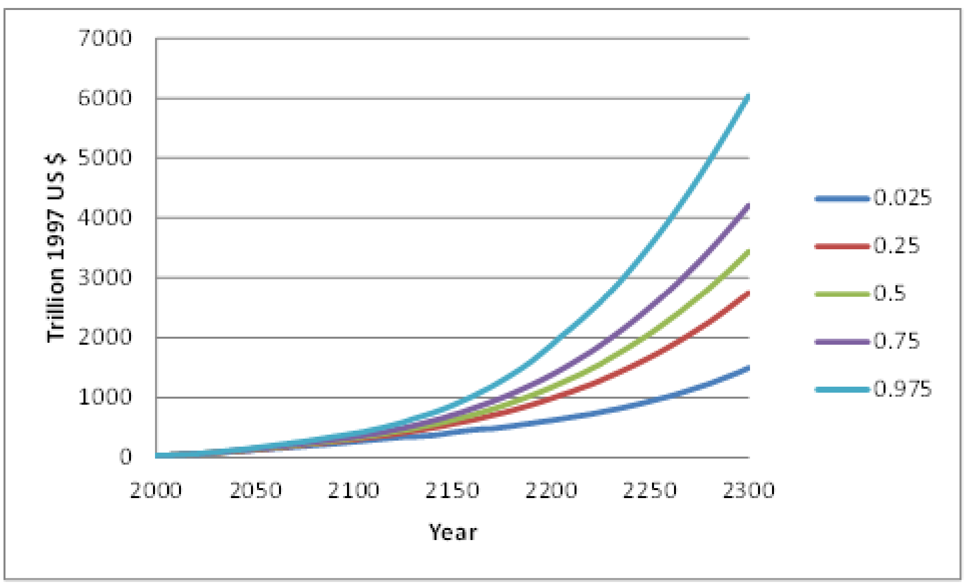

Figure 5-3: Extrapolation of Global GDP to 2300, Assuming non-U.S. Carbon Policies

5.3.3 Extrapolation of CO_2 Emissions

To extrapolate emissions beyond 2100 from scenario results, we use the carbon intensity in 2100, the rate of change of the carbon intensity in 2100, and an assumption about how the rate of change in carbon intensity (the rate of decarbonization of the economy) will evolve by 2300. For simplicity and transparency, we provide results from two bounding assumptions about the terminal decarbonization rate: a constant rate of change in carbon intensity after 2100, and a linear decline of the rate of change in carbon intensity to zero by 2300.

Carbon emissions $E(t)$ are extrapolated beyond 2100 using the carbon intensity $\phi(t)$

$$E(t) = Y(t)\ \phi(t)$$

Where

$$\phi(t) = E(t) / Y(t) \quad t = 2000,\ldots,2100 \qquad \text{[Carbon Intensity from EPPA scenario]}$$

$$g_\phi(2100) = \phi(2100) / \phi(2095) - 1$$

$$g_\phi(2300) = 0 \quad \text{or} \quad g_\phi(2300) = g_\phi(2100)$$

$$\Delta g_\phi = [g_\phi(2100) - g_\phi(2300)] / 40$$

$$g_\phi(t) = g_\phi(t\text{-}1) - \Delta g_\phi \qquad t = 2105,\ldots,2300$$

$$\phi(t) = \phi(t\text{-}1)[1 + g_\phi(t)]$$

Below, we show the resulting fractiles for global CO_2 emissions extrapolated to 2300 for the scenario sets that include non-U.S. policy uncertainty. We show the resulting fractiles of emissions for both assumptions about the rate of change in carbon intensity after 2100: constant (Figure 5-4) and declining linearly to zero (Figure 5.5).

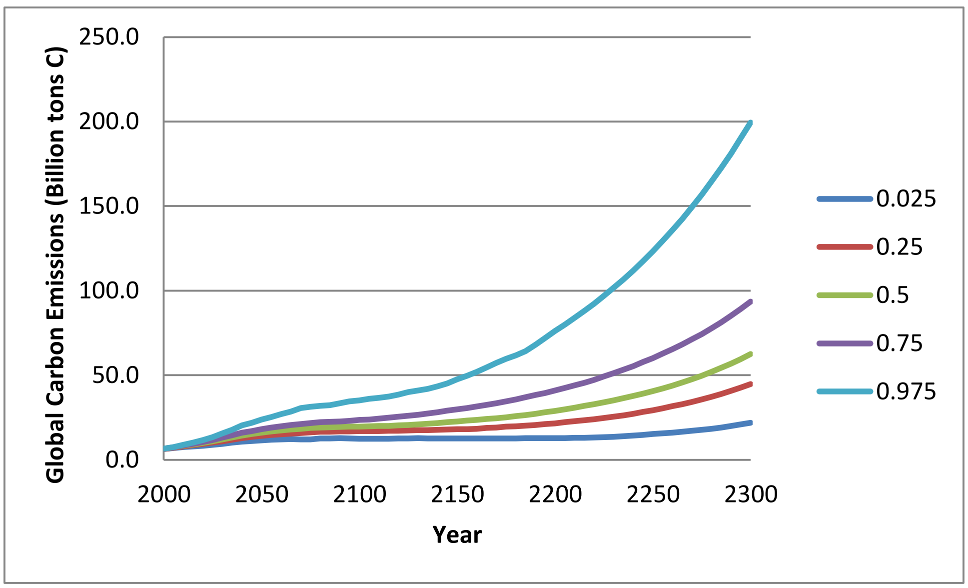

Figure 5-4: Extrapolation of Global CO2 Emissions to 2300, Assuming Rate of Change of Carbon Intensity remains constant after 2100

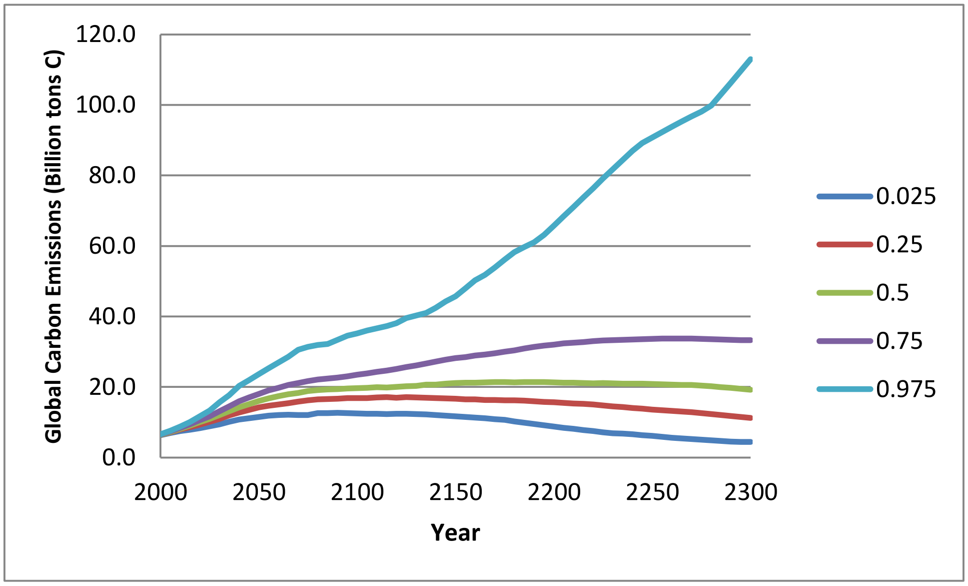

Figure 5-5: Extrapolation of Global CO2 Emissions to 2300, Assuming Rate of Change of Carbon Intensity declines linearly to zero by 2300.

6 The Socio-Economic Emissions Scenario Library

The socio-economic scenario library consists of time profiles of consistent sets of input assumptions and output variables from the EPPA Monte Carlo simulation. The scenario data are available in Excel files accompanying this report.

As described above, there are two sets of scenarios, one with no carbon prices in any region ("REF"), and another with carbon price uncertainties ("TAX"). The other uncertain parameters are constant across the two sets.

Global-level results include:

- GHG emissions (Global GHG Emissions uncertainty Results.xlsx)
  - Total GHG as CO_2-eq (Weighted by 100-year GWPs)
  - Carbon Dioxide (CO_2)
  - Methane (CH_4)
  - Nitrous Oxide (N_2O)
  - Hydroflorocarbons (HFCs)
  - Perflorocarbons (PFCs)
  - Sulfur Hexafloride (SF_6)
- Non-GHG emissions (Global Non-GHG Emissions Uncertainty Results.xlsx)
  - Sulfur Dioxide (SO_2)
  - Nitrogen Oxides (NO_x)
  - Volatile Organic Compounds (VOC)
  - Carbon Monoxide (CO)
  - Black Carbon Aerosols (BC)
  - Organic Carbon Aerosols (OC)
  - Ammonia (NH_3)
- Economic Output Measures (Global Economic Uncertainty Results.xlsx)
  - GDP
  - Consumption
  - GDP/Capita,
  - Consumption/Capita

Regionally-disaggregated results include:

- Carbon Dioxide (CO_2) emissions
  - Regional CO2 Emissions uncertainty Results REF.xlsx
  - Regional CO2 Emissions uncertainty Results TAX.xlsx

- Methane (CH_4) emissions
  - Regional CH4 Emissions uncertainty Results REF.xlsx
  - Regional CH4 Emissions uncertainty Results TAX.xlsx
- Nitrous Oxide (N_2O) emissions
  - Regional N2O Emissions uncertainty Results REF.xlsx
  - Regional N2O Emissions uncertainty Results TAX.xlsx
- Hydroflorocarbons (HFC) emissions
  - Regional HFC Emissions uncertainty Results REF.xlsx
  - Regional HFC Emissions uncertainty Results TAX.xlsx
- Perflorocarbons (PFC) emissions
  - Regional PFC Emissions uncertainty Results REF.xlsx
  - Regional PFC Emissions uncertainty Results TAX.xlsx
- Sulfur Hexafloride (SF_6) emissions
  - Regional SF6 Emissions uncertainty Results REF.xlsx
  - Regional SF6 Emissions uncertainty Results TAX.xlsx
- Nitrogen Oxides (NO_x) emissions
  - Regional NOx Emissions uncertainty Results REF.xlsx
  - Regional NOx Emissions uncertainty Results TAX.xlsx
- Sulfur Dioxide (SO_2) emissions
  - Regional SO2 Emissions uncertainty Results REF.xlsx
  - Regional SO2 Emissions uncertainty Results TAX.xlsx
- Volatile Organic Compounds (VOC) emissions
  - Regional VOC Emissions uncertainty Results REF.xlsx
  - Regional VOC Emissions uncertainty Results TAX.xlsx
- Carbon Monoxide (CO) emissions
  - Regional CO Emissions uncertainty Results REF.xlsx
  - Regional CO Emissions uncertainty Results TAX.xlsx
- Organic Carbon (OC) emissions
  - Regional OC Emissions uncertainty Results REF.xlsx
  - Regional OC Emissions uncertainty Results TAX.xlsx
- Black Carbon (BC) emissions
  - Regional BC Emissions uncertainty Results REF.xlsx
  - Regional BC Emissions uncertainty Results TAX.xlsx

- Ammonia (NH_3) emissions
    - Regional AMO Emissions uncertainty Results REF.xlsx
    - Regional AMO Emissions uncertainty Results TAX.xlsx
- GDP
    - Regional GDP uncertainty Results REF.xlsx
    - Regional GDP uncertainty Results TAX.xlsx
- Consumption
    - Regional CONSUMPTION uncertainty Results REF.xlsx
    - Regional CONSUMPTION uncertainty Results TAX.xlsx
- Carbon Prices (Only for TAX case)
    - Regional CARBON PRICE uncertainty Results TAX.xlsx
    - Only for regions: EUR, JPN, ANZ, CHN, IND
- Population
    - Regional Population uncertainty Result.xlsx

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Appendix A: Growth Rate Uncertainty by Region

This appendix shows the assumed uncertainty in economic growth as driven by labor productivity growth for each region in the EPPA model.

