Uncertainty Analysis of the Cost of Climate Policies

by

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Abstract

Every climate change policy issue is inherently limited by two questions: what are exactly the consequences of climate change for our lives? How much will it cost to deal with them? Almost twelve years after the parties of the United Nations Framework Convention on Climate Change met in Kyoto in 1992, acknowledging the fact that "change in the Earth's climate and its adverse effects are a common concern of humankind" (United Nations, 1992), no global effort is really visible yet. The reason lies in the difficulty scientists and economists have to answer those two questions. This thesis will try to understand how uncertainty on the consequences of climate change drives the cost of policy decisions. It will especially try to find out what are the main sources of uncertainty in policy costs and where should we therefore put our research and policy efforts.

In the first part of this thesis, we will perform a sensitivity analysis on the economic parameters relevant to the analysis, in order to identify the ones that most influence the cost of climate change policies. We will then develop and run a specific method to elicit experts' opinions on the uncertainty on each on these parameters. This step will allow us to conduct our uncertainty analysis under different policy assumptions and to understand better the implications of uncertainty on climate change policies.

Thesis Supervisor: Professor Henry Jacoby
Title: Co-Director, Joint Program on the Science and Policy of Global Change

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The friends I made during my time in Boston are the ones who made my graduate school experience at MIT so worthwhile. My roommates Victor, Matteo and Cornelius were always present beside me, in the best moments as well as in tougher times. The squash games I played with Ardoin, Erwan, Greg and Matthieu were essential moments of relaxation, and forced me to keep a more balanced life. I also want to thank particularly Helene for having made of this stay in the US an unforgettable moment.

I do not want to forget my parents, my sister Béatrice and her husband Antoine, whose continual encouragements were so important to me.

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Glossary

1) EPPA sectors and regions

Production Sectors		***Regions***	
Non-Energy		***Annex B***	
		USA	United States
AGRI	Agriculture	**CAN**	Canada
EINT	Energy Intensive Industry	**MEX**	Mexico
OTHR	Other Industries	**JPN**	Japan
SERV	Services	**EUR**	European Union (1995 members)
TRAN	Transportation	**ANZ**	Autralia-New Zealand
Energy		**FSU**	Former Soviet Union
		EET	Eastern Europe
OIL	Crude Oil	***Non Annex B***	
ROIL	Refined Oil	**CHN**	China
COAL	Coal	**IND**	India
GAS	Natural Gas	**IDZ**	Indonezia
ELEC	Electricity Production	**ASI**	East Asia
Consumption		**MES**	Middle-East
		LAM	Latin America
FINAL DEMAND	Non-Industrial Consumption	**AFR**	Africa
		ROW	Rest of the World

2) Uncertainty parameters

Name	**Description**
vintaging	Vintage coeficient
e-ne elas	elasticity between energy and non energy bundle
lpg	Labor Productivity Growth
AEEI	Autonomous Energy Efficiency Improvement rate
ghg-agri elas	Elasticity with ghg bundles in agricultural sector
pop	Population
ch4 indus	CH4 industrial emissions in 1997
l-k elas	Elasticity between labor and capital
ghg-non agri elas	Elasticity with ghg bundles in non-agricultural sectors
btw foss fuel	Elasticity between fossil fuels
ch4 agri	CH4 agricultural emissions in 1997
top layer	Armington elasticity
bl-bk-fossil	Markup factors for fossil backstops
fixed factor	Elasticity with fixed factor bundles
bl-bk rnew	Markup factors for renewables backstops
elec-nelec	Elasticity between electric and non-electric bundles
oil reserves	Oil reserves estimates in 1997
gas reserves	Gas reserves estimates in 1997
coal reserves	Coal reserves estimates in 1997

Chapter 1 Introduction

1.1 Context

1.1.1 Why climate change matters?

When the parties of the United Nations Framework Convention on Climate Change met in Kyoto in 1992, they began by acknowledging the fact that "change in the Earth's climate and its adverse effects are a common concern of humankind" (United Nations, 1992). After such a consensus one could wonder why no global effort is really visible almost twelve years after. The reason is that the climate issue gathers in itself so many policy complexities that it becomes a real nightmare for our institutions. There is first a major disagreement on the decision deadline between those who think climate change is a long-term concern and those who believe its effects are irreversible and must therefore be dealt with as quickly as possible. Then, there is a high level of uncertainty both at the science and at the economic level. Finally it is characterized by a misalignment of stakeholder incentives when the response should on the contrary be global. To summarize the complexity of the issue, politicians have to decide a "how?" when they barely know "what?", "when?" and "how much?"!

1.1.2 Where does uncertainty come from?

Global climate change is an extremely wide field in terms of both geographical extension and sciences implied. Many scientific laboratories like for example the Joint Program on the Science and Policy of Global Change at MIT (JP) try to model climate change effects through the interaction of scientific and economic models. Both imply a very complex set of historic data, forecasts, assumptions, theories and mathematical approximations that lead to an important level of uncertainty. Two types of uncertainty exist. There is first a structural uncertainty in the way climate and the world economy are represented mathematically: different types of models are used, such as computable general equilibrium models or econometric models. Then, there is also a parametric uncertainty, which results from the partial knowledge we have on the parameters a model is built on, like historic data and forecasts. Scientists often need an idea of what the world looked like a thousand or more years ago and what it will be like in a century: the confidence in this data is often as weak as it is crucial.

1.1.3 Why policy costs matter?

On the four questions that remain unanswered about climate change, two of them seem undoubtedly crucial for a policy response to be put in place. The first one is the question "what?": what are exactly the consequences of climate change? How will it impact our life? Not knowing what are we facing is a clear barrier to any coherent response. However any decision is also obviously constrained by the question "how much?": we could decide tomorrow to stop using our cars for example, but the cost on society would be very hard to pay. Any policy answer is therefore conditioned by the answer to these two issues. This thesis will try to understand better the connections between these questions. How do uncertainties on the consequences of climate change drive the cost of any policy response? What are the main sources of the uncertainty about policy costs? Where should we put our research and policy efforts to help solve these issues?

1.2 Thesis perspective

This thesis presents an uncertainty analysis of the cost of climate change policies. It extensively uses the help of the EPPA model, developed at the Joint Program on the Science and policy of Global Change, and builds on previous work done at the JP and elsewhere.

1.2.1 The EPPA model

The Emissions Prediction and Policy Analysis (EPPA) model is a recursive-dynamic computable general equilibrium (CGE) model, detailed by regions and by sectors, developed at the MIT Joint Program on the Science and Policy of Global Change (Yang et al., 1996, Babiker et al., 2001). It is a model of economic growth, international trade, and greenhouse gas emissions. In its current version (4.0), it extends from 1997 to 2100 in five-year steps (except for the first step which is 3-year long). As shown in the Glossary (Exhibit 1), the model is divided in 16 regions (United States, Canada, Mexico, Japan, Australia - New Zealand, Europe, Eastern Europe, Former Soviet Union, East Asia, China, India, Indonesia, Africa, Middle East, Latin America and the Rest of the World) and 10 production sectors (Agriculture, Coal, Crude Oil, Refined Oil, Gas, Electricity, Energy-intensive Industries, Other Industries, Services and Savings Good). It tracks CO_2 and non-CO_2 gases like CH_4, N_2O, HFC, SF_6, PFC, CO, NMV, or SO_2. Finally, 11 Backstop technologies can be introduced to compete with traditional technologies (solar, synf-oil, synf-gas, renewable oil, hydrogen, wind, biomass, natural gas combined cycle with and without carbon capture, integrated gasified carbon capture with sequestration and advanced nuclear). One can run the EPPA model by applying a policy scenario to every region. The model will give as output, for example, the related consumption by region as well as the CO_2 and non- CO_2 emissions.

1.2.2 Previous work

This thesis builds on the extensive work done by Prof. Mort Webster (Department of Public Policy, University of North Carolina at Chapel Hill) in his PhD thesis as well as in other papers published while he was at the Joint Program (Webster, February 2000). Professor Webster's study mainly addressed the issue of uncertainty and learning in sequential decision-making in the case of climate policy (Webster et al., 2000). Some part of his thesis dealt with the uncertainty in the level of greenhouse gases emissions (Webster et al., 2001). It used a previous version of the EPPA model.

The purpose of this thesis is to extend Webster's analysis to the cost of climate change policies. We will run the latest version of the EPPA model (EPPA 4) developed by Dr. Sergey Paltsev from the MIT Joint Program.

1.2.3 How policy costs are modeled

The way policy costs are estimated in the EPPA model is by comparing the consumption level in a no policy case with its level in the policy case considered. Costs are often expressed in percentage of consumption loss. We looked at the policy costs for four different groups of countries: two developed countries (United States and Europe) and two developing countries (China and Latin America). We detailed the costs for two different periods: a short-term horizon in 2010 and a long-term horizon in 2050. The policy case that we used in this thesis is a "stabilization case at 550 ppm": it will be detailed in paragraph 4.1.

1.3 Research approach

The uncertainty in the cost of climate change policies is driven by the uncertainty in all the input parameters of the EPPA model. The idea is to model the distribution of every input parameter and to perform a Monte Carlo analysis to understand the distribution of the final output. Several steps are to be followed. We tried to adopt in this thesis a recursive path in order to address our issue as precisely as possible. The first and irreversible step is to choose a model. The EPPA model, because it is driven by the choice of a specific policy, seems perfectly adapted to the analysis. A sensitivity analysis has then to be performed in order select from all the parameters of the model, those that most strongly influence the cost of climate policies. Then, for every parameter selected we will perform an expert elicitation and build from it a probability distribution function (PDF) quantifying its degree of uncertainty. Afterwards, we will use these PDF to propagate uncertainty across the model and obtain a PDF and a variance decomposition of the cost of climate policies, which we will use as a base for a policy analysis. We will finally focus on the sensitivity of our results to the assumptions we made, reformulating them if necessary and going through the same process again.

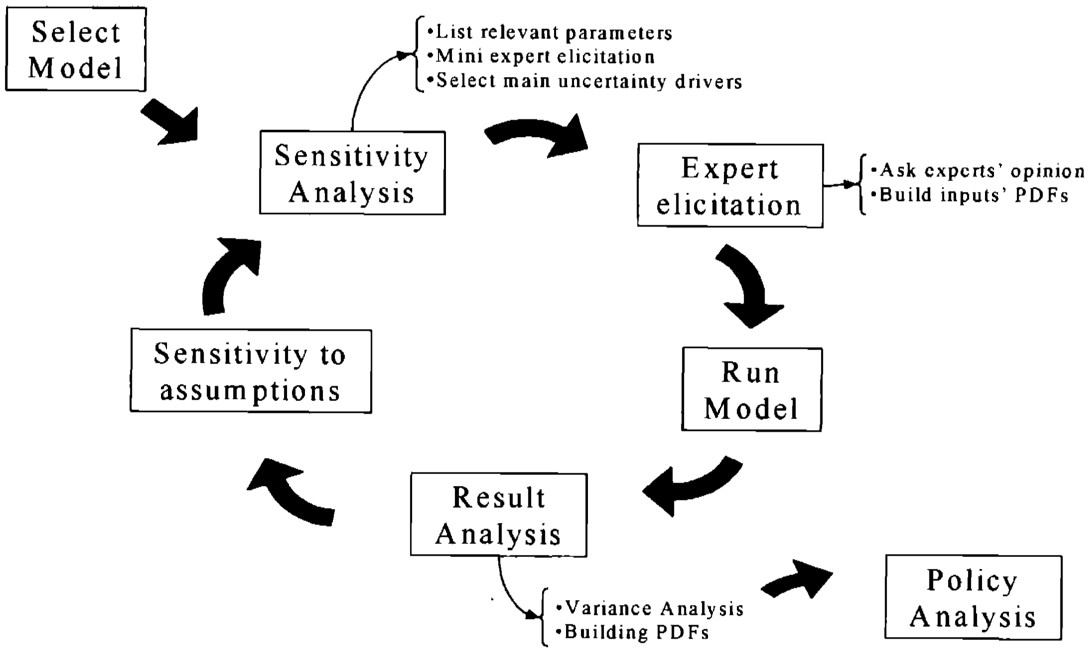

Figure 1: Research approach

Chapter 2 Sensitivity Analysis

The first part of the work was to identify the main parameters that drive the uncertainty in the cost of climate change policies. The EPPA model uses hundreds of different inputs. Not all of them could be sampled through a Monte Carlo analysis because it would have been much too computationally complex. The idea was therefore to identify the most sensible ones and to perform the analysis only on these few ones: the aim of a sensitivity analysis was to identify these parameters.

2.1 Methodology and mathematical background

2.1.1 Traditional sensitivity analysis

A first and simple approach could have been to take each input parameter of the EPPA model and to vary it by plus or minus a fixed percentage of its mean, for example ±20% for all variables (Webster, February 2000). Each variation in the input would have created a variation in the output result (the cost of climate change policies). After having done this analysis for all parameters one could have ranked them according to their effect on the output. Mathematically we could have expressed the sensitivity of each parameter as follows: given X and Y two input parameters and F(X,Y) the output, X would have been defined as more sensible than Y if and only if:

$$\frac{\delta F}{F} \cdot \frac{X}{\delta X} > \frac{\delta F}{F} \cdot \frac{Y}{\delta Y}$$

Finally there would have been a judgment to make to select the small set of inputs that would be used in the Monte Carlo testing.

2.1.2 Sensitivity analysis with different input probability distributions

The previous method had the advantage of being simple to implement. However it did not take into account the fact that two parameters generally don't have the same probability distribution. Take for example two parameters X and Y that have been declared equally sensible according to the previous test: for the same relative variation they cause an equal relative modification in the result. But suppose now that X is almost certain (its probability distribution is centered on its mean with a very small standard deviation) and that Y is very uncertain (wide distribution, big standard deviation). Although a 20%

variation in X creates the same effect than a 20% variation in Y, it is very unlikely to occur. Thus, one cannot say that X and Y equally affect the result!

A way of avoiding this mistake was to make the inputs vary not by a fixed percentage of their mean but by their standard deviation: in this way we made them vary by an equally probable gap. Mathematically the sensitivity of two parameters was compared by applying the following test: given X and Y two input parameters and F(X,Y) the output, X was said to be more sensible than Y if and only if:

$$\frac{\delta F}{F}.\frac{X}{\sigma_X} > \frac{\delta F}{F}.\frac{Y}{\sigma_Y}$$

In the previous example of two variables with very different distributions, we would have made X vary by a very small number in comparison to Y so it would have taken into account their distribution.

2.1.3 Choice of policy scenarios

Before running any simulation we had to decide the type of policy that would be imposed for the sensitivity analysis. Two types of policy are often modeled: concentration stabilization and emission stabilization. The first one would be closer to the long-term goal of international negotiations (see paragraph 4.1.1) but the second one would reveal more about the model structure. We decided therefore to conduct the sensitivity analysis with an emission stabilization scenario and to run the complete uncertainty analysis with a more realistic concentration stabilization case. A first idea to model emission stabilization was to impose simply a "Kyoto forever" constraint. Kyoto constraints were applied to all "Annex B" countries (USA, Japan, Europe, Australia, New-Zealand, Canada, Eastern Europe and Former Soviet Union) and trading in CO_2 as in other greenhouse gases (GHG) was allowed among them. However this simple policy case had two major problems. First it did not seem to be very realistic, especially for the US: permits would sell at much too a high price in 2010 (around $55 per tons of CO_2 emitted) and the political trend at that time was not towards a US ratification of the protocol. Then it did not constrain the "non-Annex B" countries, and therefore the parameters that we would have selected with this policy would only have reflected the welfare losses to developed countries. The idea was therefore to find a policy case that would be realistic and that would constrain non-Annex B as well as Annex B countries. We kept the idea of imposing an "emission stabilization case" (emissions are stabilized at a given level) with trading in CO_2 and other GHGs. We thought that a reasonable idea could be to impose two different constraints for Annex B and non-Annex B countries and to allow both groups to trade internally. Furthermore, since the "hot air" issue was still under a high political uncertainty, we decided not to include FSU in Annex B trading group. Finally, in order to be able to compare the results for Annex B and non-Annex B countries, we tried to find constraints that would lead to comparable carbon prices for the two groups. The policy chosen is laid out in Table 1: for each group of countries (Annex B without Russia, Russia and non-Annex B) it shows the type of constraint (CO_2 and other greenhouse gases emissions stabilization with trading, starting in 2010) and the resulting carbon prices. As explained before, FSU was not included in the trading system of Annex B countries and was simply constrained to its 1997 emissions.

	Annex B w/o FSU	FSU	Non Annex B
constraint	1997 emission level	1997 emission level	2003 emission level
begin in	2010	2010	2010
trading	among Annx B w/o FSU	no	among non Annx B
target	CO2 + other ghg	CO2 + other ghg	CO2 + other ghg
price 2010	$25	$28	$29
price 2050	$1,027	$537	$1,133

Table 1: Overview of the policy case used for the sensitivity analysis

2.1.4 Tornado diagram and choice of parameters

Once a sensitivity analysis had been performed on all parameters, we had to rank them according to their impact on the output result. This could be done visually using a "tornado diagram". A tornado diagram is a graph on which all the output's variations, resulting from individual modifications of the inputs, are plotted using horizontal bars which length reflects the width of the variation. It makes it possible to see on a single chart all the bars and to rank them according to their length.

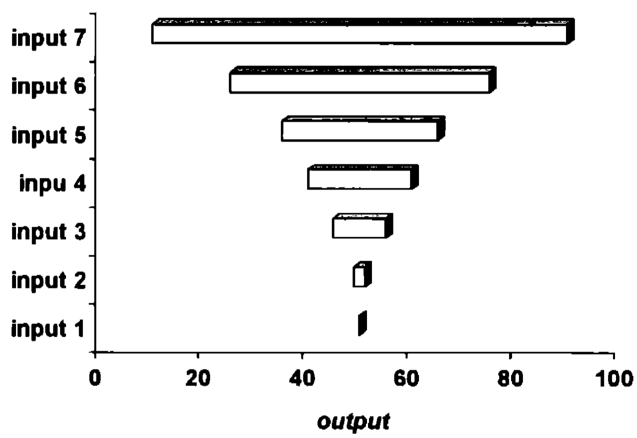

Figure 2: Example of a tornado diagram

The point was to decide which variables would we keep and which would we throw away in the Monte Carlo testing. It is obvious in the previous example that the smaller one (input 1) can be omitted in the analysis. But where should one exactly stop? In order to make this decisions we assumed that all variables were perfectly correlated: a variation of one standard deviation of one of them made all the other vary also by one standard deviation. Therefore, should all inputs increase by one standard deviation, the resulting output would be the sum of all the individual variations of the result.

$$F(X+\sigma_X, Y+\sigma_Y) = F(X,Y) + \underbrace{\frac{\delta F}{\delta X}.\sigma_X}_{\substack{\text{Variation}\\ \text{due to X}}} + \underbrace{\frac{\delta F}{\delta Y}.\sigma_Y}_{\substack{\text{Variation}\\ \text{due to Y}}}$$

This would give an upper bound of the range of possible variations. One could afterwards select a subset of variables that accounted for a reasonable amount of this total variation: we took 90% as an appropriate bound. In the previous example it would have been reasonable therefore to consider only inputs 7, 6, 5 and 4, which accounted all together for 93% of the total maximum variation.

2.2 The "mini" expert elicitation

As described before, the first stage of the sensitivity analysis was to go through all the parameters of the EPPA model, eliminate those that would surely have a negligible impact, and find an approximate standard deviation for the rest of them. From the first list of nearly 80 parameters or groups of parameters that we had listed in EPPA, we came out with a smaller set of 29 relevant inputs. They could be grouped into five main categories: macro-economic indicators, population and resource inputs, non- CO_2 emission parameters, elasticities of substitution, and backstop factors. Three scientists from the MIT Joint Program participated in this elicitation: Professor Henry Jacoby, Dr. John Reilly and Dr. Sergey Paltsev.

2.2.1 Macro-economic indicators

Three major macro-economic indicators were surely going to have an influence on the cost of climate change policies: the labor productivity growth rate, the Autonomous Energy Efficiency Improvement (AEEI) rate and the vintaging coefficient:

2.2.1.a Labor Productivity Growth rate (LPG)

The labor productivity is an indicator of how productive a worker is. Multiplied by the population it gives the amount of effective labor supply available:

$$Labor_{t+1}(R) = Labor_t(R) \cdot prod_{t+1}(R)$$

where $Labor_t(R)$ and $prod_t(R)$ represent respectively the effective labor supply available and the productivity index at time t in region R. The evolution of $prod_t(R)$ over time is determined by the labor productivity growth rate, which is modeled in EPPA as decreasing as a negative exponential from its value in 1997 to its value in 2100:

$$prod_{t+1}(R) = prod_t(R) \cdot (1 + lpg_t(R))$$

$$lpg_t(R) = (1+\alpha) \cdot \frac{lpg_0 - lpg_{100}}{1 + \alpha \exp[\beta(t-1)]} + lpg_{100}$$

where $lpg_t(R)$ is the labor productivity growth rate at time t in region R, α and β are some appropriate coefficient ($\alpha = 0.1$ and $\beta = 0.07$), and lpg_0 and lpg_{100} are the values of $lpg_t(R)$ in 1997 and 2100. In the US for example lpg_0 is 7.1% and lpg_{100} 2.2%.

However these parameters are built on historical long-term trends and are therefore only an approximation of the future. To introduce uncertainty in the productivity growth rate, we made vary the initial rate lpg_0 and kept the final rate at the same value. For the sensitivity analysis, we modified values for lpg_0 in all countries by ± 20% the initial value, which, we thought, was a fair approximation of two standard deviations:

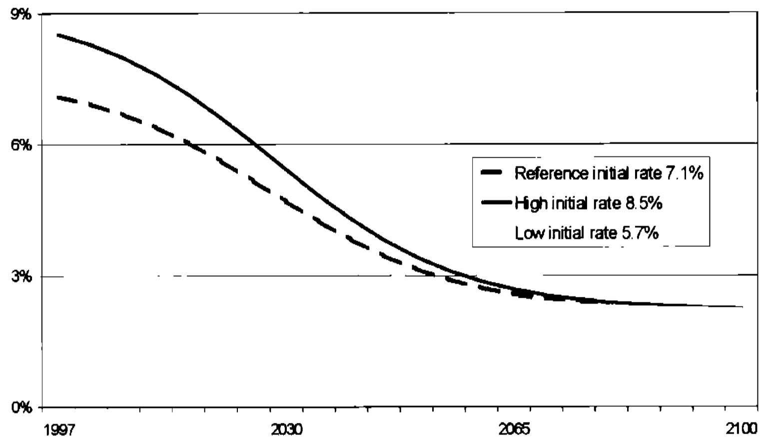

Figure 3: Three scenarios to test the sensitivity of LPG as it is modeled in EPPA

2.2.1.b Autonomous Energy Efficiency Improvement

The AEEI reflects the decrease in the amount of energy required to produce one unit of output that is not explained by price changes. It has been used in the Edmonds-Reilly model (Edmonds and Reilly, 1983) as well as in the Global 2100 model (Manne and Richels, 1990). The notion of AEEI is introduced in EPPA through a decrease in the effective energy required into non-energy sectors (ne=[Agriculture, Energy-intensive Industries, Other Industries, Services and Savings Good]), consumption (cons), government (gov) and investment (inv).

$$E_j^e(t) = \frac{E_j(t)}{AEEI_j(t)} \quad j \in (ne, cons, gov, inv)$$

where $E_j^e(t)$, $E_j(t)$ and $AEEI_j(t)$ are respectively the effective and physical energy inputs and the AEEI factor in sector j at time t. The AEEI factor has different assumptions for OECD and less developed countries but the main driver of its evolution is, like for labor productivity, the starting rate. As an example, $AEEI_j(t)$ evolves as follows for OECD countries:

$$AEEI_j(t) = \exp[r_0 \cdot (t-1) \cdot (1 - \frac{t-1}{100})]$$

r_0 being the slope of AEEI for t=1 i.e. the starting rate of AEEI.

Because AEEI is mainly a question of how we think our efficiency will evolve, it is obvious that it bears lots of uncertainty in its forecast. For the sensitivity analysis, we made the AEEI initial rate of increase vary by –30% and +35% in all countries, what we thought represented a fair approximation of two standard deviations. The following graph shows the three different evolutions of AEEI for the USA resulting from those changes:

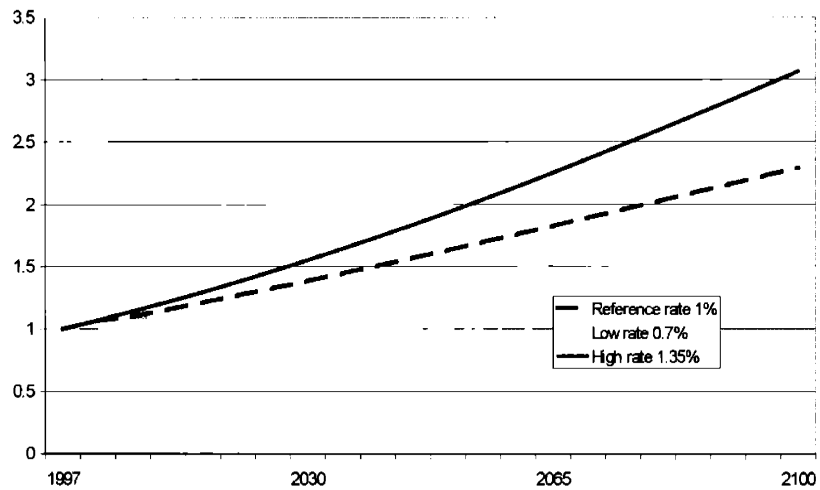

Figure 4: Three scenarios to test the sensitivity of AEEI as it is modeled in EPPA

2.2.1.c <u>Vintaging coefficient</u>

In any macro-economic model, capital is allocated according to the more efficient technology available at that time. However its is doubtful to believe that in any year, all the capital of the previous year can be moved from one technology to another: once capital (plant, equipment) is put into place, there is a limited ability to change its characteristics, although some possibilities to retrofit current capital structure exist. This phenomenon is called vintaging in the EPPA model. Often economists refer to "putty-putty" or "putty-clay" assumptions. EPPA 4 carries, for the first 20 years, five explicit vintages of capital (in EINT, ELEC, OTHR, TRAN and AGRI). A crucial parameter then determines the share of new investment that becomes "clay". If the parameter is 1.0 than all new investment takes on fixed coefficient (Leontieff) characteristics and cannot be changed or retrofit: it has no possibility to reduce energy use or CO_2 emissions in any way and remains in the economy until it is fully depreciated. If the parameter is 0 than all capital remains "putty" and in each period can be completely retrofit. It has the characteristics of new investment. This simple parameter approximates different aspects of capital flexibility, such as ability to retrofit or redeploy the capital for these uses. The result of the "mini" expert elicitation was that a reasonable range for this parameter was from 20% to 60%, reflecting the fact that we know very little about it.

2.2.2 Population and resource inputs

2.2.2.a Population inputs

Population data used in EPPA 4 are taken from UN estimates. The World population is forecast to increase from 6.5 billion in 2000 to 9.9 billion in 2100. The evolution should be quick in the first half of the 21st century and should slow down to an almost constant value after 2070. For the sensitivity analysis we thought that a standard variation should be around 2 billion in 2100. We came up with the three following scenarios:

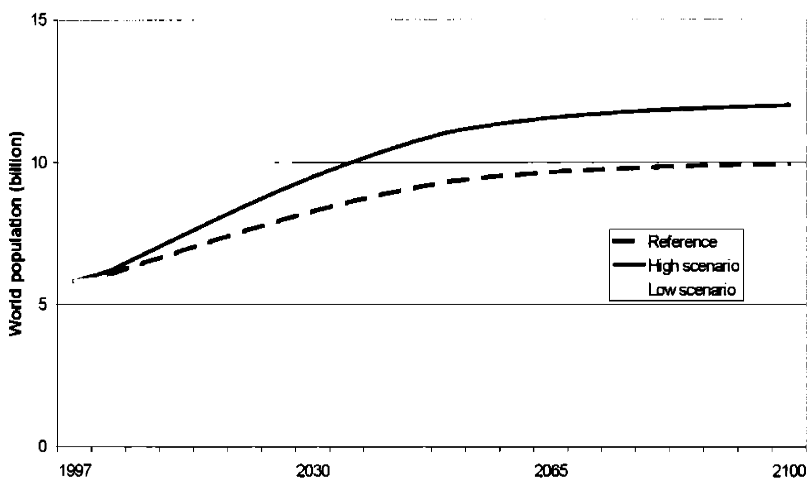

Figure 5: Three scenarios to test the sensitivity of population as it is forecasted in EPPA

2.2.2.b Resource inputs

Oil, gas and coal resources are also subject to a high uncertainty: first, one cannot precisely assess the current discovered reserves; then it is difficult to predict how much more reserves we will find in the next decades. EPPA uses the 1997 resources as a baseline for the calculations of the resource depletion. We made these data independently vary by –20% to +100% reflecting the little knowledge we have on the exact amount of reserves:

Fuel	1997 Resource (EJ)	Standard Deviation/Mean
Oil	3.52E+04	-20%/+100%
Gas	1.90E+04	
Coal	1.79E+05	

Table 2 : 1997 reserves estimates in EPPA 4 and standard deviation

2.2.3 Non CO_2 emission parameters

The EPPA model tracks the emissions of lots of different gases other than CO_2, like for example SO_2, CO, CH_4, SF_6, PFC or N_2O. For the purpose of this sensitivity analysis we only selected methane emissions (CH_4), which we believed had the greatest effect on the cost of climate change policies. We separated its emissions by sources: energy intensive industries, other industries, landfill, sewage and agriculture. For simplicity we grouped them by types in two subsets: agricultural sources on one side and industrial sources on the other. We did the sensitivity analysis for these two types independently using a standard deviation of ± 45% (Webster et al., 2001) in the 1997 emissions and keeping the same trend as the one already modeled in EPPA 4.