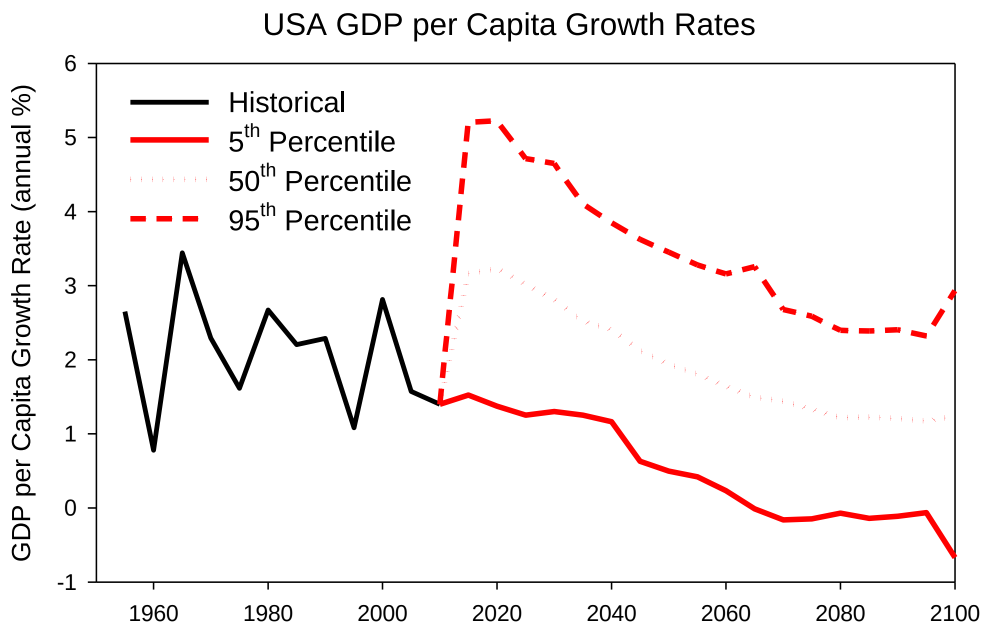

Figure A-1: USA GDP per Capita Growth Rates

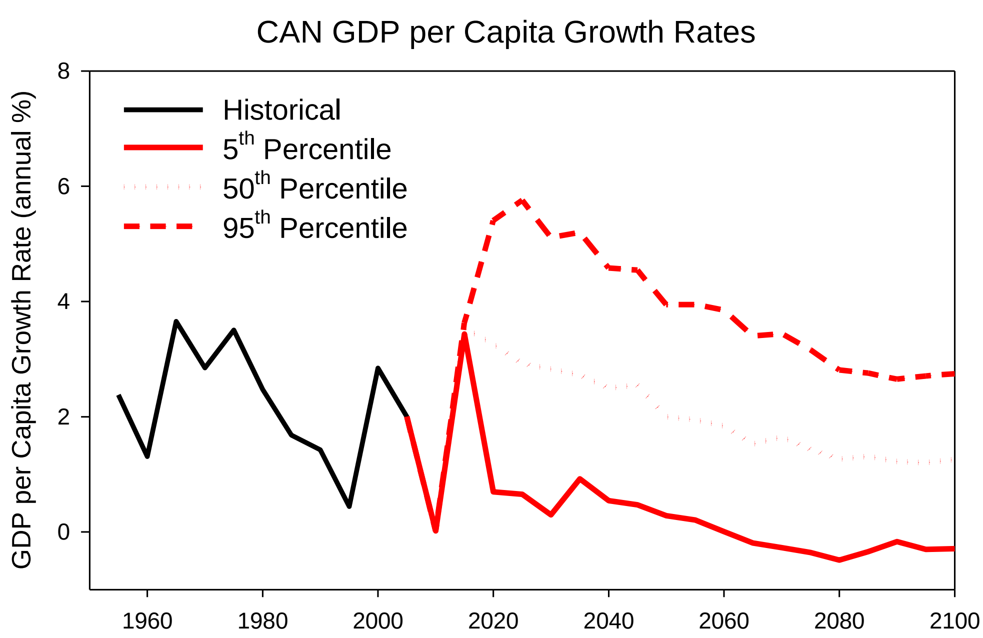

Figure A-2: Canada GDP per Capita Growth Rates

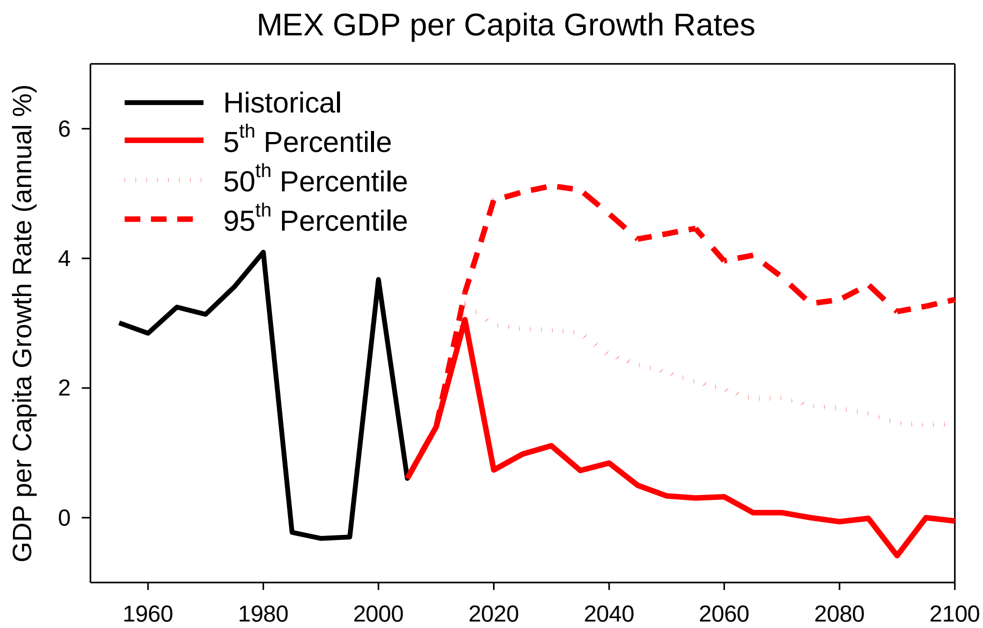

Figure A-3: Mexico GDP per Capita Growth Rates

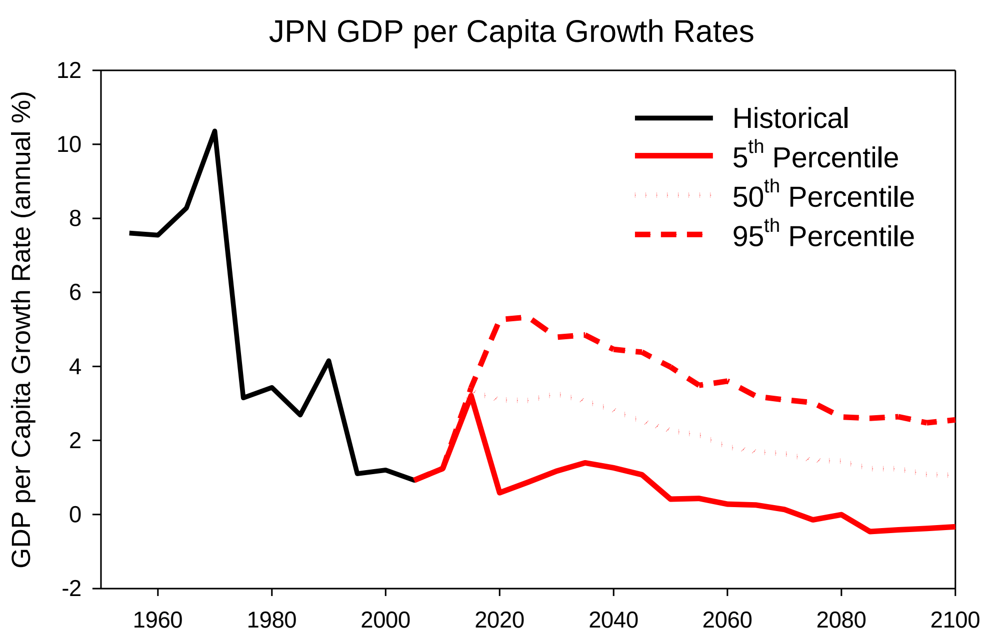

Figure A-4: Japan GDP per Capita Growth Rates

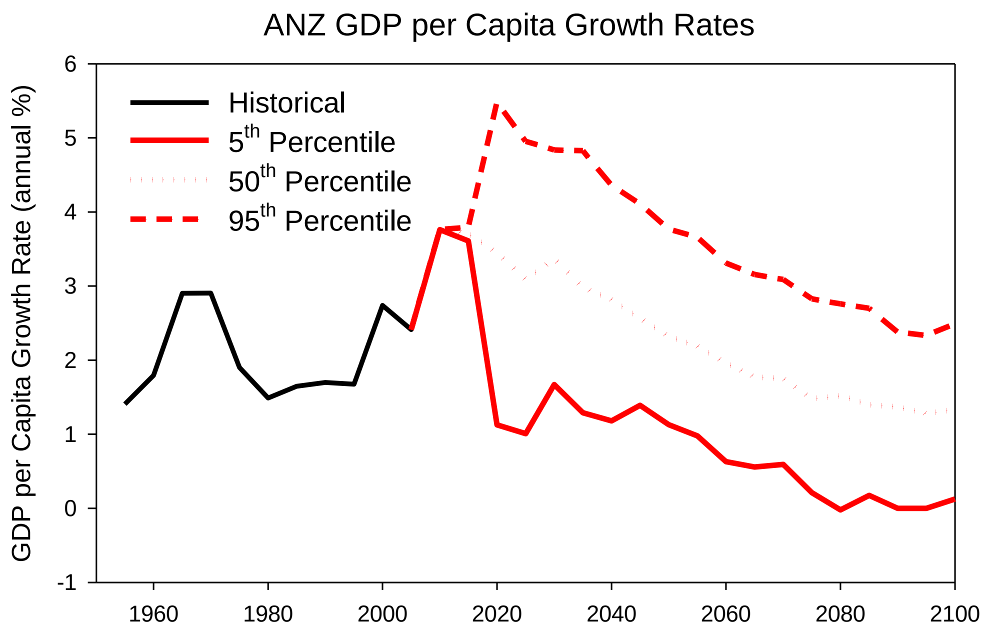

Figure A-5: Australia & New Zealand GDP per Capita Growth Rates

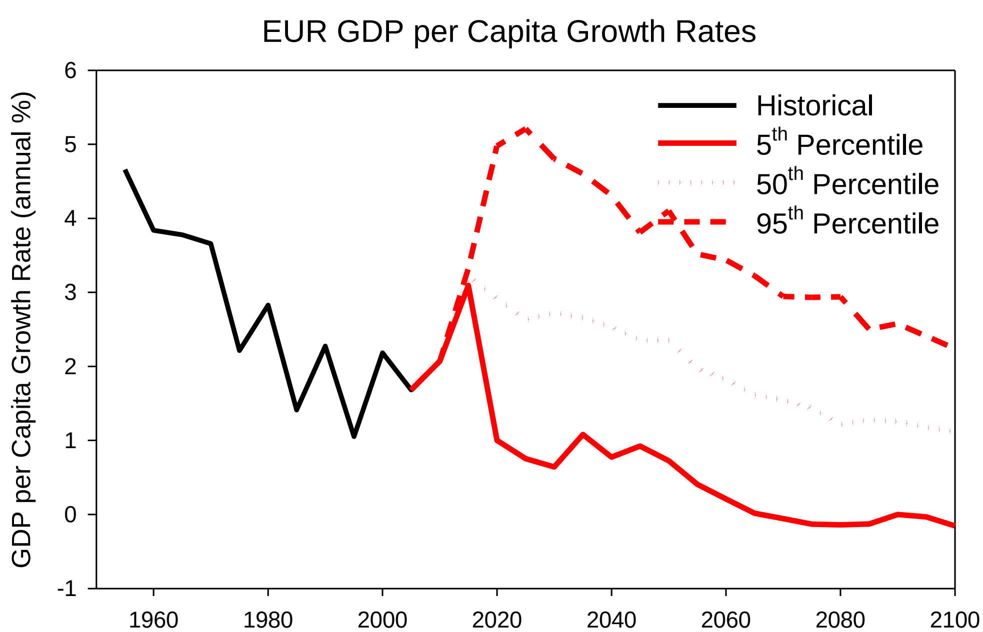

Figure A-6: European Union GDP per Capita Growth Rates

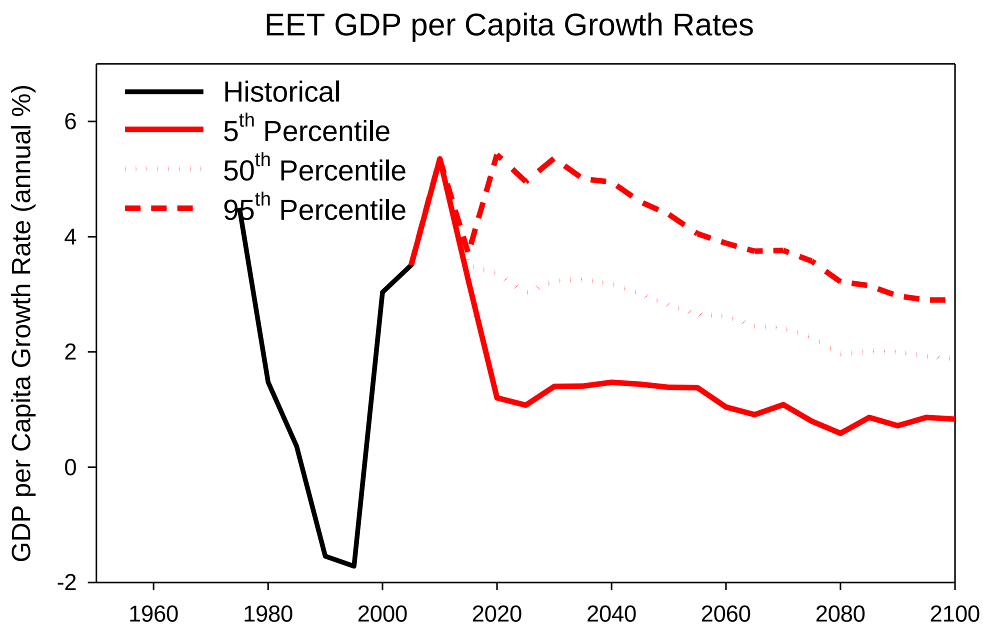

Figure A-7: EET GDP per Capita Growth Rates

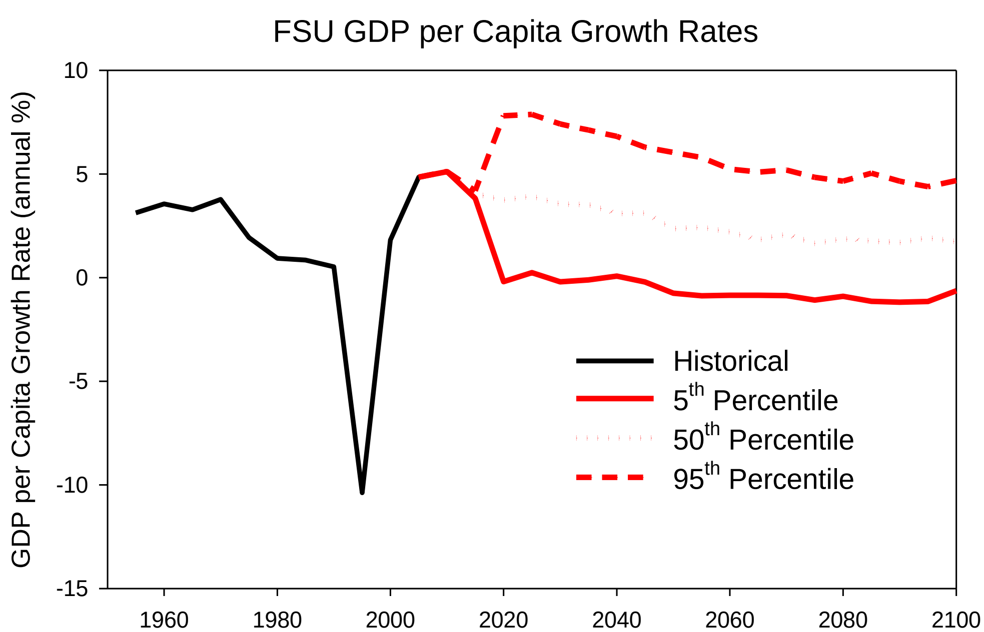

Figure A-8: Russia GDP per Capita Growth Rates

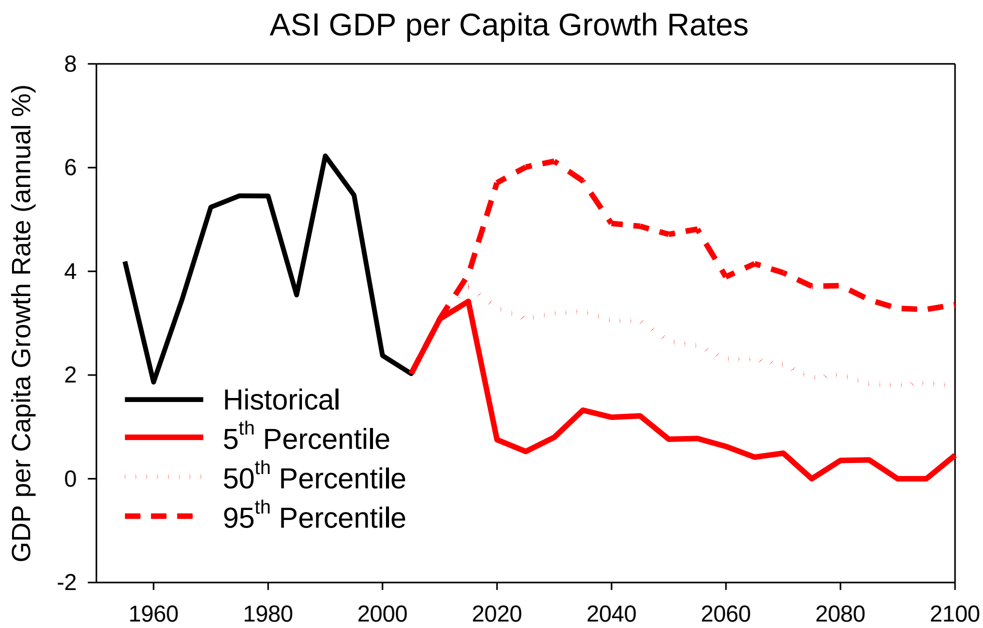

Figure A-9: ASI GDP per Capita Growth Rates

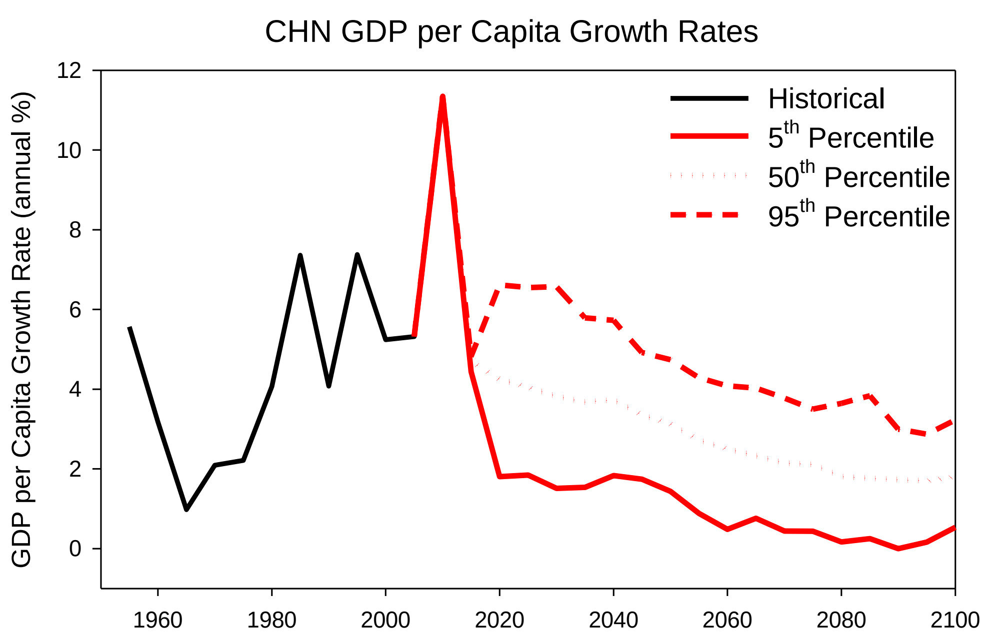

Figure A-10: China GDP per Capita Growth Rates

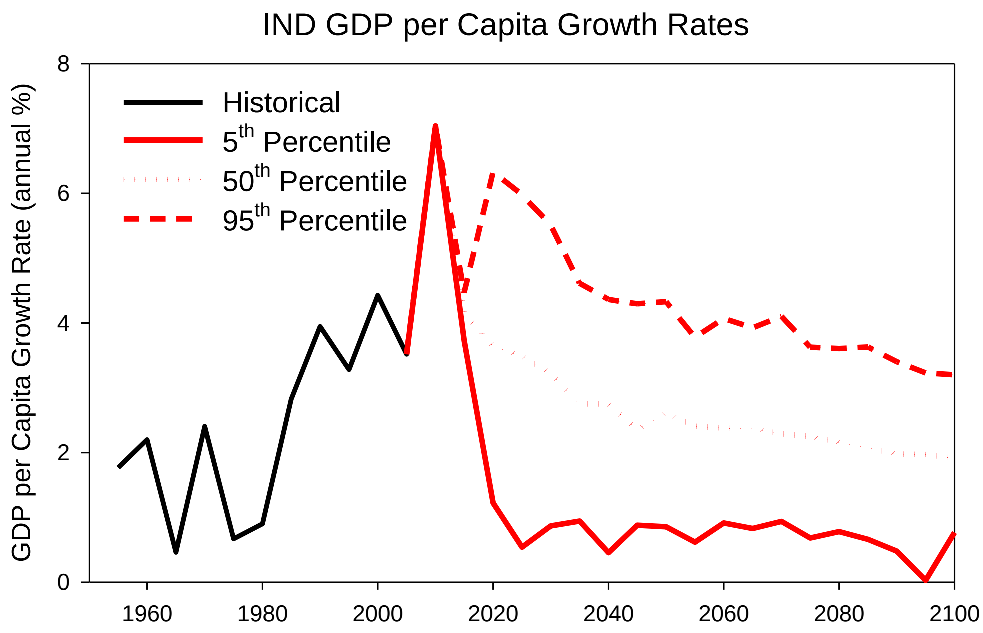

Figure A-11: India GDP per Capita Growth Rates

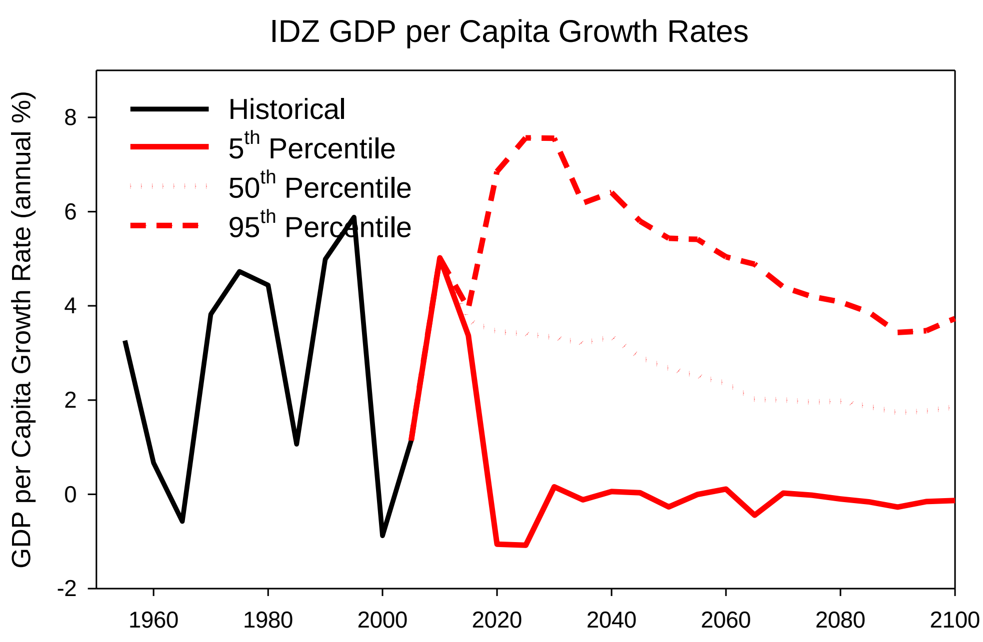

Figure A-12: IDZ GDP per Capita Growth Rates

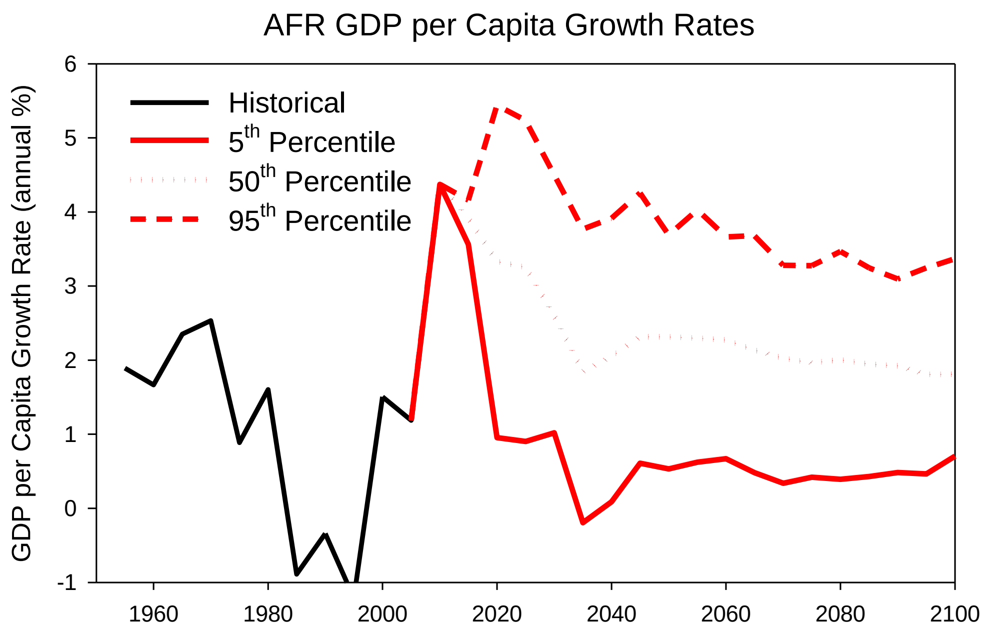

Figure A-13: Africa GDP per Capita Growth Rates

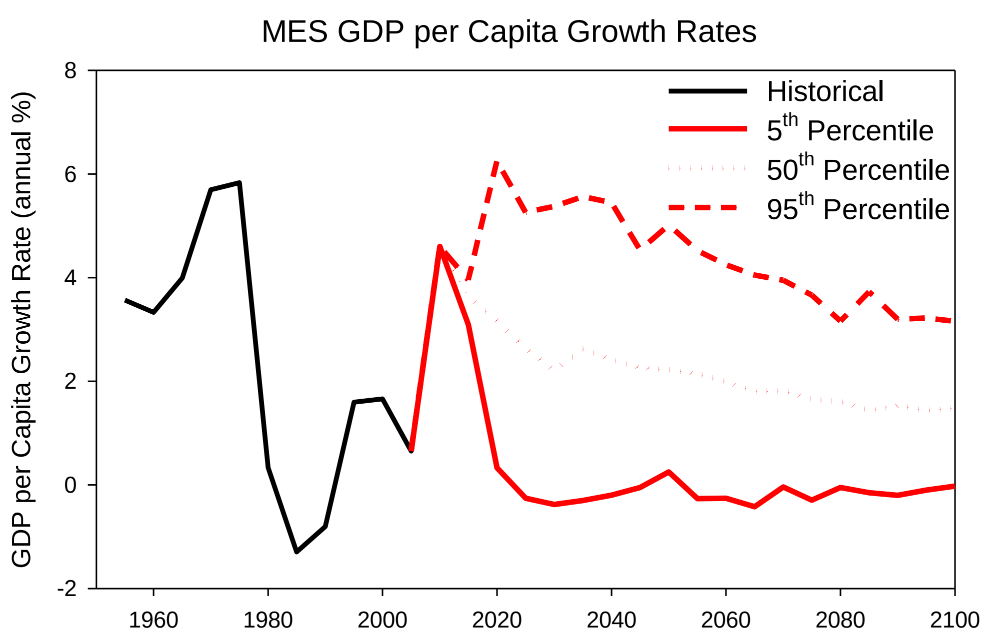

Figure A-14: MES GDP per Capita Growth Rates

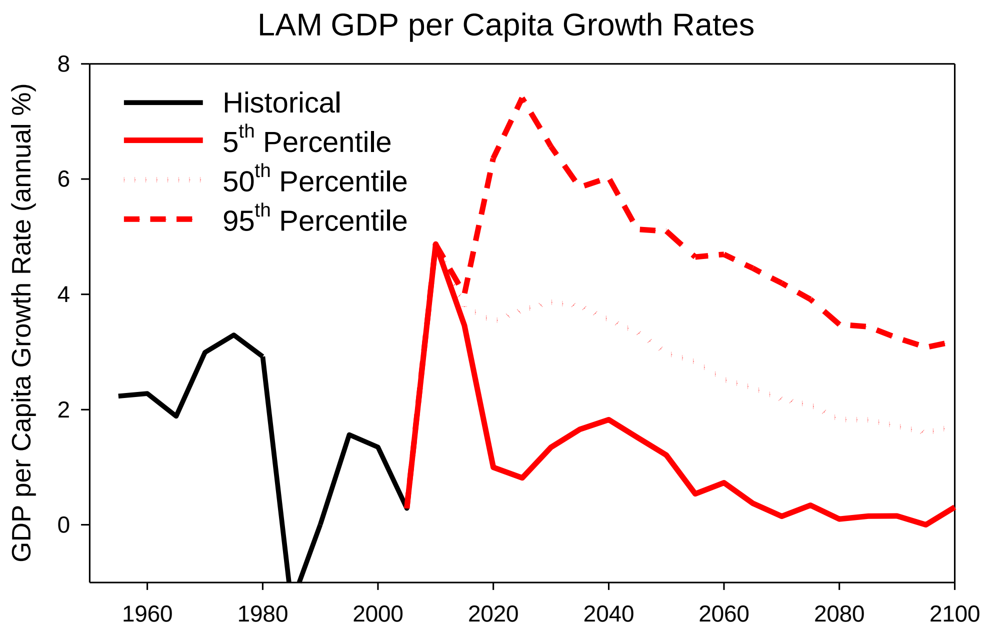

Figure A-15: Latin America GDP per Capita Growth Rates

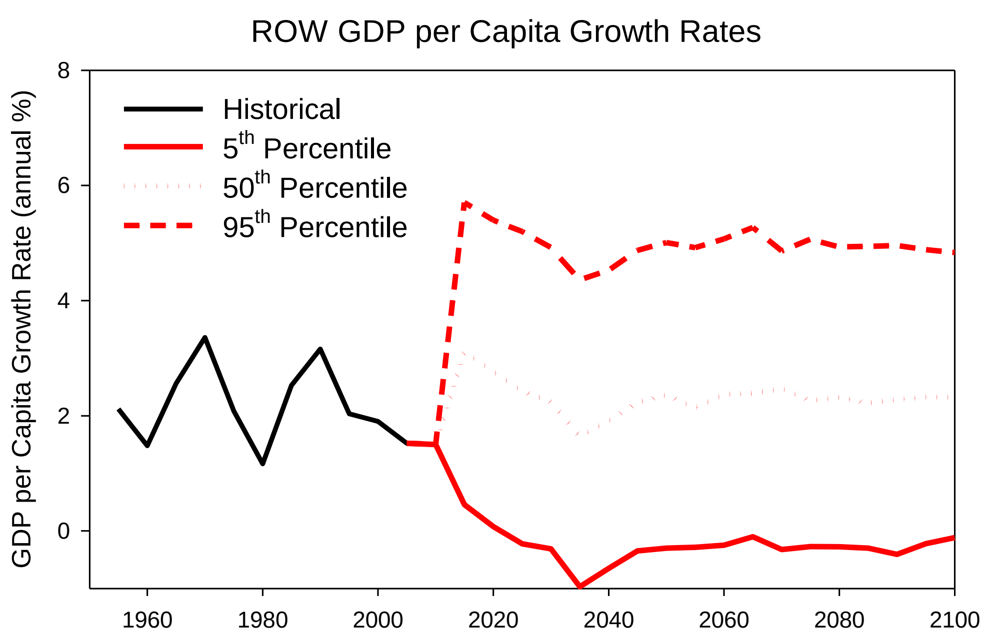

Figure A-16: Rest-of-World GDP per Capita Growth Rates

Appendix B: Developing Probabilistic Socio-Economic-Emissions Scenarios: Expert Elicitation Information Package

You are being asked to participate in this exercise to support the development of a library of socio-economic scenarios that can be used in assessing future climate change outcomes. The effort is funded by the U.S. Environmental Protection Agency's National Center for Environmental Economics (work assignment 0-11 under contract number EP-W-11-003). The resulting scenario library is intended to support analysis within the U.S. Environmental Protection Agency, but will also be made publicly available for the broader analysis community to use.

As part of the development of these probabilistic scenarios, there is a need to develop probability distributions of future greenhouse gas policy actions by various nations or groups of nations. You are being asked specifically to provide your expert judgment about the range of possible GHG limits that countries could undertake and their relative likelihood. The next phase of this interview will focus on us defining more precisely the quantities to be elicited from you.

An expert elicitation is a structured interview process with the objective of obtaining probabilistic judgments from you about specified quantities. The structure of the interview is designed to encourage you to think critically about the full range of possible outcomes. Human judgments about uncertainty are known to suffer from several cognitive biases, as we will discuss later. This process is intended to help minimize these biases through structured questioning and discussion. The interview will consist of four distinct stages:

1. **The structuring questions**, to define an unambiguous measure for each quantity to be elicited;
2. **The conditioning phase**, to describe the common cognitive biases of which you should be aware in your thinking;
3. **The encoding questions**, a series of questions to elicit your view of uncertainty in each quantity; and,
4. **The verifying questions**, to check for internal consistency and to aid you in considering the full range of possible, even if unlikely, outcomes.

Your responses will be documented in detail. We will use them to derive probability distributions for the quantities of interest. These probability distributions will be shared with the U.S. Environmental Protection Agency and the public, although your identity will be kept confidential. Note that there are several individuals who will be asked these questions. The list of participants in the elicitation process will also be shared with the U.S. Environmental Protection Agency and the public. Thus, the fact that you have participated in the expert elicitation will be known to the public, while your specific responses will remain confidential.

A.1 Structuring Questions

The purpose of this step is to define an unambiguous measure for each quantity to be elicited. Below is a set of open-ended questions that attempt to define unambiguous quantities (i) which would represent the concepts that we want to elicit, and (ii) about which you would feel comfortable making statements.

a. Assuming that the U.S. does not undertake additional policies to reduce greenhouse gases, will governments in non-U.S. regions undertake any additional actions/policies to reduce greenhouse gas emissions?

b. *What actions/policies by a government would constitute a restriction on greenhouse gas emissions?*

c. *Can you describe GHG actions in terms of a percentage reduction of emissions target in a given year?*

d. *If so, relative to what? A historical year? Baseline/BAU emissions for that year?*

e. *How do you think about actions by regional aggregates such as EU, Latin America, Africa, or Southeast Asia? For which countries are you comfortable providing individual judgments rather than using regional aggregates (e.g., China, India, Brazil, Canada, Australia)?*

f. *Are there issues in unambiguously defining a "start-year" for GHG policies?*

g. *Over what time horizon are you comfortable providing even probabilistic judgments? Could you form judgments for, e.g., 2025, 2050, and/or 2100?*

h. *Are there exogenous events that might change your assessed probabilities of policies?*

Further specific questions and the resulting definition of quantities to be elicited will depend on your responses to the above. Your responses will be documented in detail.

A.2 Conditioning Phase

The purpose of this step is to describe the common cognitive biases and to encourage you to be aware of them in your thinking.