2.2.4 Elasticities of substitution

Each sector in EPPA is modeled as a constant elasticity of substitution (CES) function that is composed of several different nests. We decided to study five different groups of elasticities:

- Elasticities reflecting the international trading between countries: top layer armington elasticities
- Elasticities related to greenhouse gases emissions other than CO_2: we specially focused on CH_4 and N2O and we separated the agricultural sector from the others
- Elasticities between fossil fuels
- Elasticities related to technical changes: the easiness to deplete resources (fixed factor elasticity), to switch from energy to non energy composites (energy vs. non-energy elasticity), from electricity to non electricity inputs (electricity vs. non-electricity elasticity)
- Elasticity within the value added bundle (elasticity between labor and capital)

The following example gives a simplified representation of the way the agricultural sector is modeled. Every CES function is represented by a branch in which all ramifications are linked by the same elasticity of substitution:

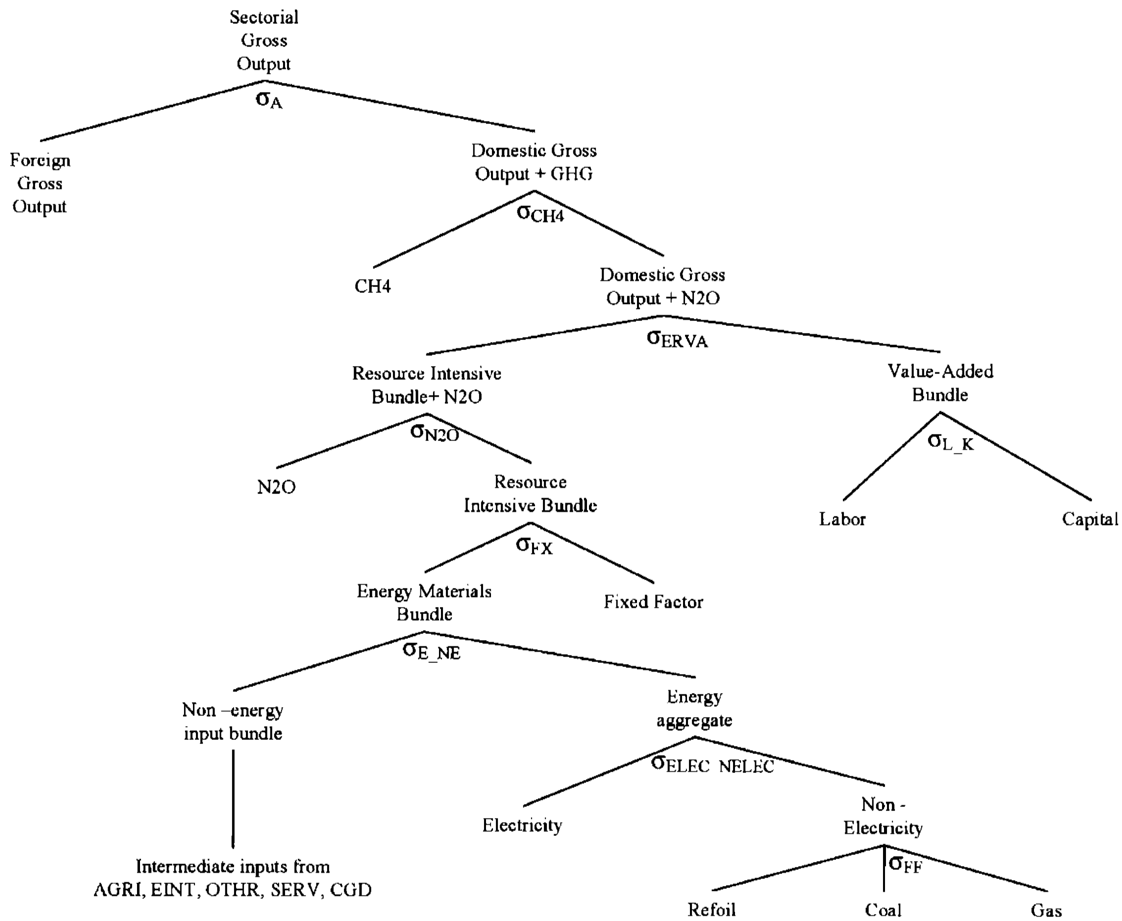

Figure 6: The agricultural sector in EPPA

For each of these elasticities we estimated a reasonable approximation of its standard deviation:

Symbol	Signifaction	Value in AGRI	Standard Deviation
σA	Top layer armington	3	-33%/+200%
σCH4	Btw CH4 emissions and gross output	0.04	-10%/ 0.3
σERVA	Btw energy resource composite and value added	0.7	not tested
σN2O	Btw N2O emissions and resource intensive bundle	0.05	-10%/ 0.3
σFXF	Btw fixed factor and energy material bundle	0.6	-50%/+100%
σL_K	Btw labor and capital	1	-20%/+20%
σE_NE	Btw energy and non-energy bundle	0.4	-25%/+25%
σELEC_NELEC	Btw elec and non-elec bundle	0.5	-40%/+40%
σFF	Btw fossil fuels	1	-40%/+40%

Table 3: Elasticities of substitution for the agricultural sector: values in EPPA4 and standard deviation

2.2.5 Backstop factors

One major element of EPPA is that it models the appearance of new and more efficient (backstop) technologies over time. Currently in EPPA 4, eleven technologies exist: solar, synf-oil, synf-gas, renewable oil, hydrogen, wind, biomass, natural gas combined cycle with and without carbon capture, integrated gasified carbon capture with sequestration and advanced nuclear. These technologies gradually appear in the economy depending on their relative costs. To represent these costs, EPPA introduces labor and capital "mark-up" factors that make the backstop technologies originally more expensive than the standard ones, gradually more and more comparable and finally less costly. Since carbon sequestration technologies had not yet been included in EPPA 4 when we performed our sensitivity analysis we decided to focus only on fossil fuel backstops (synf-oil and synf-gas) and renewable backstops (solar, wind, biomass). We studied them separately because the sources of uncertainty in their cost were different. To perform the sensitivity analysis we made vary by plus or minus 50% the remaining of the difference between the markup and 1:

Factor	Technology	Value in EPPA 4	Standard Deviation
Labor input markup factor	synf-oil	2.8	1+50%(X-1) / 1+150%(X-1)
	synf-gas	3.5	
	biomass	1.4	
	solar	1.54	
	wind	1.3	
Capital input markup factor	synf-oil	2.8	1+50%(X-1) / 1+150%(X-1)
	synf-gas	3.5	
	biomass	1.4	
	solar	1.54	
	wind	1.3	

Table 4: Mark-up factors for backstop technologies: value in EPPA4 and standard deviation

2.3 Tornado diagrams and selection of uncertainty drivers

Now that, thanks to the "mini" expert elicitation, we had determined a coherent range of variations for the selected inputs, the sensitivity analysis in itself could be performed. For each parameter identified before we ran the EPPA model[1] four times: with the low and high parameters given by the elicitation, both in a no policy and a policy case. This gave, for each parameter a low and a high value of the welfare loss and therefore a low and high value of the cost of climate change policies. The last step was to select among the parameters tested the ones we would keep for the uncertainty analysis.

2.3.1 Tornado diagrams

We focused in this study on the cost of climate change policies for four different groups of countries: two developed regions (United States and Europe) and two developing regions (China and Latin America). Some factors that were very important in the first years appeared to be completely outset by others after a century: this is why the analysis had also to take into account different time horizons: a short-term horizon in 2010, and a long-term vision in 2050.

The graphs in ANNEX (p #73) show the policy costs in 2010 and 2050 for the US, Europe, China and Latin America, expressed in percentage of consumption loss for a standard-deviation-long variation in each parameter. We studied the costs for the two periods separately.

2.3.1.a Policy costs in 2010

The first tornado diagrams in 2010 showed a clear predominance of the first six or seven parameters over the other ones. We noticed a few interesting observations:

Elasticity of substitution between the energy and non-energy bundles

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[1] Only a preliminary version of EPPA 4 was available when we performed the sensitivity analysis. The final version with carbon sequestration technologies was finished in time for the full uncertainty analysis.

The elasticity of substitution between the energy bundle and the non-energy bundle (the value added bundle in most cases) seemed to be much more important for developed countries (in the first position for the US and second for Europe) than for developing countries (6th rank for Latin America and 7th for China). One could explain this particularity using the formula that links in CES functions (the ones used by the model) the demand elasticity and the elasticity of substitution:

$$\varepsilon_d = \sigma \cdot (1 - \alpha)$$

where ε_d, σ and α are respectively the demand elasticity for energy, the elasticity of substitution between energy and non-energy composites and the share of energy in the factor's payment (cf. the classic denomination of CES functions). In developed countries the energy share is much smaller than in developing countries in which energy is used less efficiently: one famous example of a developed and efficient country is Japan, which generally has very small α. Therefore an identical variation in the elasticity of substitution created a bigger distortion in the demand elasticity in developed countries than in developing countries: the consumption level in developed countries was thus more sensitive to the uncertainty on the elasticity of substitution between the energy and non-energy bundles.

Scale variables

We called scale variables all the parameters that give an idea of the "size" of an economy: population, labor productivity growth and AEEI. These variables appear as coefficients to exponential functions in the model. They played therefore a very important role for developing countries as well as for developed countries.

Resource variables

In all countries, uncertainty in the amount of reserves available seemed to have no effect on the cost of climate change policies. This surprising result was only due to the way the EPPA model is built: the resource depletion model is only used after the year 2010. Before this horizon the model uses directly the projections of fuel prices. Therefore the variable "reserves" in EPPA was only relevant after 2010.

Vintaging

Vintaging seemed to be crucial to the uncertainty on policy costs in all regions except Latin America. The high level of capital stock in both China (a developing country much more industrialized than Latin America) and developed countries could account for this difference.

Elasticity of substitution between GHGs and domestic output in the agricultural sector

This parameter only appeared to be crucial in developing economies, where the agricultural sector is still a major part of the economy (first rank for Latin America and China). On the other hand, in developed countries such as US or Europe it was only in the 7^{th} rank.

2.3.1.b Policy costs in 2050

Although new factors appeared in some countries only, the global trend in 2050 was towards a standardization of the important parameters across countries: developing countries looked more similar to developed countries in 2050 than in 2010.

Elasticity of substitution between energy and non-energy bundle

This parameter came again in the first rank for every region. This time it was almost as important for developing countries than for developed countries. In 2050, developing countries are more advanced than before and their economy is therefore more efficient and closer to those of developed countries.

Scale variables

Once again scale variables appeared to be very important in the welfare loss uncertainty. However Latin America seemed to be much less sensitive to AEEI than the other regions: this was in fact due to the way energy efficiency improvement rate was modeled in the preliminary EPPA version we used for our sensitivity analysis. For some less developed regions including LAM, AEEI was thought to be evolving differently than for others, quickly decreasing in the first decades and growing slowly afterwards.

Backstop technologies

In a longer horizon, new technologies might be developed. The model allows the introduction of fossil and renewable technologies. Only fossil backstops appeared to play an important role in the uncertainty analysis. With high carbon taxes (around \$1,000 per ton of CO_2 in our policy case) they became less costly than traditional ones because they pollute less. Therefore, although in 2010 they were not really competitive, here in 2050 they seemed to be key to the energy production process. We observed however that they were less important in oil exporting countries like Latin America (mainly Venezuela), where traditional technologies kept playing a crucial role.

Fixed factor elasticity

The fixed factor elasticity is an artificial addition to the production function blocks: it represents for the energy sectors (oil, gas, coal) the ease with which resources are extracted from the soil. The tornado diagrams showed that this parameter had a significant importance in the overall uncertainty, especially for oil exporters like Latin America.

Armington elasticity

Although the US, Europe and Latin America did not seem to be very much influenced by the level of Armington elasticity, it appeared to have some importance for the Chinese consumption: this can be explained by the fact that the Chinese economy highly depends on its exports and imports.

The question was now to determine which exact set of factors should be selected? In the choice of parameters we were pushed in two opposite directions: on the one hand we would have liked to include as many parameter as possible in order to build a precise probability distribution function for the cost of climate change policies; and on the other hand we could not include too many parameters because it would have been too complex, reducing the time we needed to do a complete expert elicitation on each of them. We tried to include as many parameters as necessary to have a good view of how our output was behaving.

2.3.2 Choice of parameters

As explained in paragraph 2.1.4, the idea was to evaluate, for each parameter, its contribution to the maximum deviation of the output result. As we saw in the previous paragraph, the relative importance of parameters depended a lot on the time-horizon we considered (short or long-term) as well as on the country we studied.

Regarding the time dependence, we decided to separate the two studies and to consider each parameter's contribution for both 2010 and 2050. For the country dependence, we chose to weight each parameter's contribution in each different country by the relative level of emissions of this country. For example, with two parameters, 1 and 2, with respective contributions p_1 and p_2, and two countries A and B, with respective levels of emissions Em^A and Em^B, contributions of 1 and 2 globally were computed as follows:

$$p_1 = p_1^A \cdot \frac{Em^A}{Em^A + Em^B} + p_1^B \cdot \frac{Em^B}{Em^A + Em^B}$$

$$p_2 = p_2^A \cdot \frac{Em^A}{Em^A + Em^B} + p_2^B \cdot \frac{Em^B}{Em^A + Em^B}$$

This was to reflect the fact that between two parameters of similar importance in two different countries, the more important one in terms of climate policy was the one of the more polluting country because the policy of this country would have more effects on global warming.

The way we chose the list of parameters that we were going to elicit was by representing on a chart the cumulative contribution to the overall uncertainty in percentage terms. The following diagram shows this chart for the 2010 horizon:

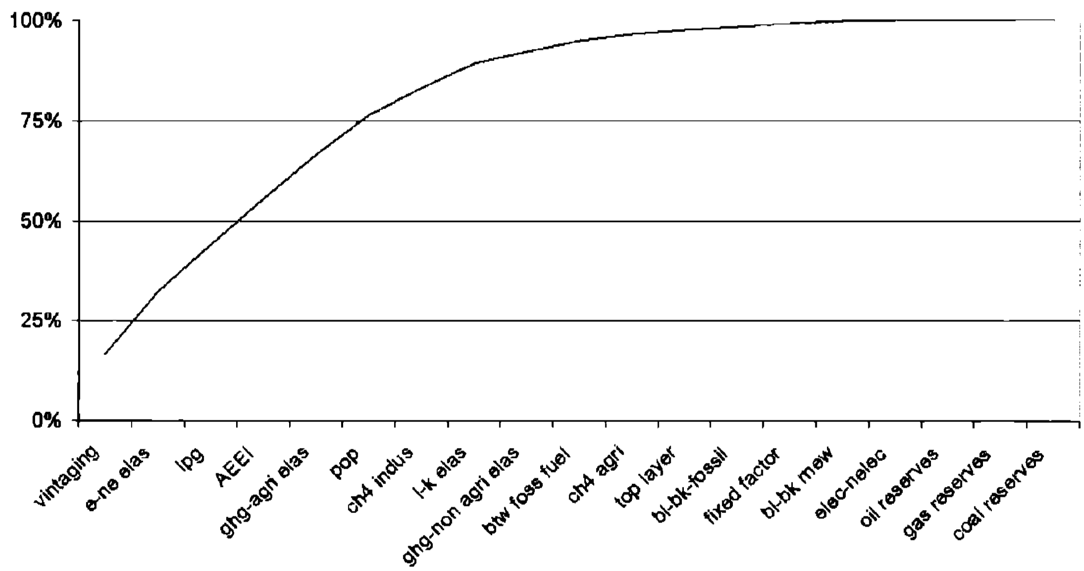


Figure 7: Cumulative contribution to the policy costs uncertainty in 2010

This graph shows on the x-axis all the parameters that we have tested, ranked by decreasing importance (vintaging is the most important one here), and on the y-axis the percentage of the overall uncertainty that we would assess if we were to choose all the parameters more important than the one we are considering.