It has been well-documented by psychologists that human judgments about uncertainty regularly exhibit **biases and overconfidence** (i.e., the true value is outside the provided confidence interval more frequently than expected). These biases are a consequence of a set of **cognitive heuristics** that humans use in forming judgments about complex quantities such as probabilities and correlations. Below we present some excerpts from a seminal article by Amos Tversky and Daniel Kahneman (1974).

Representativeness

Many of the probabilistic questions with which people are concerned belong to one of the following types: What is the probability that object A belongs to class B? What is the probability that event A originates from process B? What is the probability that process B will generate event A? In answering such questions, people typically rely on the representativeness heuristic, in which probabilities are evaluated by the degree to which A is representative of B, that is, by the degree to which A resembles B. For example, when A is highly representative of B, the probability that A originates from B is judged to be high. On the other hand, if A is not similar to B, the probability that A originates from B is judged to be low.

For an illustration of judgment by representativeness, consider an individual who has been described by a former neighbor as follows: "Steve is very shy and withdrawn, invariably helpful, but with little interest in people, or in the world of reality. A meek and tidy soul, he has a need for order and structure, and a passion for detail." How do people assess the probability that Steve is engaged in a particular occupation from a list of possibilities (for example, farmer, salesman, airline pilot, librarian, or physician)? How do people order these occupations from most to least likely? In the representativeness heuristic, the probability that Steve is a librarian, for example, is assessed by the degree to which he is representative of, or similar to, the stereotype of a librarian. Indeed, research with problems of this type has shown that people order the occupations by probability and by similarity in exactly the same way (1). This approach to the judgment of probability leads to serious errors, because similarity, or representativeness, is not influenced by several factors that should affect judgments of probability.

- *Tverksy and Kahneman (1974).*

Availability

There are situations in which people assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind. For example, one may assess the risk of heart attack among middle-aged people by recalling such occurrences among one's acquaintances.

Similarly, one may evaluate the probability that a given business venture will fail by imagining various difficulties it could encounter. This judgmental heuristic is called availability. Availability is a useful clue for assessing frequency or probability, because instances of large classes are usually recalled better and faster than instances of less frequent classes. However, availability is affected by factors other than frequency and probability.

For example, the impact of seeing a house burning on the subjective probability of such accidents is probably greater than the impact of reading about a fire in the local paper. Furthermore, recent occurrences are likely to be relatively more available than earlier occurrences. It is a common experience that the subjective probability of traffic accidents rises temporarily when one sees a car overturned by the side of the road.

- *Tverksy and Kahneman (1974).*

Anchoring and Adjustment

In many situations, people make estimates by starting from an initial value that is adjusted to yield the final answer. The initial value, or starting point, may be suggested by the formulation of the problem, or it may be the result of a partial computation. In either case, adjustments are typically insufficient (4). That is, different starting points yield different estimates, which are biased toward the initial values. We call this phenomenon anchoring.

In a demonstration of the anchoring effect, subjects were asked to estimate various quantities, stated in percentages (for example, the percentage of African countries in the United Nations). For each quantity, a number between 0 and 100 was determined by spinning a wheel of fortune in the subjects' presence. The subjects were instructed to indicate first whether that number was higher or lower than the value of the quantity, and then to estimate the value of the quantity by moving upward or downward from the given number. Different groups were given different numbers for each quantity, and these arbitrary numbers had a marked effect on estimates. For example, the median estimates of the percentage of African countries in the United Nations were 25 and 45 for groups that received 10 and 65, respectively, as starting points. Payoffs for accuracy did not reduce the anchoring effect.

- *Tverksy and Kahneman (1974).*

A.3 Encoding Questions

The purpose of this step is to elicit your view of uncertainty in the identified concepts or variables (e.g., carbon tax or percentage reduction of emissions below reference). For each concept, and for each region/country as defined above in Section 1, we will ask the following questions:

a. *What is a numerical value for this variable such that there are only 1 in 20 odds (5% probability) that the true value turns out to be HIGHER than your value?*

b. *Suppose the true value was HIGHER. Under what conditions would this be true? Describe this world. Do you now wish to revise your estimate?*

c. *What is a numerical value for this variable such that there are only 1 in 20 odds (5% probability) that the true value turns out to be LOWER than your value?*

d. *Suppose the true value was LOWER. Under what conditions would this be true? Describe this world. Do you now wish to revise your estimate?*

e. *What is a numerical value for this variable such that there is an equal likelihood of being higher or lower (median)? If not clear, elicit a "best-guess" (mode).*

f. *Sketch PDF for expert by hand. In viewing it, do they have any additional thoughts or revisions to suggest? [NOTE: Interviewer will fit the provided judgments to a PDF and graph in real-time to provide feedback for participant. Judgments can then be modified as needed to best reflect participant's views.]*

A.4 Verifying questions

After eliciting for individual regions/countries, you will be asked the following additional questions about pairs of regions to help elicit the correlation structures:

a. *Suppose the U.S. does not enact any significant policy. Does this change what most/all countries will do?*

b. *Given your responses about Country A, would you like to reconsider your responses regarding Country B?*

c. *Suppose Country A enacts policy X (choose upper 95% value) from your distribution. Does that change what Country B will do? B's 1 in 20 upper bound? B's 1 in 20 lower bound? What if Country A does nothing?*

d. *Engage in open-ended discussion about the quantities elicited, and gather further thoughts from the experts about what conditions might change their responses.*

Appendix C: Pooled Expert Distributions of Future Carbon Prices

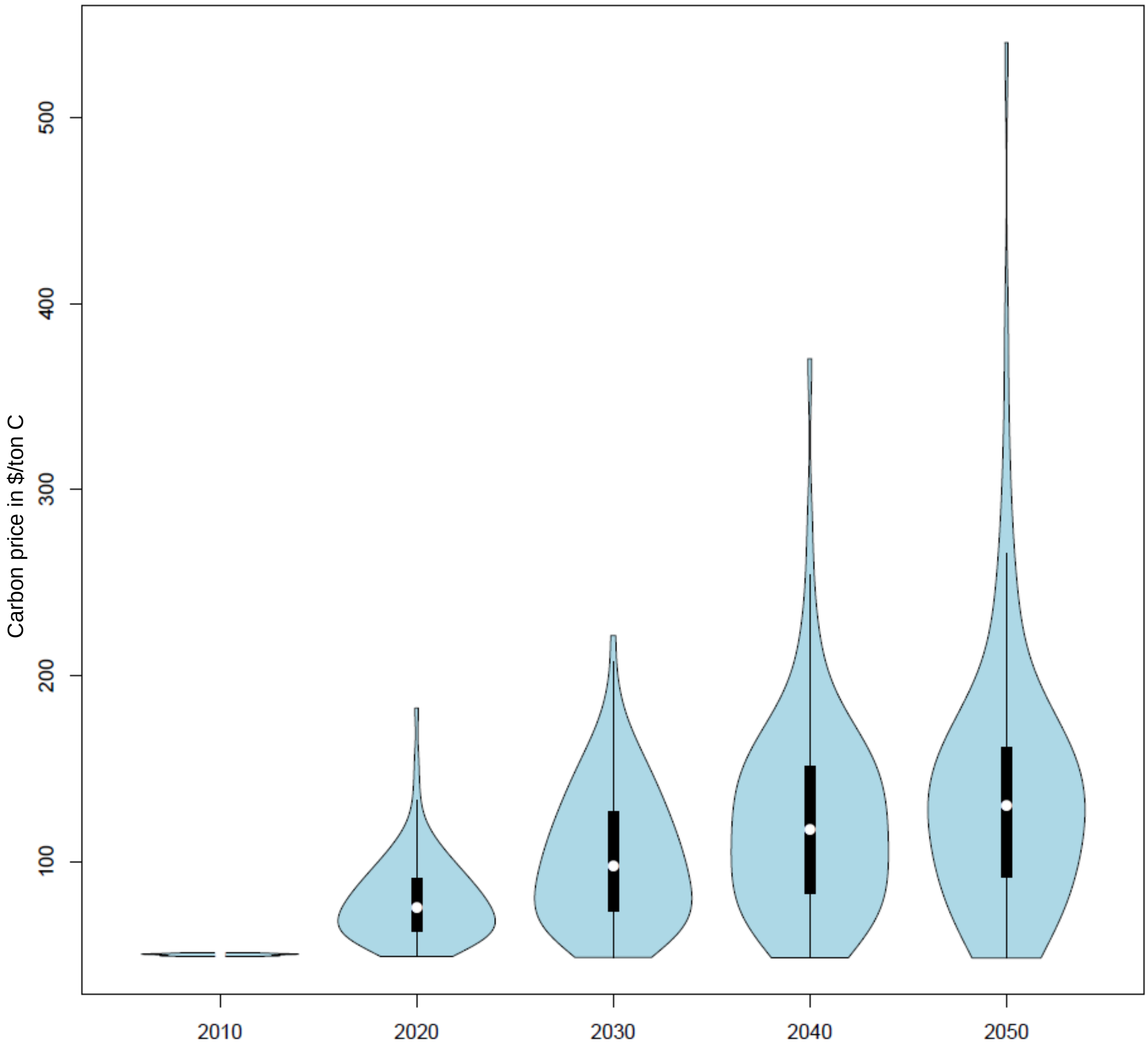

Figure C-1: Time Profile of the Pooled Carbon Price Distribution for Europe

Table C-1: Carbon Price Distributions for Europe

Year	Distribution	Shift
2015	Beta(1.1139,2.5344,51.768,96.793)	
2025	Beta(1.1752,2.6383,50.14,183.35)	
2035	Beta(1.8773,4.618,38.315,296.74)	
2050	Weibull(2.4247,130.74)	15.393
2060	Loglogistic(-207.44,343.82,10.398)	

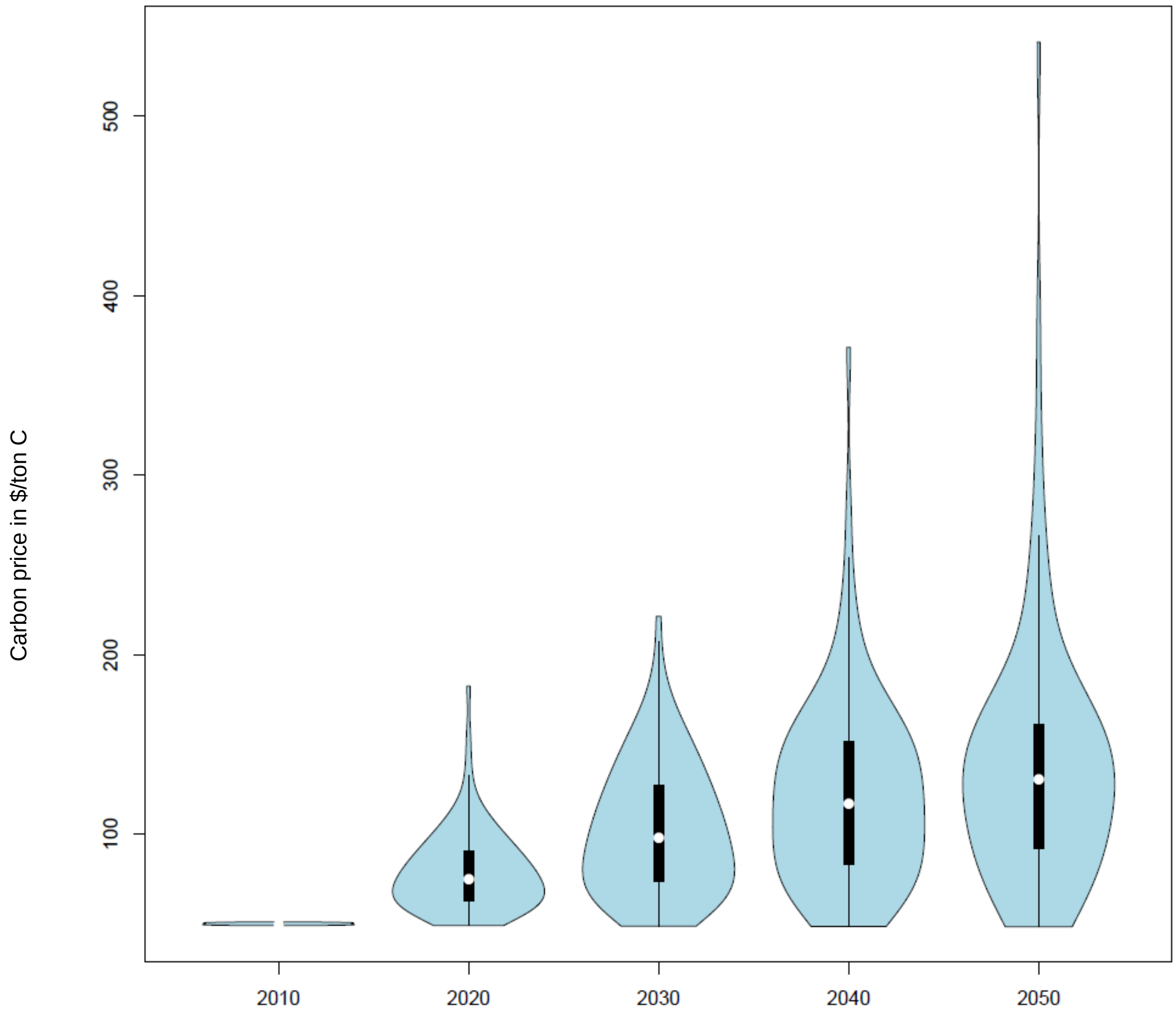

Figure C-2: Time Profile of the Pooled Carbon Price Distribution for Japan

Table C-2: Carbon Price Distributions for Japan

Year	Distribution	Shift
2015	**Beta (0.79274,3.0202,-4.7342,218.6)**	
2025	**Beta(0.37856,0.64063,0.29094,262.61)**	
2035	**Beta (0.77023,4.9077,-15.526,1251.2)**	
2050	**Beta (1.9262,8.9789,-105.11,1504.1)**	
2060	**Weibull (1.7518,360.73)**	**-127.08**