For the 2050 timeframe we obtained the following graph:

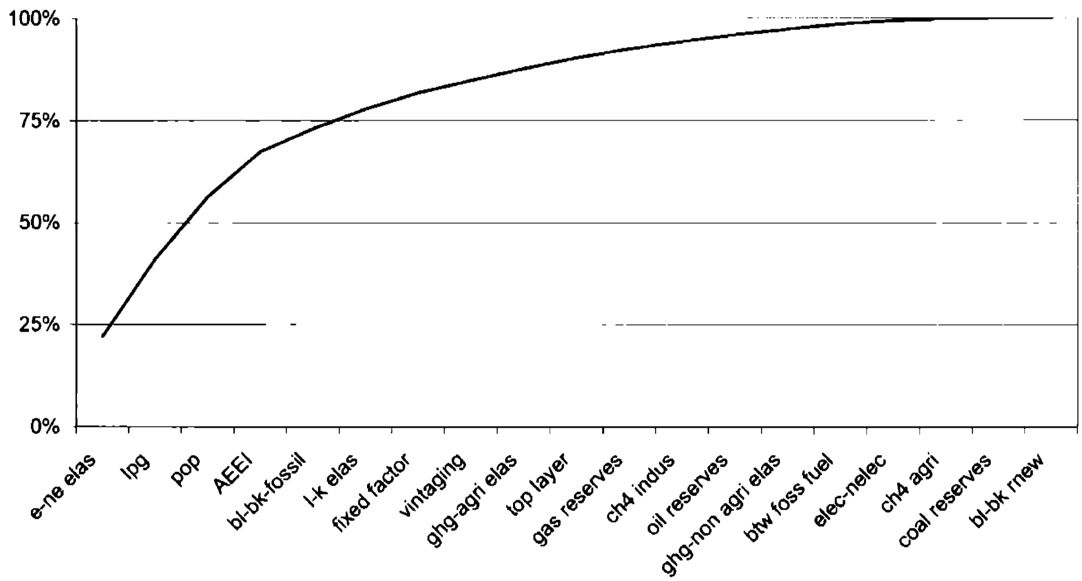


Figure 8: Cumulative contribution to the policy costs uncertainty in 2050

After having estimated the relative contributions of the different parameters in 2010 and 2050, one had to make a choice and determine a list of the parameters that were going to be selected for the elicitation. As explained before we had to find the smaller set of parameters that accounted for a reasonable percentage of the global uncertainty, both in 2010 and 2050.

First we estimated that a "reasonable percentage" would be reached if the set of variables selected accounted for 90% of the global uncertainty in the two horizons. The two graphs above helped us a lot in choosing the smaller set: for each graph (in 2010 and 2050) we just had to go through all the parameters from left to right and stop when we had reached more than 90%. Then we concatenated the two lists and came out with ten parameters that were together responsible for a high percentage of the overall uncertainty in the two periods. The ten parameters and their own contribution are shown below:

	Contribution to policy costs uncertainty	
	2010	**2050**
vintaging	16.4%	3.0%
e-ne elas	15.8%	22.0%
LPG	11.7%	19.0%
AEEI	11.5%	11.1%
ghg-agri elas	11.2%	2.8%
pop	9.6%	15.3%
ch4 indus	6.7%	2.5%
l-k elas	6.4%	4.8%
bl-bk-fossil	0.8%	5.6%
fixed factor	0.8%	4.0%
TOTAL	**90.8%**	**90.1%**

Table 5: Uncertainty drivers selected after the sensitivity analysis

This subset of parameters accounted for more than 90% of the maximum deviation in the output result (i.e. the deviation that would happen if all the inputs were perfectly correlated) and could therefore be retained as the list on which we would perform a full expert elicitation.

Chapter 3 Full Expert Elicitation

The second step in the uncertainty analysis was to gather economics and environmental experts to seek a consensus on how to model the uncertainty for the subset of parameters we had selected. This step was essential because it was the base on which we would work to propagate uncertainty in the EPPA model and find a probability distribution function for the cost of climate change policies. We will present in a first part the mathematical steps that were to be followed to perform an expert elicitation. We will explain then the complexity that arose from performing probability assessments. We will finally detail the views of our different experts.

3.1 Building, combining and correlating PDFs: a mathematical background

3.1.1 Building a PDF from an expert elicitation

3.1.1.a Principle

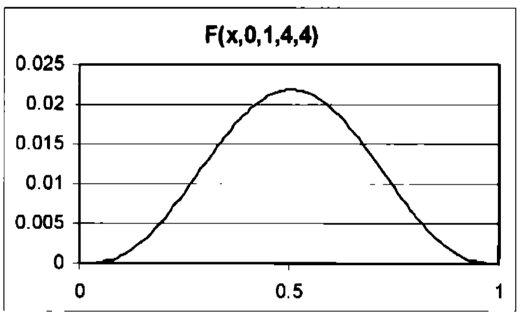
A probability distribution function represents for every infinitesimal bin [x, x+dx], the probability that the parameter's value be in that bin. It is therefore quite an abstract idea and one could not ask directly an expert for a PDF. However there are plenty of side questions that can lead to the determination of a PDF. Instead of asking for a whole function one can ask for special points or characteristics of this function like the mean, the median, the mode (most likely value), the standard deviation or any fractiles. The protocol generally followed is to ask for two end points (like the 5% and the 95% fractiles), the median (the 50% fractiles) and a lower bound (often 0). It seems to be the one with which experts are the most comfortable. However, some other protocols can be followed too (see paragraph 3.2). Then one can use these data to compute the PDF that would fit the best the characteristics given by the expert.

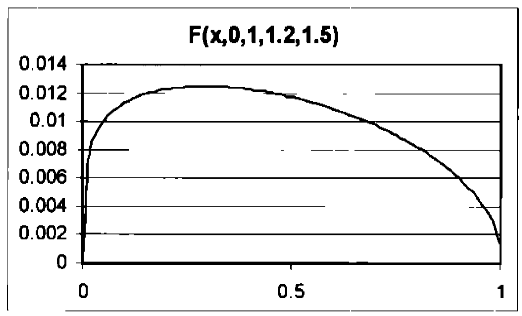
3.1.1.b The example of beta PDFs

Lots of different types of PDFs exist: beta, normal, lognormal, binomial, exponential etc. We will give in this paragraph a mathematical example of the construction of a PDF given some predefined characteristics. For simplicity we will only try to fit beta PDFs to our data. These functions are widely used in expert elicitations because they allow the modeling of lots of different shapes and have finite end points (Webster et al., 2001). A beta PDF has two inherent parameters that give its shape, and two end points. Mathematically it is expressed by:

$$F(x,A,B,\alpha,\beta)=\begin{cases}\dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}x^{\alpha-1}(1-x)^{\beta-1} & A<x<B\\[2ex] 0 & \text{otherwise}\end{cases}$$

Here are some example beta PDFs: F(x,0,1,4,4) and F(x,0,1,1.2,1.5).





3.1.1.c <u>Fitting PDFs to data</u>

If we take the example shown before we see that, in order to determine completely a beta PDF, one has to give at least four characteristics (a beta PDF is defined by four parameters). Let's use the protocol defined before (with a lower bound set at 0 in this example). The problem can be clearly stated:

Given f_5, f_{50}, f_{95}, respectively the 5%, 50% and 95% fractiles,

we have to find $A, B, \alpha, and \beta$ that verify the four following equations:

$$A=0 \qquad (1) \qquad \int_A^{f_5} F(x,A,B,\alpha,\beta)dx = 5\% \qquad (3)$$

$$\int_A^{f_{50}} F(x,A,B,\alpha,\beta)dx = 50\% \qquad (2) \qquad \int_A^{f_{95}} F(x,A,B,\alpha,\beta)dx = 95\% \qquad (4)$$

Solving such a problem can be done using either the "solver" function of Excel or appropriate software like @RISK.

3.1.2 Combining PDFs

Once one has found PDFs that fitted each expert's view on a given parameter, there is still to "combine" them in a way to find a global distribution for this parameter. There are lots of controversies on the different combining methods. Three main types of approaches exist (Webster, February 2000).

A first possibility is to propagate each expert's opinion separately (Morgan and Keith, 1995). This method has the advantage of avoiding the issues raised with the combination of human judgments. However it requires either that every expert give an opinion on every variable elicited even if he has no expertise at all on the subject, or that all possible combinations of judgments be presented, which in our case would lead to a much too complex and useless database.

A second way requires experts to reach a consensus on each parameter and to come out with a single distribution (Dalkey, 1967): since our range of experts included people in different geographic places, it was technically difficult to gather them and ask them to come out with a single distribution

A last approach is to combine the expert opinions in some way (Genest and Zideck, 1986; Winkler, 1986). Some suggest weighting experts differently depending on their knowledge on the subject, granting more value to those who have the more expertise in the domain. Others propose weighting them by the difference between their estimate and the mean of all the estimates (the closer to the mean having the bigger weight). Most scientists however express the utmost reluctance in applying the previous methods pointing out the bias associated with the choice of weights. Titus and Narayanan (1995; 1996) suggest weighting equally every expert, assuming that the fraction of them holding an opinion is a first approximation of the probability of this opinion to be true.

We believed that weighting PDFs was indeed extremely risky because it required a subjective judgment on how to weight the experts. On the other hand, since the existing literature seemed to suggest that different studies probably needed different approaches and that no one method was appropriate, we decided to simply average the PDFs, giving each of them the same weight.

Let's suppose for example that three experts took part in the elicitation, resulting in three beta PDFs, $F_1, F_2, and\ F_3$. For each infinitesimal bin [x, x+dx], the global PDF would be defined by:

$$F(x)dx = \frac{F_1(x) + F_2(x) + F_3(x)}{3} dx$$

The following graph shows the result of such an averaging for three experts (units are arbitrary):

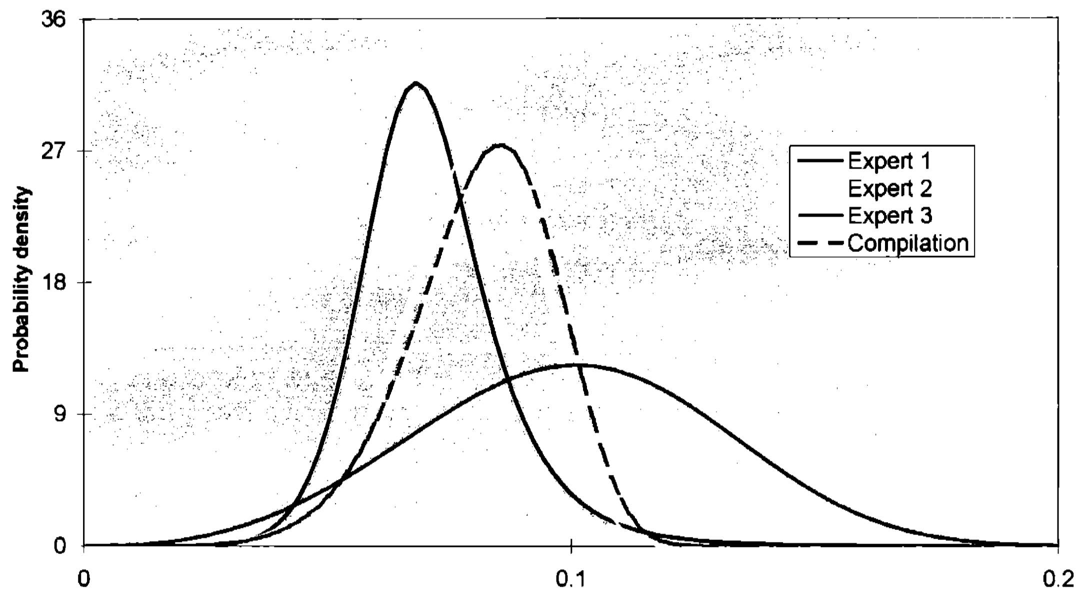


Figure 9: Example of combination of three different PDFs

3.1.3 Correlating variables

Once a distribution had been found for every variable, the next step was to perform a last elicitation with all the experts who collaborated in the previous elicitations, in order to understand how all the parameters were correlated together. This step was essential to the accuracy of our model. Failing to consider potential correlations between variables and assuming therefore that they were all independent could have led to a dramatic underestimation of the output uncertainty. Indeed the effects of two parameters varying independently tend to offset each other, whereas they will add to each other if they are correlated.

In the previous examples we only considered the case of beta PDFs. However one could think of a lot of other distributions to fit the characteristics given by an expert. A software widely used in uncertainty analysis, called @RISK, makes it possible to find between more than 20 different types of distributions the one that best fits the equations. Once this distribution has been found a simple model can be programmed to divide the x-axis in small bins, average the different probabilities in each bin and fit another distribution to the result obtained. Therefore the previous protocol could have been realized with much more distribution types, which made it even more accurate.

3.2 Preliminary issues

3.2.1 Standard protocols

Expert elicitation is not always straightforward: first it relies on probabilistic judgments that can be biased (Tversky and Kahneman, 1974; Morgan and Henrion, 1990). Then, it requires using judgments from multiple experts who might disagree. Several protocols have tried to cope with these two difficulties like the Stanford/SRI assessment protocol or the Morgan-Henrion protocol. Both of these define clear steps that are to be followed.

3.2.1.a Introduction-motivation

Both previously mentioned protocols refer to a "motivating" phase during which experts are explained the background of the analysis (why are we interested in doing an uncertainty analysis on this parameter?). This phase is generally thought to be less than half hour long.

3.2.1.b Technological discussion

Morgan and Henrion introduce a specific phase during which experts explain during an hour or more their view on how to approach the issue in the best way: what would be the most convenient way to define the parameter, how could we model the uncertainty. Although no real elicitation occurs during this phase, it is recommended to take as many notes as possible to be able to understand better the reasoning behind the elicitation itself.

3.2.1.c "Structuring" the elicitation

Experts are now supposed to 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. This phase is also useful to make them understand what sort of data they will be asked. They should be familiarized with probabilistic vocabulary like median, mode, mean, fractiles etc.

3.2.1.d <u>The "conditioning" phase</u>

The purpose of this phase is to help experts think in terms of cognitive biases or judgments anchoring. Morgan and Henrion specially advise to briefly explain them the issues associated with expert elicitation by doing a quick psychological literature review. Experts often welcome very well this review because it helps them become more aware of the kind of biases that may change their judgments.