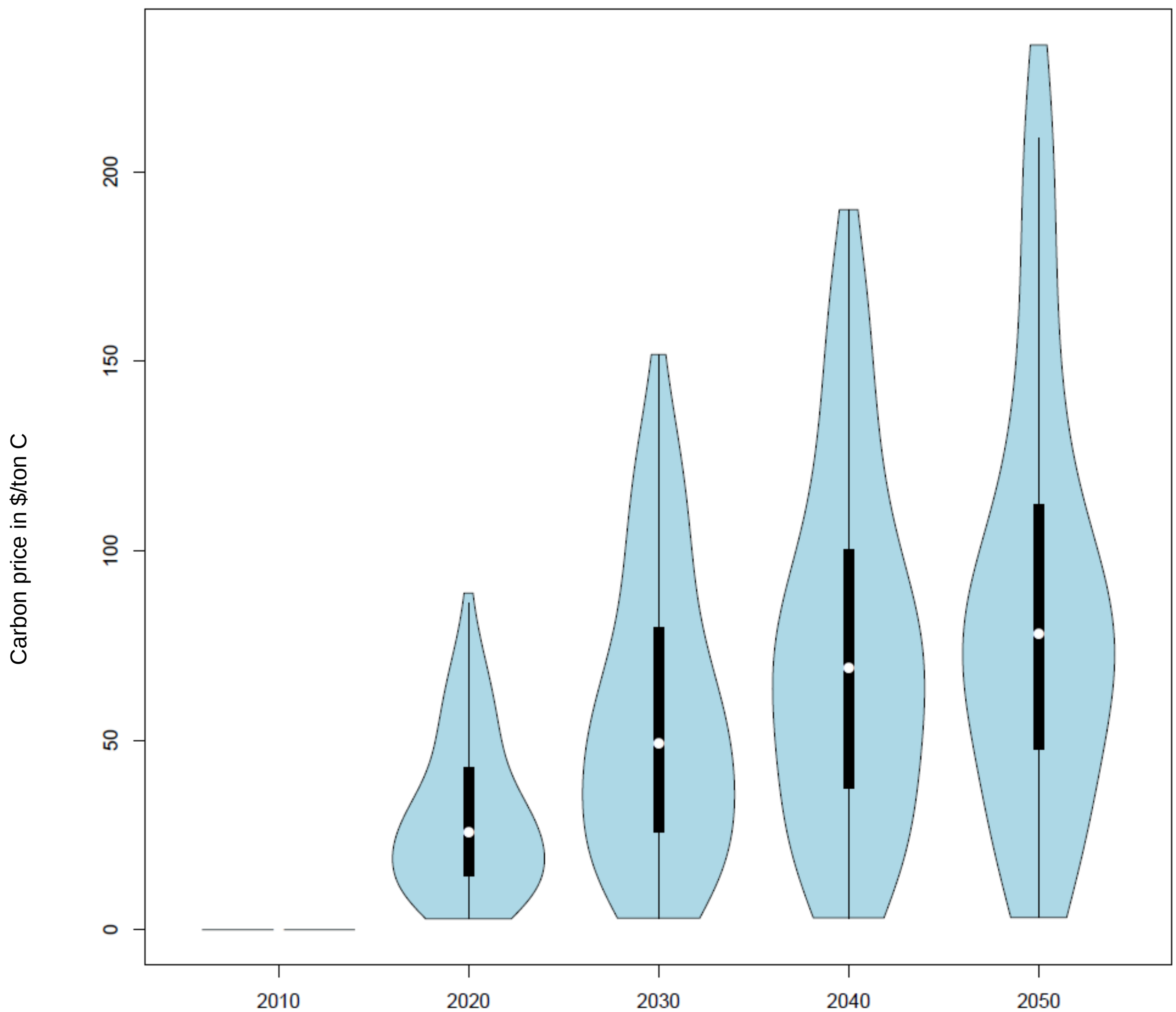

Figure C-3: Time Profile of the Pooled Carbon Price Distribution for Australia / New Zealand

Table C-3: Carbon Price Distributions for Australia / New Zealand

Year	Distribution	Shift
2015	Weibull (1.2901,16.003)	2.0815
2025	Weibull (1.3584,48.568)	0.38426
2035	Beta (1.5642,3.7963,-3.3426,232.8)	
2050	Loglogistic (-66.213,143.23,4.7701)	
2060	Loglogistic (-40.129,124.16,3.9455)	

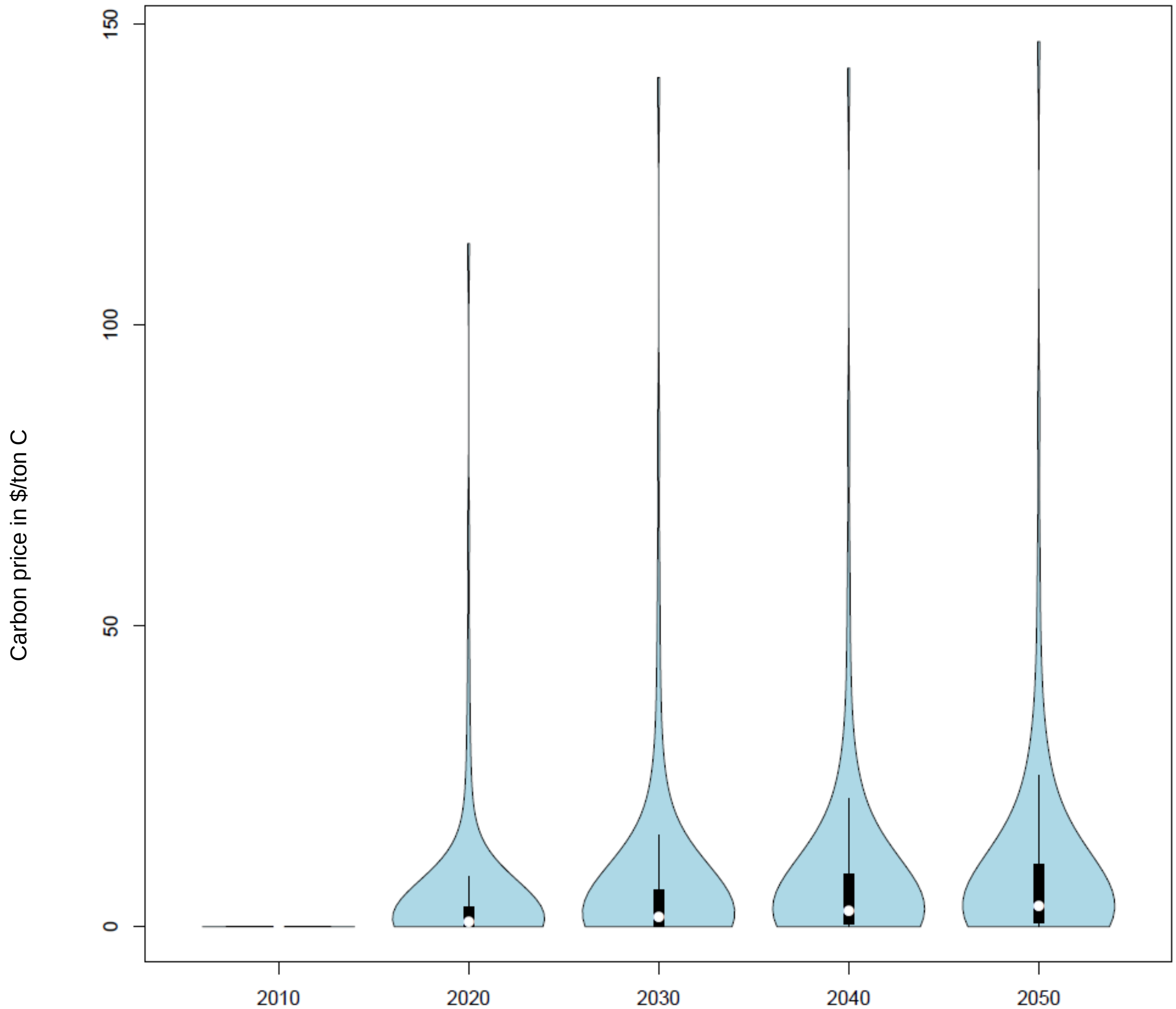

Figure C-4: Time Profile of the Pooled Carbon Price Distribution for China

Table C-4: Carbon Price Distributions for China

Year	Distribution	Shift
2015	Weibull (0.47813,1.0262)	-0.062191
2025	Weibull(0.4606,2.5038)	-0.13857
2035	Gamma(0.36709,17.559)	-0.04391
2050	Gamma(0.44349,18.815)	-0.03523
2060	Gamma(0.4845,19.09)	-0.04448

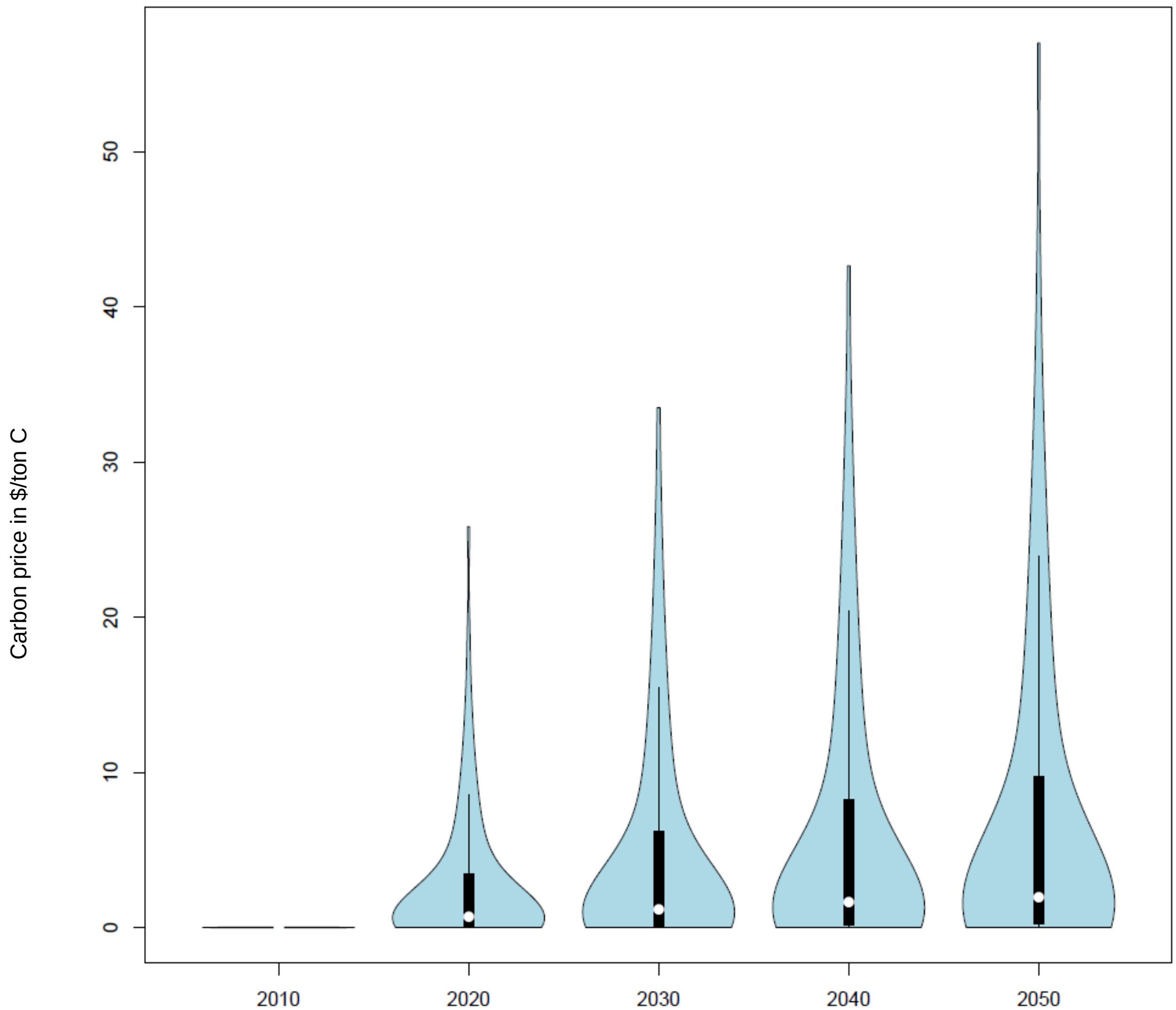

Figure C-5: Time Profile of the Pooled Carbon Price Distribution for India

Table C-5: Carbon Price Distributions for India

Year	Distribution	Shift
2015	Beta (0.26574,2.5256,-0.0025496,16.014)	
2025	Beta(0.25459,2.2398,-0.0046988,37.832)	
2035	Beta(0.26974,1.808,-0.0011329,40.859)	
2050	Gamma(0.31169,25.378)	-0.00024
2060	Gamma(0.32252,26.91)	-0.00034