3.2.1.e <u>The "encoding" phase</u>

This is the fundamental part of the elicitation process. It basically consists in asking experts some characteristics of the probability distribution function that will allow us to build it afterwards. There are several ways of finding the characteristics of a PDF through expert elicitation: a first way is to ask experts to give a low and a high-end point (the 5% and 95% fractiles for example) so that they can clearly state the range that they are considering (this is indeed the best way to cope with the natural anchoring of human probability assessments) 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. Since different experts can prefer different methods, one can let every expert choose the method he likes more and compare afterwards the PDFs obtained.

3.2.1.f <u>The "verifying" phase</u>

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.

3.2.1.g <u>Combining PDFs</u>

Two different approaches exist to deal with experts who have different judgments. One can either require the experts to come to a consensus (Dalkey, 1967) or combine in a way the different results (Genest and Zidek, 1986; Winkler, 1986) by for example weighting equally each prediction. As noted above, we chose in this paper to combine the different assessments that we had obtained in order to reflect the wide range of judgments on macro-economic data.

3.2.2 Our approach

In the different elicitations that we have performed for this analysis, we presented to our experts a simple protocol that tried to gather all the phases described before. Since we were pretty much limited by the time we had, the purpose of this third protocol was to come with some results as accurate as possible in the shorter amount of time. Our protocol was composed of five stages:

- Introduction: explain the purpose of the meeting, give duration
- 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 have to be analyzed independently from the others
  - Begin with a specific country/sector
- Double-checking: has this job been done before? Is there any other elicitation available?
- 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 corresponds this value?

    Could you think of any scenario that would lead to a higher/lower value?

    Why couldn't you have lower/higher values?
  - Output checking: ask for an output that would result from these estimates
  - Calibration with other experts/consistence with current model

   - Scope extension: without any other elicitation is it possible to apply these estimates to other sectors/countries?

- Compile estimates: do experts accept that their estimates be compiled with the others to have a single PDF?

In order to give experts a global view of the process they were going to go through, I gave each of them, before the interview, the following chart: it summarized the different stages and showed in a clear way the recursive process of writing down estimates:

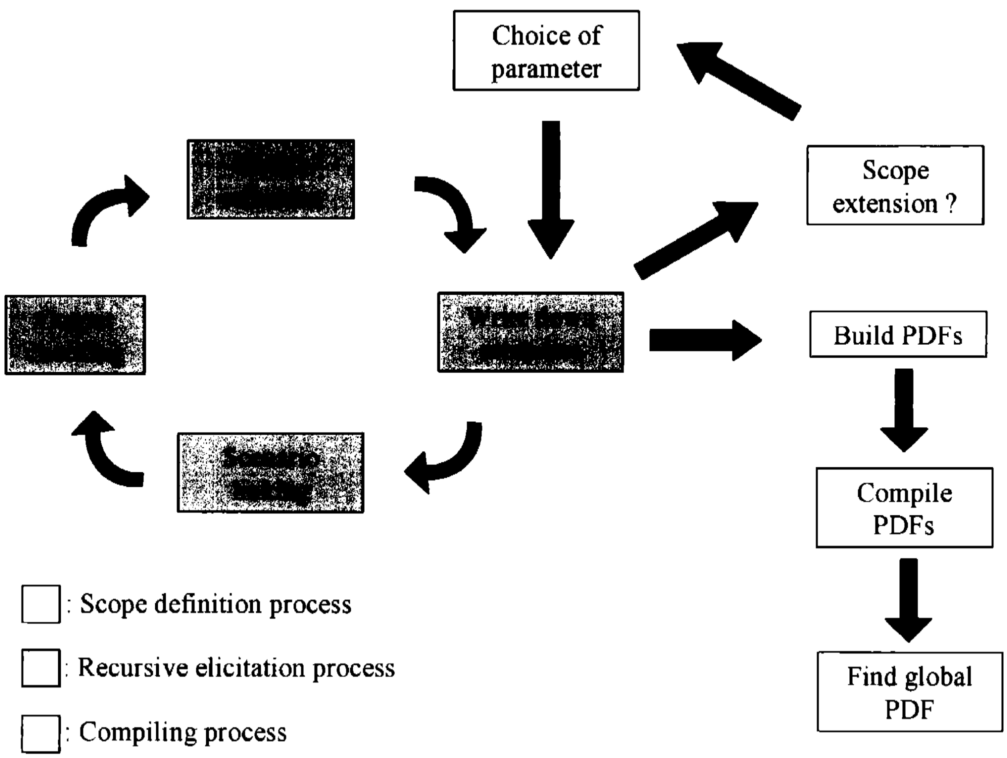


Figure 10: The elicitation process

3.3 The elicitation process

For each of the ten parameters that the sensitivity analysis had identified, we went to see experts and asked them what they thought about the uncertainty in these parameters. We will present in a first part the experts involved in each of the elicitations and the hypothesis made. We will then show the result of our combinations. We will finally detail our reasoning to build the correlation matrix.

3.3.1 Elicitation details: experts and hypothesis

3.3.1.a Macro-economic indicators

Labor Productivity Growth rate (LPG)

As a first approximation of the uncertainty in the labor productivity growth rate, we used the EPPA reference values as the mean of the distribution and applied the standard errors in historical growth found by Prof. Mort Webster from the University of North Carolina at Chapel Hill[2]. In order to capture the uncertainty in this parameter, he followed a three-step process: in a first step he studied the historical standard error in LPG, using samples from 1950 to 2000, which he aggregated by regions, in five-year time steps. His study showed that correlation between LPG in different countries was either not significantly different from 0 or its effects were negligible: we therefore decided to assume that LPG was independent in all regions. He then subtracted the projections of the EPPA model for the GDP growth rate from the projections for the population growth rate in order to have a provisional estimate of the reference labor productivity growth rate. Indeed, by definition:

$$GDP = Population \cdot Productivity \Rightarrow \ln(GDP) = \ln(Population) + \ln(Productivity)$$

$$\frac{1}{GDP}\frac{dGDP}{dt} = \frac{1}{Population}\frac{dPopulation}{dt} + \frac{1}{Productivity}\frac{dProductivity}{dt}$$

[2] In subsequent versions of this analysis, these results might be used to condition an expert elicitation of the type applied to other parameters below. The same opportunity is available for the AEEI, considered next.

$$\Rightarrow LPG = \frac{1}{GDP}\frac{dGDP}{dt} - \frac{1}{Population}\frac{dPopulation}{dt}$$

Finally he applied the historical standard error he had found to the EPPA reference value. The following table shows, for each of the 16 EPPA regions, the standard error on the initial and final LPG rates (see paragraph 2.2.1.a). For some countries like FSU or EET, since the historical data showed some periods of negative growth, the PDFs obtained by Webster were taking negative values. We believed that having a negative factor (meaning a steady decline in the economy over the century) would not be accurate and we therefore decided to throw out the samples below 0 in our simulation.

Standard error on intital and final Labor Productivity Growth															
USA	CAN	MEX	JPN	ANZ	EUR	EET	FSU	ASI	CHN	IND	IDZ	AFR	MES	LAM	ROW
19%	49%	49%	65%	19%	22%	60%	60%	28%	60%	20%	30%	48%	19%	53%	26%

Table 6: Standard errors found by Webster on initial and final LPG rates

Autonomous Energy Efficiency Improvement rate (AEEI)

Here again we used the work done by Prof. Mort Webster. His idea was to first analyze the historical trends of energy intensity in the different EPPA regions for the last 20 years. In order to capture the idea of AEEI, he readjusted energy quantities for the change in energy prices, assuming the demand elasticity for energy was approximately 0.3. He could therefore obtain the non price-driven evolution of energy intensity. Finally he transformed his estimates using the following relation between energy intensity and AEEI:

$$E^e(t) = \frac{E\ (t)}{AEEI\ (t)} \Rightarrow AEEI = {}^{1}\!/_{Energy\_Intensity}$$

The following table shows the result of his work: uncertainty is modeled by changing the AEEI initial rate of increase (cf. 2.2.1.b "Autonomous Energy Efficiency Improvement"):

Standard error on intital AEEI growth rate															
USA	CAN	MEX	JPN	ANZ	EUR	EET	FSU	ASI	CHN	IND	IDZ	AFR	MES	LAM	ROW
17%	73%	73%	73%	44%	41%	73%	73%	20%	73%	95%	73%	73%	73%	73%	55%

Table 7: Standard errors found by Webster on initial AEEI growth rate

Vintaging coefficient

The elicitation of this parameter was fairly straightforward. Five experts participated in it: Professor Henry Jacoby, Professor Dick Eckaus, Dr. John Reilly, Dr. Sergey Paltsev and Andreas Loeschel. The results are presented below:

	Experts					
	Jacoby	**Reilly**	**Paltsev**	**Eckaus**	**Loeschel**	**Fractile**
Vintaging coeficient	30%	30%	20%	44%	20%	**5%**
	50%	60%	45%	59%	35%	**50%**
	80%	100%	80%	77%	70%	**95%**

Table 8: Result of the elicitation for the vintaging coefficient

3.3.1.b <u>Population inputs</u>

Although there is a lot of data available on population forecasting, the elicitation for this parameter resulted to be quite difficult. The main obstacle was that almost all the databases available (like the UN database) carefully avoid associating any probability to their set of possible scenarios. Therefore building PDFs for population forecasts seemed pretty challenging. As a first approximation we decided to ask experts how probable were the UN scenarios. We chose the three "central" scenarios proposed in the UN database: medium, high and low fertility rates. The result of the elicitation was that these three cases were assumed to represent respectively the mean and plus or minus one sigma deviation to the mean. The table below shows the result of this elicitation for the population in 2030:

	Population by country in 2030 (in Million)															
	USA	CAN	MEX	JPN	ANZ	EUR	EET	FSU	ASI	CHN	IND	IDZ	AFR	MES	LAM	ROW
Mean-sigma	348	36	120	118	27	658	250	116	1518	1318	1281	250	1284	40	643	1466
Mean	370	37	134	121	28	685	258	120	1659	1451	1417	278	1398	43	711	1615
Mean+sigma	393	38	148	124	29	712	267	123	1807	1589	1557	306	1514	47	775	1767

Table 9: Population uncertainty in 2030

3.3.1.c <u>Baseline emissions of CH_4 from industrial sources</u>

For this parameter we decided to keep with the extensive study done by Webster (2001). We applied the fractiles he had found to build a probability distribution function.

	CH4 emissions from industry	Fractile
Tg CH4	35.4	2.50%
	138.9	50.0%
	289.5	97.5%

Table 10: Baseline CH_4 emissions from industry (1997)

3.3.1.d Elasticities of substitution

Elasticity between energy and non-energy bundle

We detailed this parameter for 7 different EPPA sectors: the five non-energy sectors (AGRI, EINT, OTHR, SERV, TRAN), the consumption sector (CONS) and the electric sector (ELEC). Each of these sectors have a specific structure in EPPA and the kind of elasticity that we were studying did not always linked the same two nets: for the consumption sector and the agriculture sector we were interested in the elasticity between the energy and the non-energy inputs (cf. Figure 6: The agricultural sector in EPPA) whereas for the rest of the sectors the relevant elasticity was the one between the energy and the value-added bundle (Labor and Capital). We did not detail the parameter by country assuming that technology was evenly distributed across regions and that therefore the elasticities between the energy and non-energy (or value-added) bundle were the same in all countries.

Six experts were consulted for this parameter: Professor Henry Jacoby, Professor Dick Eckaus, Dr. John Reilly, Dr. Sergey Paltsev, Dr. Mustafa Babiker and Dr. Andreas Loeschel. As an example, the graph below shows the result of their estimation for the elasticity between the energy and value-added bundle in the energy intensive (EINT) sector.

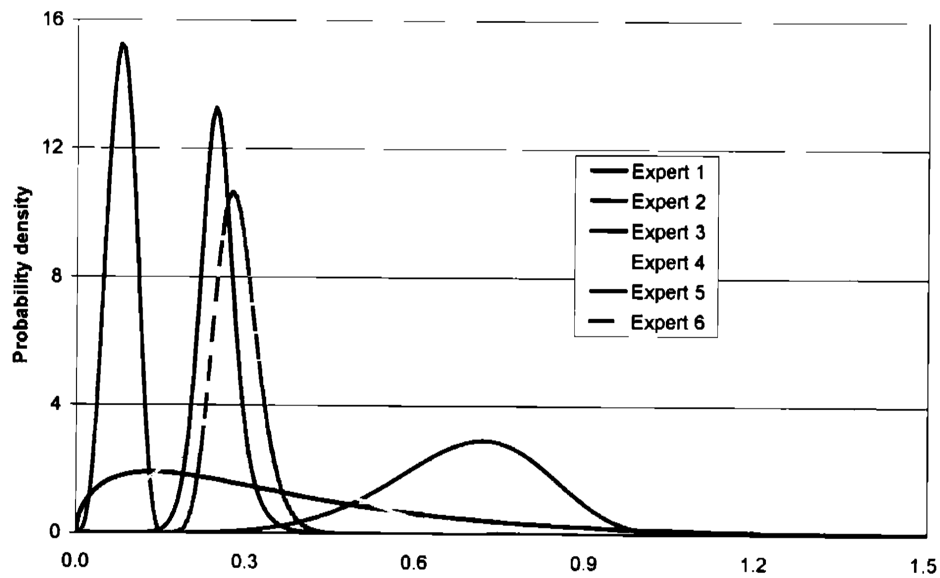


Figure 11: Example of elicitation results for the "e-ne" elasticity in the EINT sector

Fixed factor elasticity

In the EPPA model, the fixed factor elasticities only matters for the agricultural sector and for fossil fuel sectors (coal, oil and gas). In AGRI it represents land use. Since it has no effect on energy use, we decided to leave it unchanged and to focus only on the non-electric energy sectors. In some regions of the world (US, Europe, Japan) the oil and gas resource are either negligible (Japan) or the exploitation of the resource is fairly mature such that the future production path is relatively constrained by technical considerations (Europe, US). We chose to focus instead on those regions that have large unexploited resources, including areas of the FSU, Middle East and Africa. In principle these "swing" regions could greatly increase their production over the next decades, but there may be political (OPEC directives), economic (prices not high enough) or technical (introduction of backstop technologies) reasons why they may not. The way we performed the elicitation was by asking experts, for different possible prices in 2050, what would these regions' production be relative to 2003, how dramatically did they think they could expand their production (95% percentile) and how low could they restrain it (5% percentile)? From these data points we were able to build three possible supply curves representing the uncertainty associated with oil and gas extraction abilities. We then fitted the fixed factor elasticity in EPPA that gave corresponding production levels for similar prices. We went to see two different experts, Dr. Andreas Loeschel, visiting scientist at the MIT Joint program and Mr. Michael Lynch, President of Strategic Energy & Economic Research, Inc. We obtained the following results:

	Expert 1	Expert 2	
Fixed factor elasticity	0.25	0.34	5%
	0.50	0.47	50%
	0.96	1.25	95%