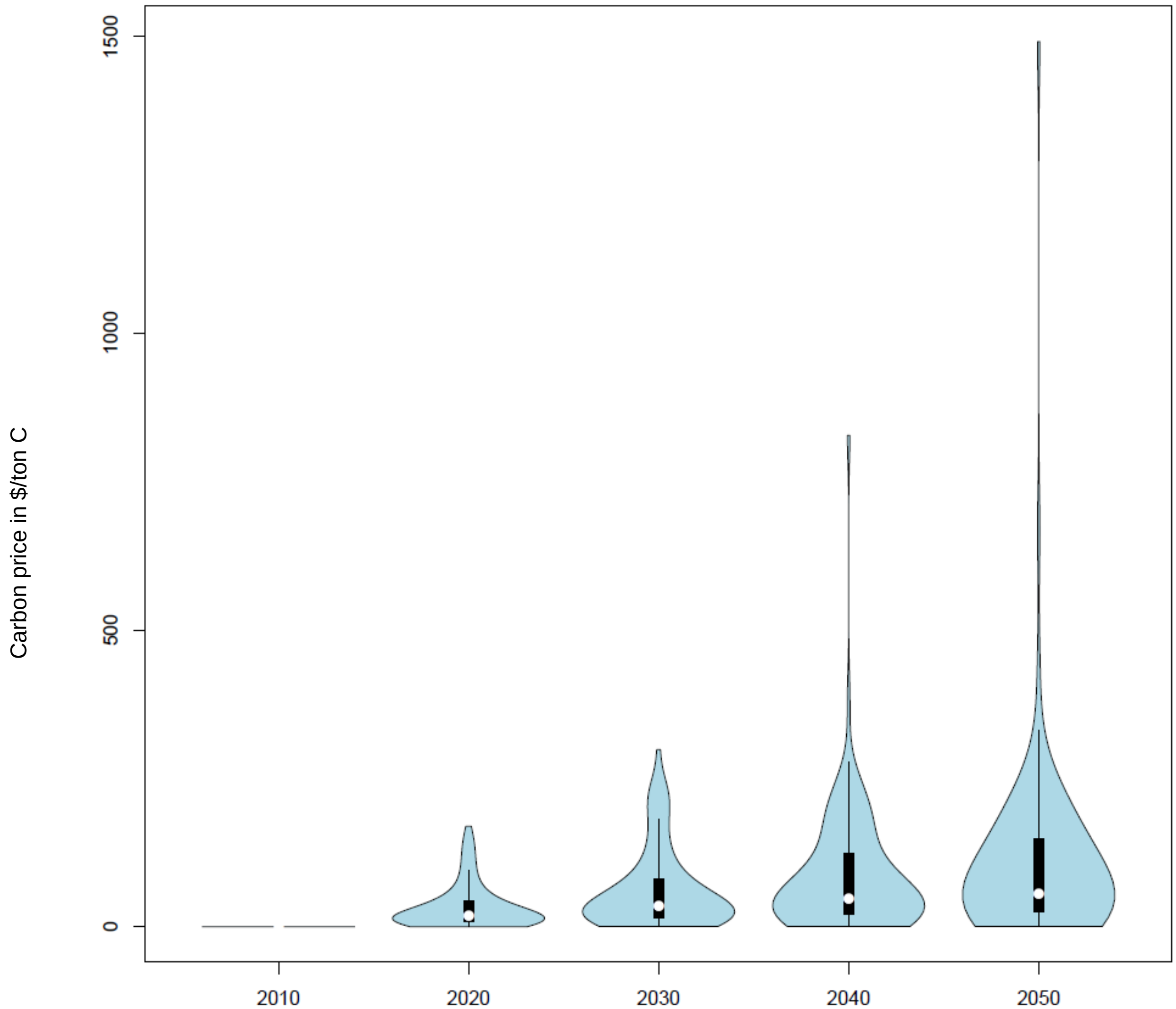

Figure C-6: Time Profile of the Pooled Carbon Price Distribution for Canada

Table C-6: Carbon Price Distributions for Canada

Year	Distribution	Shift
2015	InvGauss(21.353,13.912)	-1.457
2025	InvGauss(58.137,34.601)	-4.6757
2035	Lognormal(91.675,156.12)	-3.2591
2050	Weibull(0.85056,89.016)	3.07
2060	Weibull(0.87648,99.849)	2.6998

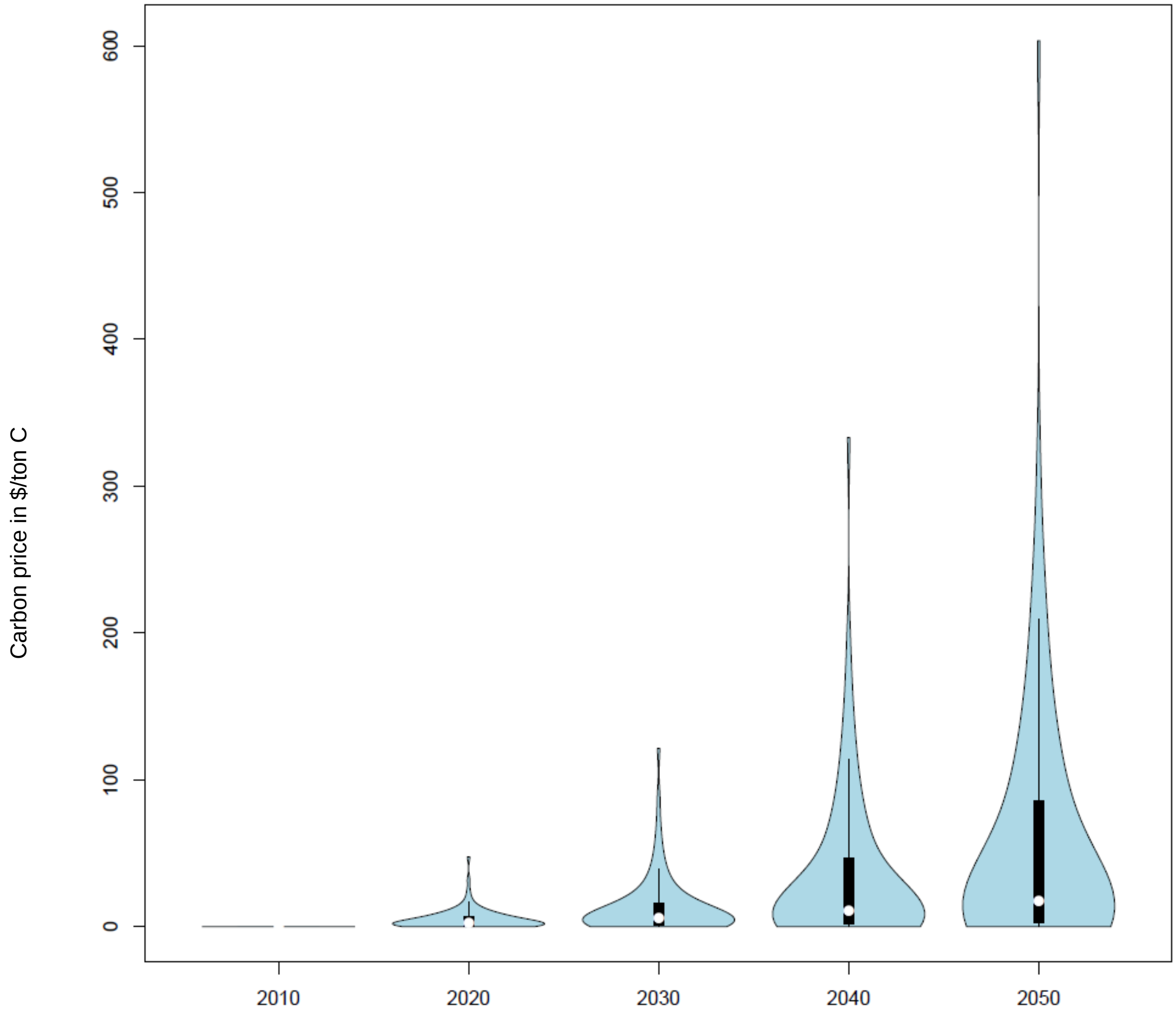

Figure C-7: Time Profile of the Pooled Carbon Price Distribution for Russia

Table C-7: Carbon Price Distributions for Russia

Year	Distribution	Shift
2015	Beta (0.63342,7.4698,-0.044523,35.568)	
2025	Beta (0.52525,5.6733,-0.014983,87.441)	
2035	Gamma(0.41251,54.261)	0.030511
2050	Beta (0.32707,4.1379,0.079836,831.14)	
2060	Gamma(0.32263,309.15)	0.093568

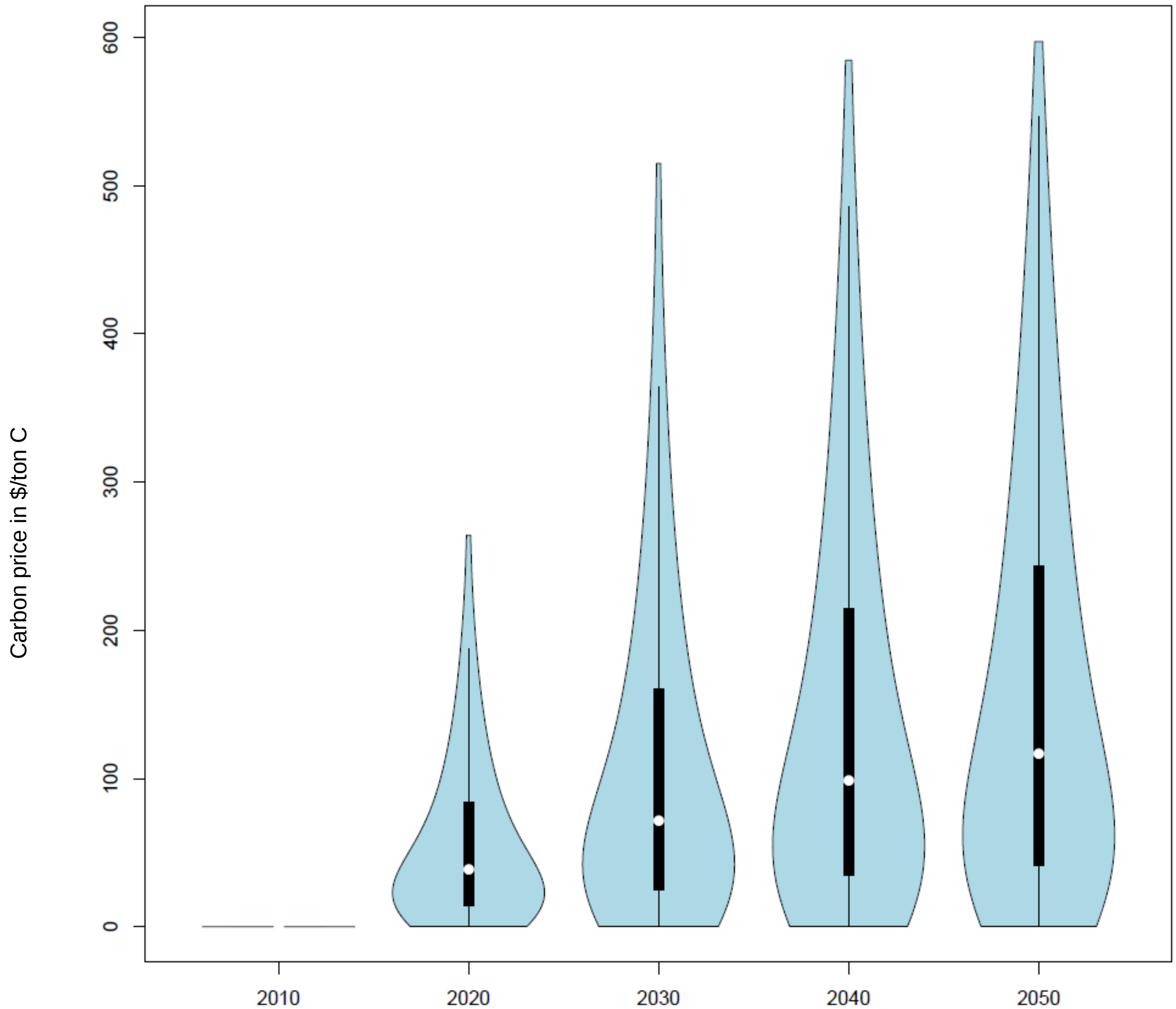

Figure C-8: Time Profile of the Pooled Carbon Price Distribution for Middle East

Table C-8: Carbon Price Distributions for Middle East

Year	Distribution	Shift
2015	Gamma(0.94054,34.704)	-0.13521
2025	Gamma(0.80271,109.19)	0.091728
2035	Beta (0.64741,2.6277,2.0915,638.51)	
2050	Beta (0.69794,2.3678,1.4971,697.59)	
2060	Beta (0.75237,2.5886,0.17662,769.32)	