Table 11: Result of the elicitation for the fixed factor elasticity

Labor-Capital elasticity

The elasticity between labor and capital is a crucial parameter in the model: it appears in both the energy and non-energy sectors. It has been the subject of a wide research and plenty of articles deal with the uncertainty attached to it. We decided to approach the problem with an econometric study. We used the work done by Balistreri (2002) that detailed the long-term estimates for a variety of sectors. We aggregated these into the EPPA sectors by weighting them by their sectoral payments. Since Balistreri's paper did not study the electric sector we had to use the estimate of a comparable sector: we decided that the "metal and mining" sector was a reasonable choice since it was very capital intensive like the electric sector. We found the following fractiles:

	EPPA SECTOR							
	AGRI	ENOE	ELEC	EINT	OTHR	SERV	TRAN	Fractile
L-K elasticity	0.03	0.70	0.67	0.72	0.59	1.01	0.67	**5%**
	0.31	0.81	0.99	1.10	1.17	1.51	0.89	**50%**
	1.13	0.93	1.31	1.48	1.76	2.01	1.12	**95%**

Table 12: Labor-Capital elasticity: uncertainty estimates

CH_4-N_2O elasticities in the agricultural sector

The elicitation of this parameter requires a fairly technical approach and we decided therefore as a first step, to ask scientists at the Environmental Protection Agency: we collaborated for this work with Francisco de la Chesnaye, lead economist at the Non- CO_2 GHG & Sequestration Office, Benjamin DeAngelo and Casey Delhotal from the Office of Atmospheric Programs. It has proved useful to represent economic opportunities for abating CH_4 and N_2O using a marginal abatement curve. Most of these curves are based on current technologies, and particularly for the agricultural sector they show no ability to abate more than a small share of current emissions. The abatement curve simply "ends" around $200/TCE. We decided to ask experts how uncertain was the amount of abatement (in % of total baseline CH_4 and N_2O emissions) associated with prices of $50, $100 and $200 per TCE? We regressed these estimates assuming a constant elasticity of substitution production function and found the following fractiles:

	USA	JPN	EUR	ANZ	FSU	EET	CHN	IND	MES	LAM	ASI	ROW	Fractile
CH4 elasticity	0.01	0.01	0.01	0.01	0.005	0.01	0.01	0.01	0.005	0.01	0.01	0.005	**5%**
	0.02	0.01	0.01	0.02	0.01	0.02	0.03	0.01	0.01	0.01	0.03	0.01	**50%**
	0.04	0.02	0.02	0.03	0.02	0.03	0.06	0.02	0.02	0.02	0.08	0.02	**95%**

Table 13: CH_4 Abatement curve elasticity: uncertainty estimates

	OECD	LDC	FSU	EET	Fractile
N2O elasticity	0.01	0.01	0.007	0.008	**5%**
	0.02	0.02	0.009	0.011	**50%**
	0.02	0.02	0.011	0.014	**95%**

Table 14: N_2O Abatement curve elasticity: uncertainty estimates

However these estimates were based on existing data and we felt that, since technologies were surely going to evolve on the timescale we were interested in, we ought to make also the elasticities evolve to represent the improvement in the easiness to abate emissions. We thought that in 2100, for carbon prices around $2000 per TCE as the EPPA model predicts, the abatement could be as high as 30% of total emissions. Such a level of abatement would correspond to a higher elasticity than what the short-term estimates of the EPA indicated (around 0.06). Therefore we added a time dependency in EPPA, making the CH_4 and N_2O elasticities increase linearly from the EPA values in 1997 to our long-term guess in 2100.

3.3.1.e <u>Backstop factors</u>

We performed the elicitation on five backstop technologies: synf-oil, gasified coal, natural gas combined cycle with (NGCC) and without carbon capture (NGCAP) and finally integrated gasified carbon capture with sequestration (IGCAP). We asked experts how uncertain were for them the capital and labor markup factors for these technologies. We 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. They came out with the following fractiles:

	Expert 1	Expert 2	Expert 3	
Synf-oil markup	2.0	2.1	2.5	5%
	3.5	4.3	4.3	50%
	5.0	5.8	6.0	95%

	Expert 1	Expert 2	Expert 3	
Gas. Coal markup	3.4	1.9	3.9	5%
	4.3	3.0	5.2	50%
	6.5	6.5	6.9	95%

Table 15: Markup factors for synf-oil and gasified coal

	Expert 4	Expert 5	
IGCAP	1.1	1.1	5%
	1.1	1.2	50%
	1.4	1.3	95%

	Expert 4	Expert 5	
NGCAP	1.1	1.1	5%
	1.2	1.2	50%
	1.3	1.2	95%

	Expert 4	Expert 5	
NGCC	0.8	0.9	5%
	0.9	0.9	50%
	1.0	1.0	95%

Table 16: Markup factors carbon capture and combined cycle backstops

3.3.2 Compiling PDFs: from the mathematical to the practical way

We detailed before (see paragraph 3.1.2) the issues associated with compiling expert opinions. We exposed a common method to compile PDFs by averaging probabilities in each elementary bin [x, x+dx]. This was definitely an appropriate method of compilation. However we saw two major limitations to it:

- First, it required a substantial amount of calculation: for every expert and every parameter, we had to build a PDF with @RISK, export the data to an excel spreadsheet, divide the x-axis in identical bins, average the probabilities in each bin and then fit a PDF to the resulting data. With an average of three to four experts per parameter and a total of over 30 PDFs to build, this would have meant 90 to 120 iterations of the previous process.

- Then it did not seem to be appropriate for a limited pool of experts with significantly different views (which has often been the case in our elicitations). We considered the extreme example of two experts very confident on two different values for a parameter. The result of the previous method of combination would be a PDF with two bumps at the two modes forecasted by the experts (see Figure 12). Samples resulting from it would be close to what either the first or the second expert had believed. We thought that such results would be inconsistent because disagreements between experts reflected more for us the lack of knowledge on a parameter than the duality of its value. Such a method did not seem therefore appropriate. A better approach should lead to a very wide PDF that would include the two values forecasted by our experts.

We therefore decided to adopt a more practical and appropriate method of combination. Instead of averaging each elementary bin, we approached the problem by averaging the fractiles given by the experts. This method appeared to be first much less computationally complex than the previous one because it only required fitting one PDF to the average of all fractiles (therefore only 30 iterations and not 120). Then by averaging the starting points, the median and the end points, it avoided the two-bump-like results. Figure 12 shows the results of these two methods on a case (elicitation for the elasticity between the energy and value-added bundle in the EINT sector) where two experts strongly disagreed with others:

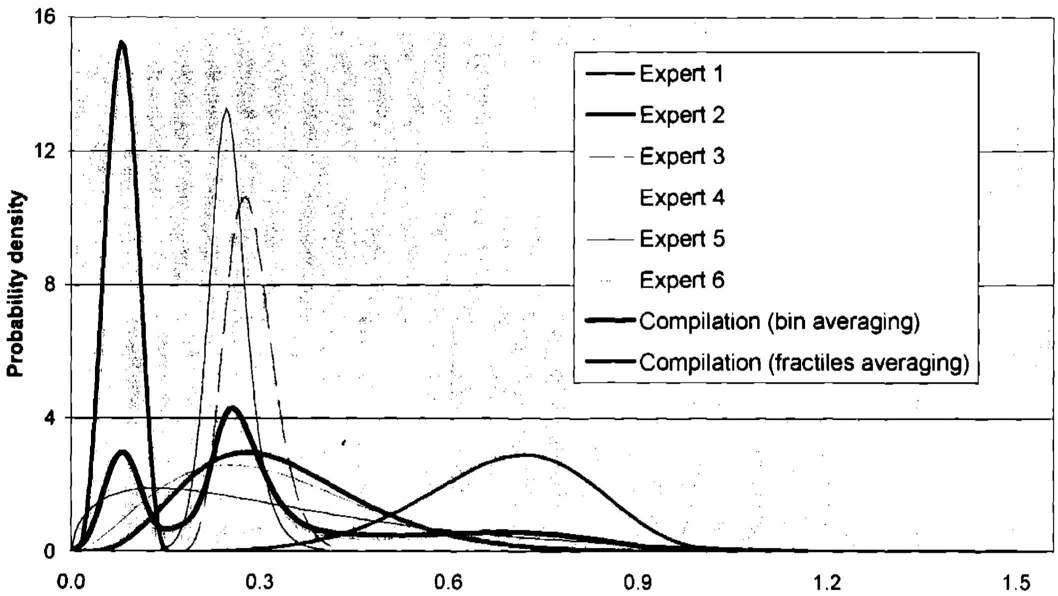


Figure 12: The two compilation methods in the "e-ne" EINT example

Experts 1 and 2 have fairly different views than experts 3 to 6. The first compilation method leads to a three-bump distribution with vast portions of low probability between the bumps. This kind of PDF is certainly not realistic. The second method leads to a wider distribution probably closer to reality.

Once this method had been applied to all parameters, we could build a PDF for each of them. The table below presents the result of all the elicitations compiled per parameter. For each of them we detailed its median as well as its standard error[3]:

		Median	Standard error	PDF type
energy/non energy elasticity	EINT	0.3	0.1	gamma
	OTHR	0.4	0.2	beta
	ELEC	0.2	0.1	gamma
	SERV	0.4	0.2	beta
	AGRI	0.2	0.1	gamma
	CONS	0.4	0.2	log-logistic
	TRANS	0.4	0.2	log-logistic
Labor Capital elasticity	AGRI	0.3	0.4	beta
	ENOE	0.8	0.1	gamma
	ELEC	1.0	0.2	beta
	EINT	1.1	0.2	beta
	SERV	1.5	0.3	gamma
	OTHR	1.2	0.4	beta
	TRANS	0.9	0.1	gamma
	CGD	1.5	0.3	gamma
Fixed factor elasticity	OIL-GAS	0.5	0.1	beta
Population (millions)	World 2100	9937	1442	beta
CH4 emissions	mmt	144.5	65.3	weibull
Vintaging		52%	16%	gamma

		Median	Standard error	PDF type
CH4 elasticity in AGRI	us	2%	1.2%	pearson
	jpn	1%	0.4%	weibull
	eur	1%	0.3%	beta
	anz	2%	0.5%	beta
	fsu	1%	0.5%	beta
	eet	2%	0.5%	beta
	chn	3%	1.9%	log-logistic
	ind	1%	0.5%	beta
	mes	1%	0.4%	beta
	lam	1%	0.5%	beta
	asi	4%	2.6%	pearson
	row	1%	0.4%	beta
N20 elasticity in AGRI	oecd	2%	0.3%	gamma
	ldc	2%	0.3%	gamma
	fsu	1%	0.1%	gamma
	eet	1%	0.4%	gamma
Backstop factors	synf-oil	4.0	1.0	beta
	gas. Coal	4.4	1.1	pearson
	IGCAP	1.2	0.1	log-logistic
	NGCAP	1.2	0.1	beta
	NGCC	0.9	0.04	beta

Table 17: Elicitation summary

3.3.3 The correlation matrix

As we explained before (see paragraph 3.1.3), the last step was to ask our experts how correlated our parameters for any one nation or region were to each other. It appeared that asking for correlations was a difficult task. Several difficulties arose:

- The first obstacle was that experts did not have a broad enough knowledge of the other parameters we were asking them to correlate. Thinking about correlation requires everyone to

[3] Probability distributions are not always symmetric though. For each parameter the software @RISK determined the type of PDF that best fitted the data: "beta", "log-logistic", "weibull", "pearson" etc.. Beta distributions were the most chosen type of PDF.

step back from his normal point of expertise and to think more broadly about how this particular point might interact with the others.

- But the main difficulty in asking for correlations was that it seemed very hard to associate a degree of correlation with two variables: we tend to understand pretty well if two variables are correlated (their covariance is 1) or not (covariance null). But it seems to be much more difficult, and sometimes almost impossible to say if the covariance is closer to 0.3 or to 0.8 for example. Therefore there is a natural bias towards the two ends, 0 and 1: experts will tend to say that two variables with a small degree of correlation are uncorrelated and, vice-versa, two variables with a high degree of correlation will be seen as perfectly correlated.

We had to come out with some simplifications. As a first step we decided to ask them for correlations across "types" of parameters assuming a correlation of 1 among each "type": for example we asked them for the correlation between vintaging and energy-non energy elasticities as a whole rather than between vintaging and energy-non energy elasticity in AGRI. This simplified greatly our matrix, which narrowed from 30 by 30 to 10 by 10. Then we tried to help experts choosing a degree of correlation by showing them plots of two variables correlated differently. This helped them visualize what exactly meant a correlation of 0.5 for example. In particular, they acknowledged that from 0 to 0.7, no trend was really visible on the graphs. We decided therefore to simplify the problem by building our matrix with three possible values: 0 for uncorrelated variables, 0.8 for slightly correlated variables and 1 for perfectly correlated variables. The result of the elicitation is showed below:

	vintaging	e-ne elas	LPG	AEEI	ghg-agri elas	pop	ch4 indus	l-k elas	bl-bk-fossil	fixed factor
vintaging	1									
e-ne elas	0.8	1								
LPG	0	0.8	1							
AEEI	0.8	0.8	0.8	1						
ghg-agri elas	0	0.8	0.8	0.8	1					
pop	0	0	0	0	0	1				
ch4 indus	0	0	0	0	0	0	1			
l-k elas	0.8	0.8	0.8	0.8	0.8	0	0	1		
bl-bk-fossil	0	-0.8	-0.8	-0.8	-0.8	0	0	-0.8	1	
fixed factor	0	0	0	0	0	0	0	0	0	1

Table 18: Correlation matrix

The reasoning to build such a matrix was the following:

- A high labor productivity growth would lead to more growth in the economy, more technologies developed, more options possible and therefore more capital/labor and energy/non-energy substitutions

- A high labor productivity growth would also increase the learning effect in each sector and thus increase the autonomous energy efficiency improvement rate

- For high LPG or AEEI or elasticities, backstop technologies would become less costly

- Highly vintaged economies are generally characterized by high elasticities and AEEI

- Vintaging is otherwise independent of any other variable

- A high AEEI generally indicates a vigorous economy in which more technologies developed and therefore in which elasticities are higher

- Population, CH_4 emissions and Fixed factor elasticity are independent of any other variable

- Elasticities are correlated among themselves

These results completed the elicitation process. For each parameter selected from the sensitivity analysis, a probability distribution function was available. Also a correlation matrix linking these parameters had been estimated. The next step in our study (see Figure 1: Research approach) was to use @RISK to simulate samples of each of these variables using a Latin-Hypercube sampling (Iman and Helton, 1988) and run the EPPA model. The running process required several steps:

- The excel spreadsheet generated by @RISK had first to be transformed into as many files (we called them "coll/i/" files, "i" being the number of the sample considered) as we had samples, each of these files containing one sample of each uncertain parameter. We performed the analysis with 250 samples, which seemed reasonable to obtain results accurate enough.

- The structure of EPPA had then to be modified so that each time the model called for one parameter it looked into the appropriate "coll/i/" file and then produced an output file numbered by the same "i".