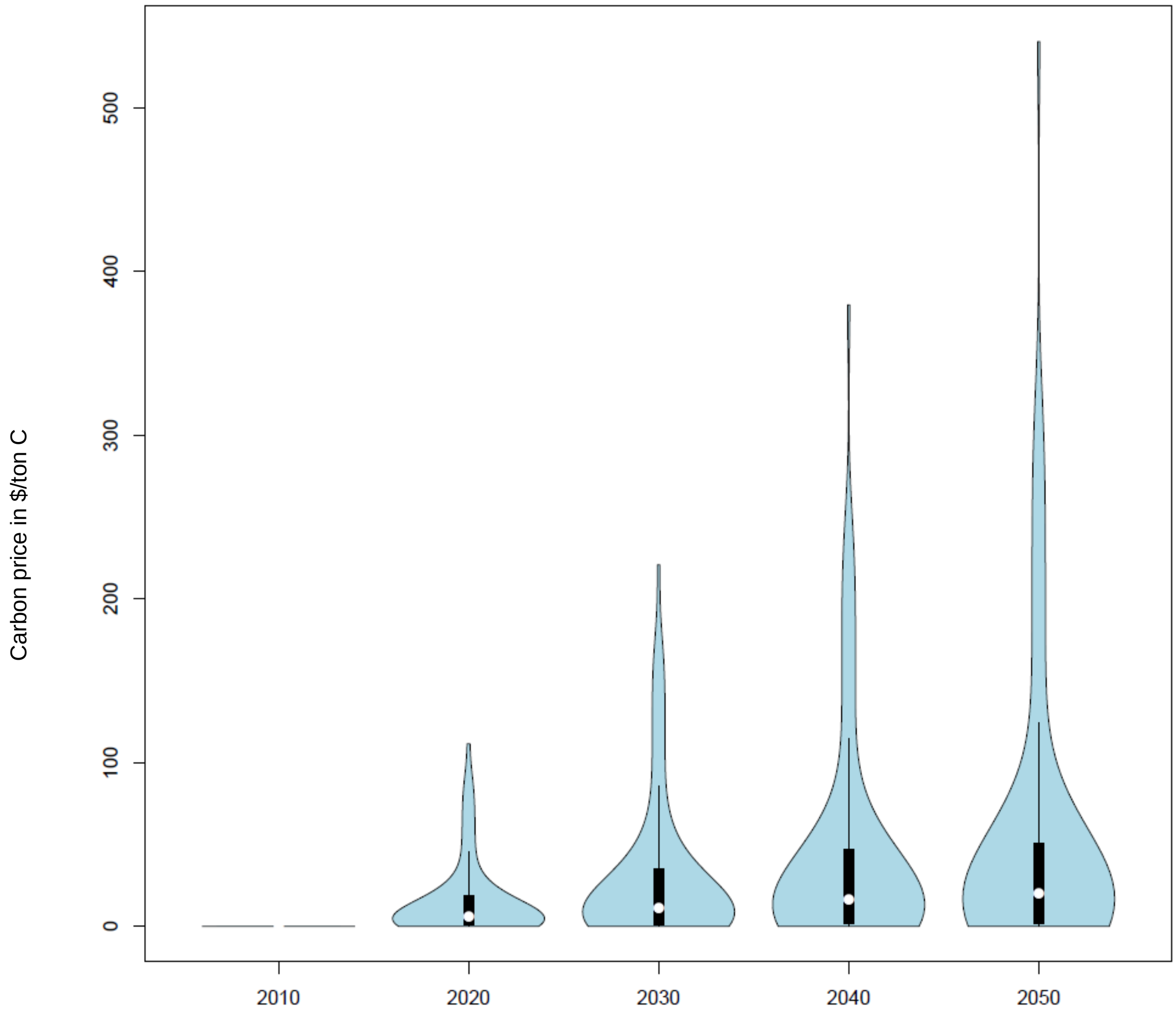

Figure C-9: Time Profile of the Pooled Carbon Price Distribution for Latin America / Brazil

Table C-9: Carbon Price Distributions for Latin America

Year	Distribution	Shift
2015	Gamma(0.38244,24.006)	0.0015782
2025	Gamma(0.36451,65.849)	0.0040356
2035	Gamma(0.35045,110.09)	0.010914
2050	Gamma(0.34226,156.46)	0.011905
2060	Gamma(0.33629,182.85)	0.01147

Appendix D: Impacts of Including Uncertain Future Carbon Prices

This Appendix provides summary statistics and figures to describe the effects of truncating very low carbon prices from the policy uncertainty, and the impacts on global emissions of including this uncertainty. Table D-1 shows the fraction of sample scenarios for which the carbon price is $0/ton C. Note that some of these zeros would be been non-zero from the original expert distributions, but would have taken on values of less than $6/ton C ($1.6ton CO_2) for all regions except for China and India, which have had values of less than $10/ton C ($2.8/ton CO_2).

Figure D-1 shows the relative shares of cumulative global CO2 Emissions over 2000-2100 (based on the EPPA reference scenario. We show the shares for four sets of regions:

- USA;
- Regions with expert elicited uncertainty in future policy and included in the analysis: EUR, JPN, ANZ, CHN, IND;
- Regions with expert elicited uncertainty in future policy but omitted from the analysis: CAN, RUS, LAM, MES, AFR
- Regions for which experts provided no information: MEX, EET, ASI, IDZ, ROW.

Figure D-2 shows the probability density functions for global CO_2 emissions in 2050 from the set with policy uncertainty included and from the set without policy. Note that because of the other, more significant uncertain parameters included, the effect of the policy uncertainties is difficult to detect. A better indication is given in Figure D-3 and Table D-2, which show the probability density of changes in global CO_2 emissions in 2050, and the fractiles of emissions changes for several decades, respectively, that result from including the policy uncertainty.

Table D-1: Fraction of Samples Truncated to $0/ton C

Year	JPN	ANZ	EUR	CHN	IND
2015	18%	5.3%	0%	92%	85%
2025	18%	4.8%	0%	92%	83%
2035	8.3%	0.8%	0%	92%	80%
2050	0.3%	0.5%	0%	92%	80%

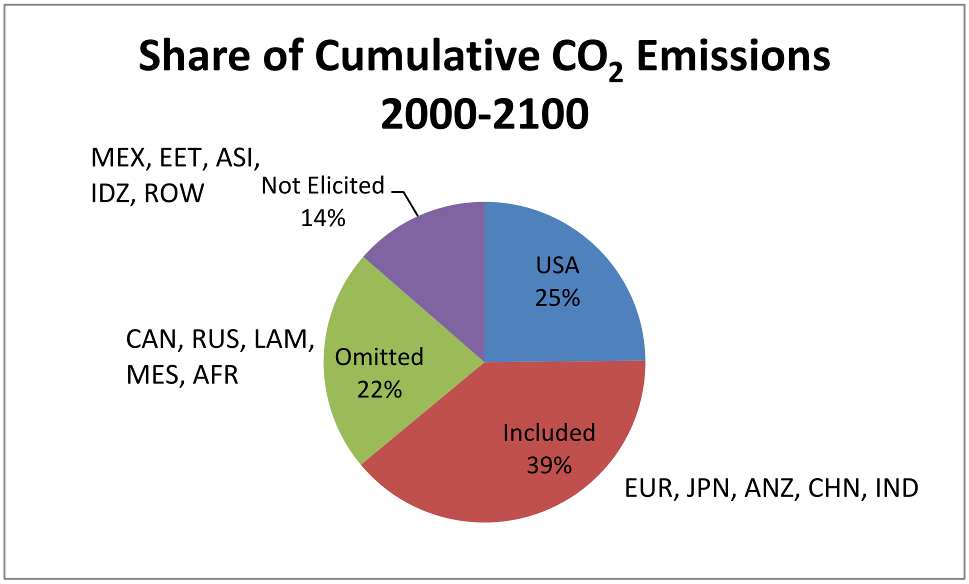

Figure D-1: Relative Shares of Cumulative Global CO_2 Emissions

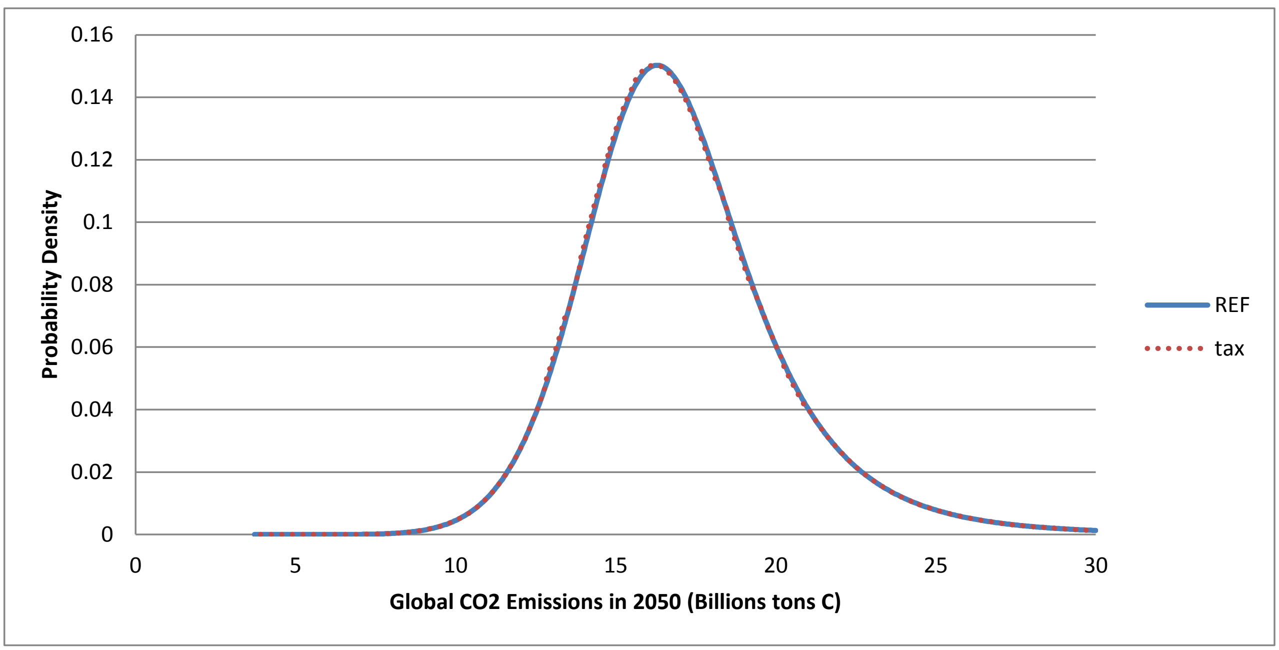

Figure D-2: Probability Density Function of Global CO_2 Emissions in 2050 with and without Policy Uncertainty

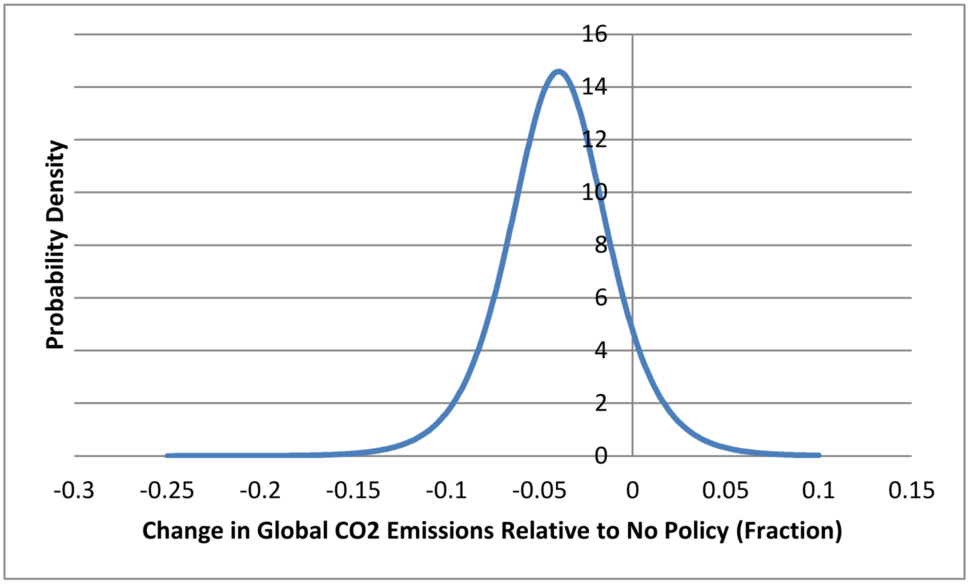

Figure D-3: Probability Density Function of Change in Global CO_2 Emissions in 2050 from Including Policy Uncertainty[10]

Table D-2: Change in Global CO_2 Emissions from Including Policy Uncertainty

Fractile	0.025	0.25	0.5	0.75	0.975
2025	-9%	-3%	-2%	-1%	1%
2035	-13%	-4%	-3%	-2%	0%
2050	-15%	-6%	-4%	-2%	0%
2050	-15%	-6%	-4%	-2%	0%

[10] Note that there is a net increase in CO_2 emissions for some of the scenarios (i.e., the positive portion of the distribution's tail). This is due to inter-regional leakage resulting from heterogenous climate policies across the regions.