- We then set up a program to automatically run a reference and a policy case for each sample, so we could compute a welfare loss between the two.
- Finally we extracted from all the output files, the welfare loss for the country we were interested in and in the horizon we were focusing on.

Each of these steps required the set up of short C-programs (see ANNEX p77).

Chapter 4 Stabilization: cost and policy implications

As we stood in December 2003, it seemed less and less probable that the targets suggested by the Kyoto protocol would frame the international policies of the next century. However this did not mean that the long-term goals of the protocol would be abandoned. We tried in this paper to adopt an international policy that was in the same time aligned with the objectives put forward by the United Nation Framework Convention on Climate Change and that seemed reasonable knowing the current state of the climate negotiations. We then performed our uncertainty analysis and tried to draw from it the policy implications that would frame the future of the negotiations. We will present in a first part our policy scenario and the reasons why we chose it. We will then expose the insights that we could gather from the results of our uncertainty analysis.

4.1 Stabilization at 550 ppm as a long-term goal

4.1.1 Why should we stabilize concentrations?

Our first concern in the process of finding a policy scenario to run our uncertainty analysis was to stick as close as possible to the long-term goals proposed by the UNFCC. In the second article of the founding text of the Convention, this goal is clearly expressed:

> *"The ultimate objective of this Convention and any related legal instruments that the Conference of the Parties may adopt is to achieve, in accordance with the relevant provisions of the Convention, stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system."*

This focus on concentrations rather than on emissions can seem a little odd at a first look. Why are concentrations the issue? This is indeed one core question in climate change policies that is often overlooked or not understood by the public. The answer is that climate change is a "stock" problem. One can understand that with simple stock and flow diagrams like the ones below: stocks are represented as boxes, and flows as arrows leaving from or arriving at these boxes.

As a first step we can model the natural equilibrium of the Earth's temperature introducing the following simple diagram: the stock of heat in the surface layers depends on the inflow of energy radiated by the sun and on the outflow radiated back to the atmosphere. The more heat in the layers the hotter the surface temperature and the bigger the energy radiated (a hot object radiates more than a cold one). This constitutes a balancing loop that keeps the heat in the surface layers at equilibrium.

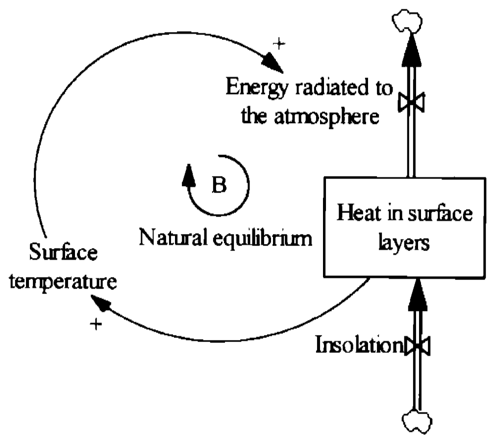


Figure 13: Natural equilibrium of the Earth's temperature

Concentration of CO_2 in the atmosphere can also be represented as follows. Total concentration is increased by, on the one-hand fossil fuel emissions (transformation of fossil fuels in energy and CO_2 emissions), and on the other hand natural emissions from biomass (plants, trees etc.). It is decreased by the natural gross removal from plants and ocean uptake (we ignored geological carbon sequestration for simplicity). The exchange between the stocks can be modeled as follows:

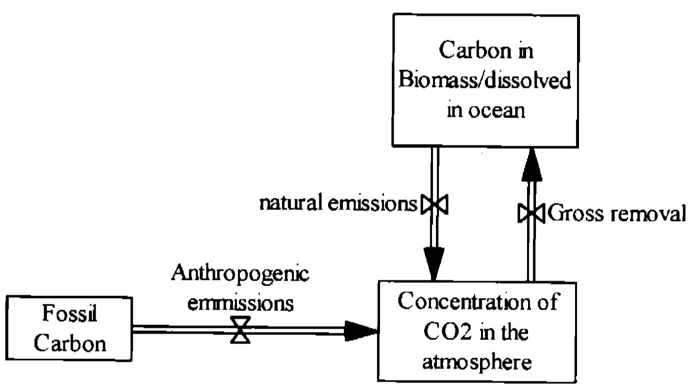


Figure 14: What modifies CO_2 concentrations?

The two diagrams can now be connected together: the more CO_2 in the atmosphere, meaning the bigger the concentration of CO_2, the less energy will be radiated back from the Earth. This is the greenhouse effect.

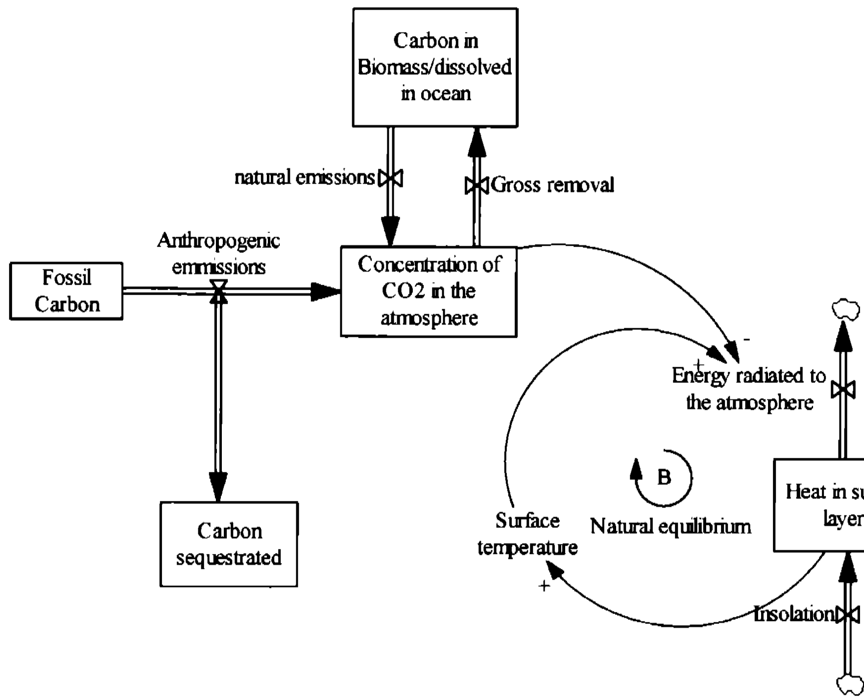


Figure 15: Climate change as a stock issue

The key idea in this diagram is that the link is not between emissions and temperature but between CO_2 concentration and temperature. People generally tend to think that as soon as they will decrease their emissions, the Earth will cool down and the problem will be solved. Therefore they prefer not worrying now and wait till it is time to act. But this simple model shows that this conception is intrinsically wrong. It is not enough to decrease emissions. Emissions are just a flow that makes the total concentration increase. Therefore decreasing emissions will only slow down the rate at which concentration increases but it will not solve the problem.

4.1.2 Why at 550 ppm?

As we saw in the previous part, the long-term goal to which we should tend to is emission stabilization. The scientific and political issue is now to determine at which level should concentration be stabilized in order to *"prevent dangerous anthropogenic interference with the climate system"*. Numerous studies have been done on this topic. The data presented by the Intergovernmental Panel on Climate Change (IPCC, 1996a) give an overview of what stabilization would imply. Current CO_2 emissions are around 4 tons per capita with maxima in Northern America at 20 tons per capita and minima in most of Africa below 1 ton per capita. Current concentrations of CO_2 in the atmosphere are around 360 ppm (parts per million),

- Stabilization at this level would imply an immediate reduction in emissions between 50% and 70% and further reductions thereafter
- Stabilization at 450 ppm for CO_2 and somewhat above current concentrations for the other greenhouse gases would lead to an increase in global temperature from 1.5°C to 4°C, the largest warming in the past 10 000 years
- Stabilization at 550 ppm would lead to an even bigger increase in global temperature from 2°C to 5.5°C. It would imply an average level of CO_2 emissions per capita around 5t before the year 2100 and 3t afterwards.

There is still a large uncertainty on the exact level that would prevent "*dangerous interference with the climate system*". However a consensus seems to emerge on the 550 ppm level: indeed several parties to the UNFCCC, including the European Union (EU), have proposed that, "*concentrations lower than 550 ppm should guide limitation and reduction efforts*" (AGBM, 1996a, para. 41). We decided therefore to set up our policy scenario so that concentrations would stabilize at this 550 ppm level.

4.1.3 How the burden should be shared?

Once we have decided the long-term goal towards which we want to tend, we still don't have solved the question of who will bear the costs of this stabilization. There is definitely an equity issue in this question. As the data on emissions per capita show (see paragraph 4.1.2) the main part of current and past emissions is due to developed countries. As the UNFCC indicates in its preliminary statement:

> *"Noting that the largest share of historical and current global emissions of greenhouse gases has originated in developed countries"*

Therefore it would be unfair to share the burden of current reductions between developed and developing countries. The UNFCC acknowledged this fact and stipulated in the third article of its Convention:

> *"The Parties should protect the climate system for the benefit of present and future generations of humankind, on the basis of equity and in accordance with their common but differentiated responsibilities and respective*

capabilities. Accordingly, the developed country Parties should take the lead in combating climate change and the adverse effects thereof."

We decided in our policy scenario to introduce two commitment periods:

- From 2005 to 2025, developed countries would be the only ones to bear the burden of the stabilization[4]. A trading mechanism would allow them to trade pollution permits. Developing countries would be given their reference emissions and would not participate in the trading process.

- After 2030, we believed the burden should be shared between developing and developed countries according to their respective emissions: if stabilization required a global decrease of 10% of total emissions for example, each group should reduce by 10% its own emissions, with the ability to sell or buy emissions permits.

The following table shows the corresponding quotas (in proportion of 1997 emissions) for the four regions we studied as well as the resulting total CO_2 emissions leading to a stabilization of concentrations at 550 ppm.

	Quotas (x 1997 CO2 emissions)				World emissions
	USA	EUR	CHN	LAM	(mmt)
2005	1.3	1.3	1.3	1.0	7500
2010	1.3	1.3	1.5	1.1	7793
2015	1.2	1.2	1.7	1.2	8071
2020	1.2	1.2	2.0	1.3	8395
2025	1.1	1.1	2.3	1.4	8766
2030	1.5	1.5	1.5	1.5	9138
2035	1.6	1.6	1.6	1.6	9362
2040	1.5	1.5	1.5	1.5	9329
2045	1.5	1.5	1.5	1.5	9248
2050	1.5	1.5	1.5	1.5	9113
2055	1.5	1.5	1.5	1.5	9104
2060	1.5	1.5	1.5	1.5	9098
2065	1.5	1.5	1.5	1.5	9006
2070	1.5	1.5	1.5	1.5	8778
2075	1.4	1.4	1.4	1.4	8428
2080	1.3	1.3	1.3	1.3	7966
2085	1.2	1.2	1.2	1.2	7490
2090	1.2	1.2	1.2	1.2	7008
2095	1.1	1.1	1.1	1.1	6490
2100	1.0	1.0	1.0	1.0	5972

[4] With the exception of Russia to which we did not impose the additional burden to compensate for emissions of developing countries

Table 19: Regional quotas and total CO_2 emissions leading to a stabilization at 550 ppm

From 2005 to 2025, China and Latin-America were given their reference emissions whereas the US and Europe were constrained in the same proportion of their 1997 emissions. From 2030 onwards, all four regions had to bear an equivalent burden. Figure 17 to Figure 24 show the results from such a policy.

4.2 *Policy costs and implications*

As we explained in the introduction to this paper the main issue in climate change negotiations is the misalignment of stakeholders' incentives when the policy response should on the contrary be global. The results of our uncertainty analysis helped us understanding this misalignment. Although the policy we had chosen to implement distributed the burden evenly across regions, the analysis showed that costs were not fairly distributed, some regions suffering from a bigger consumption loss than others. We will fist present in this part how our study helped us understanding why an international agreement was needed to deal with the climate issue. We will then show, in the light of our results, which difficulties may arise from such an agreement.

4.2.1 Why an international agreement is needed to deal with the climate issue?

The first question that comes to mind when we speak about climate change is why exactly is a global response needed, and why should an international treaty coordinate this response. Couldn't we think that, like in the SO_2 example, each country could set up its own policies to respond to the threat of climate change? What exactly made the SO_2 story a success and the CO_2 one a failure (at least until now)? I would like to answer this question using the two-dimensional space that Granger Morgan introduced (Morgan, July 1993). Morgan classifies risks using two orthogonal axes or scales: risks are more or less controllable (horizontal axis) and more or less observable (vertical axis). Depending on where a risk is positioned on this two-dimensional space, policies responses will differ.

4.2.1.a <u>Climate change is uncontrollable by one single country</u>

The first difference between SO_2 pollution and global warming is the scale of the associated risks. In the case of SO_2, risks are mainly local: health impacts on the population (asthma and other respiratory effects), acid rains, soil and water pollution, building corrosion etc. On the contrary climate change is a global risk: sea level rise, global warming etc. impact every country more or less equally, one country's behaviors have an effect on all the other countries. Therefore it cannot be solved by any unilateral action: it requires a global initiative. To put it in the terms used by Morgan, risks associated with climate change are "uncontrollable" by one single country.

4.2.1.b <u>Climate change risks are not fully observable</u>

The other difference with SO_2 is that the effects of climate change still bear a high level of uncertainty. In the case of SO_2 health and environmental effects are well known, the cost to deal with them well forecasted: the risk was "observable". For climate change, one cannot exactly predict how much CO_2 will be emitted in one century or by how much the sea level will rise? More importantly, the cost to deal with these issues is highly uncertain. After having run the EPPA model a sufficient number of times (with a Latin Hypercube sampling 250 runs seemed a reasonable number) we could estimate the uncertainty associated with these parameters. We found first that, if no policy were put in place the level of total CO_2 emissions in 2100 would be around 32.7 GtC on average, with a standard deviation of 9.1 GtC (roughly one third of the mean). The following graph shows the results of the uncertainty runs (represented as a histogram) as well as the probability distribution function fitted on them.

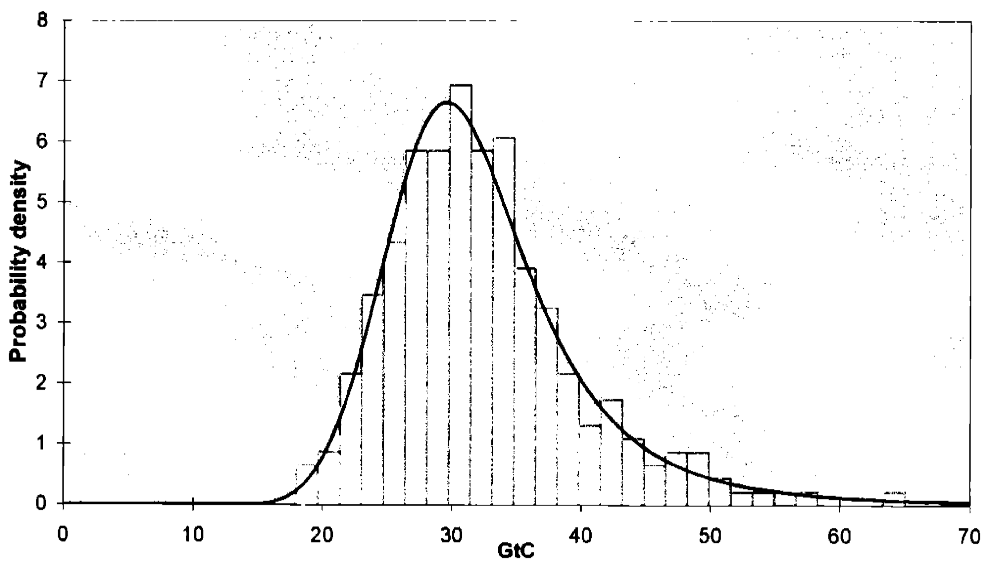


Figure 16: Uncertainty in global CO_2 emissions in 2100

Moreover, we found that the standard error on the cost of climate policies represented in any year a substantial amount of the average cost. Uncertainty was increasing with the forecasting horizon starting from an average of roughly 16% (in percentage of the mean) in 2010 to up to 93% in 2050. Some regions especially had extremely high uncertainty like the US with a mean of 0.3% of welfare loss in 2050 and a standard error of more than 4%. Even in the regions where our forecasts seemed the more reasonable, for example in Latin America, standard deviation still represented 69% of the mean.

Risks associated with climate change seem therefore to be both "uncontrollable" unilaterally and "not observable". These characteristics create the need for a regulation: climate change is an economic and environmental externality and if no regulation is put in place the result will be what Olson called a "collective action dilemma" (Olson, 1971), everybody waiting for the others to act. They also push towards a multilateral response because no country can unilaterally solve the problem. Therefore the only efficient way to deal with the climate change issue seems to be through an international agreement.

4.2.2 Which difficulties may arise from such an agreement?

Even if the need for a multilateral convention on climate change is clearly identified, some countries' recent refusal to ratify the first protocol proposed on this subject showed that an agreement was far from being reached. Our uncertainty analysis helped us understanding why each country had a specific point of view on an issue that should on the contrary concern all of them equally The main reason seemed to be the misalignment of stakeholders' incentives. It resulted indeed that, although the policy case we had chosen to run seemed fair, its costs were not equitably distributed. Moreover their level of uncertainty was varying significantly among regions.

4.2.2.a A burden inequitably shared

Our results showed that on average, costs were inequitably distributed. First, they did not seem to affect every developed country in the same way. The following graph shows the average welfare loss for Europe and the United States. Although both countries were asked to reduce the same percentage of their baseline emissions (1997 level), Europe was facing a higher welfare loss:

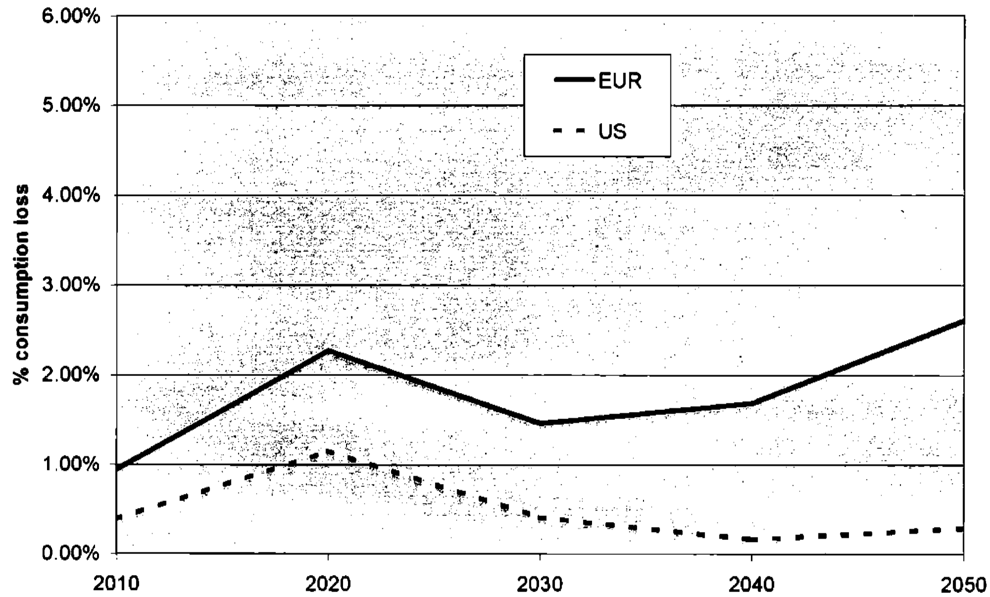


Figure 17: Average welfare loss for Europe and the US

The reason welfare loss actually decreased on average between 2020 and 2030 is that during this period developed countries have been relieved of some of the burden: developing countries started entering the stabilization protocol and the reduction effort became shared between more countries. As shown on Table 19, quotas for Europe and the US went from 1.1 up to 1.5 times 1997 emissions. Moreover the emission trading system was extended to all nations making it even easier to comply with targets.

Also developing countries seemed to be affected more heavily. After the first commitment period, they started supporting the global effort. However, because they were growing at a higher rate than developed ones, the required reduction put on them a heavier burden. Indeed although Europe and the US were losing on average less than 2% of their consumption in 2050, China and Latin America were suffering from losses higher than 17% on average. The following graph shows this discrepancy:

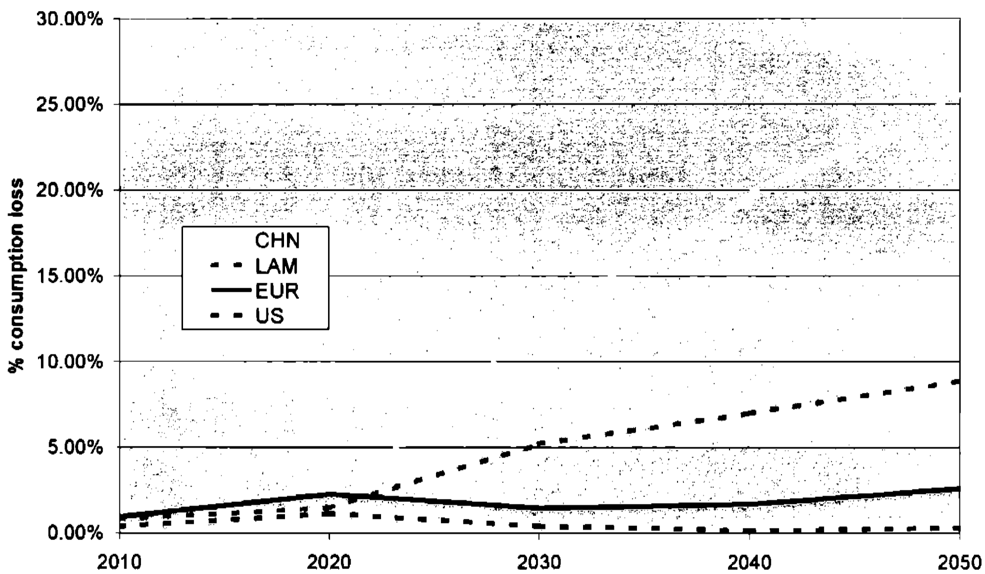


Figure 18: Average welfare loss for Europe, US, China and Latin America

We noted that the percentage of consumption loss in China and Latin America in 2050 appeared to be surprisingly high. However one has to balance it with the actual consumption growth in real terms. For example, even with more than 25% of welfare loss in China, consumption was still growing in real terms as the following graph shows:

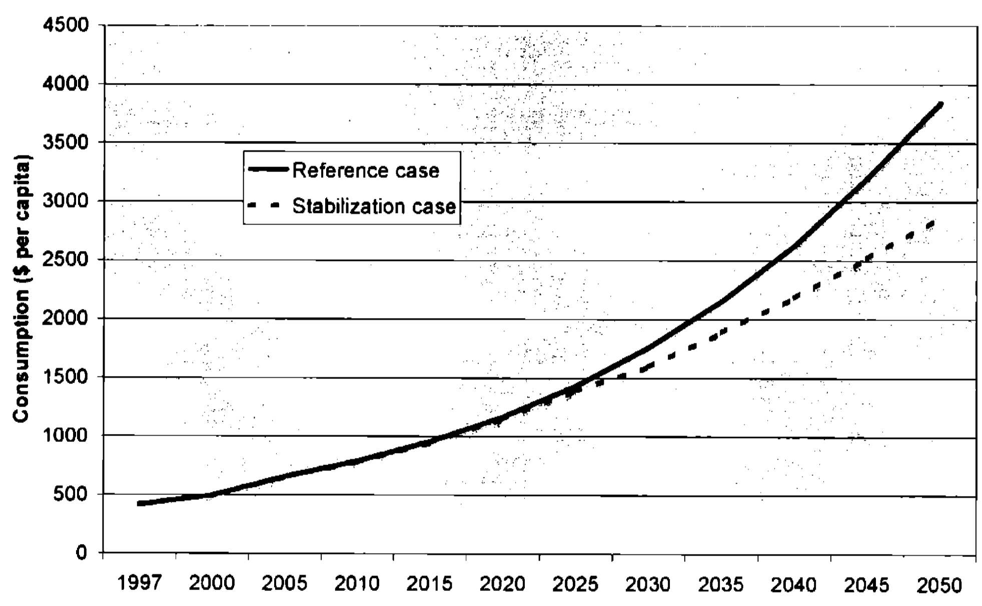


Figure 19: Average Chinese consumption per capita

Therefore, although the policy we had chosen to implement seemed fair, the resulting costs did not seem to be equally shared across countries. This was surely a first explanation of the misalignment of stakeholders' incentives. Developing countries would be very reluctant to enter such an agreement, looking at the costs they would have to bear in the future.

In our policy case, we had decided to leave developing countries apart for the first commitment period. However if we had allowed them to be part of the emission permits trading process and if in the same time we had given them their reference emissions, they would have been able to reduce in a way their emissions and to sell permits. Such a policy case would have therefore resulted in a welfare gain for developing countries during the first commitment period. These gains would have counterbalanced the losses of the second period and would have probably given positive incentives for these countries to ratify such an international agreement.

4.2.2.b A burden unequally uncertain

A second source of misalignment seemed to be the differences in the uncertainty in policy costs faced by each country. First we found that, in the US, the welfare loss could take a very wide range of possible values: its standard error represented up to fifteen times its mean in 2040 and almost fourteen times ten years after. With the extension of the trading system to all regions the median of the distribution gradually declined from 2025 to 2050, traducing the fact that the US could sell more and more permits to developing countries. It became actually negative in 2050 (-0.01% of consumption loss) showing that more than half of the possible outcomes were in fact welfare gains. The following graph shows the uncertainty associated with the US welfare loss. The average scenario, as well as the two-standard deviations range and the 5% and 95% fractiles are represented:

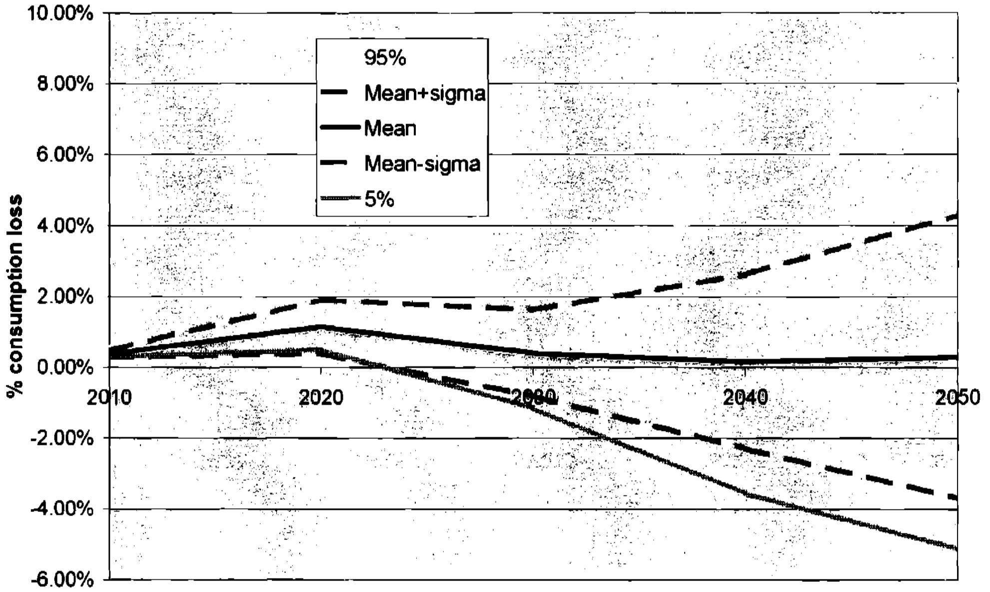


Figure 20: Uncertainty in the US welfare loss

Europe was also facing an important level of uncertainty. However it was still lower than in the US, both in real terms and in proportion of the mean: standard errors were growing from 0.2% of consumption in 2010 to more than 3% in 2050 (see Figure 21: Uncertainty in the European welfare loss).

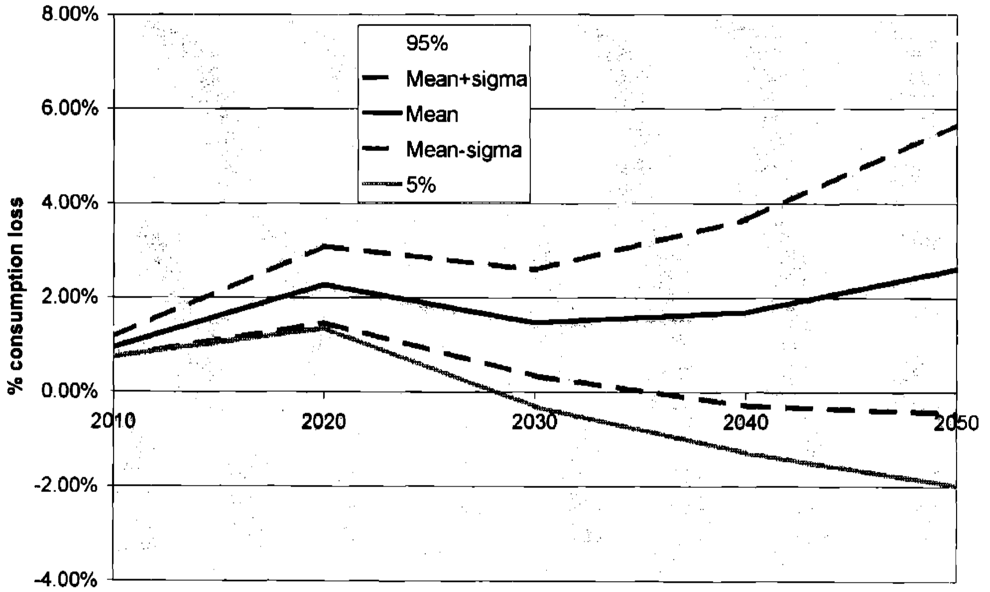


Figure 21: Uncertainty in the European welfare loss

Finally uncertainty associated with the welfare loss of developing countries appeared to be especially high (see Figure 22 and Figure 23).

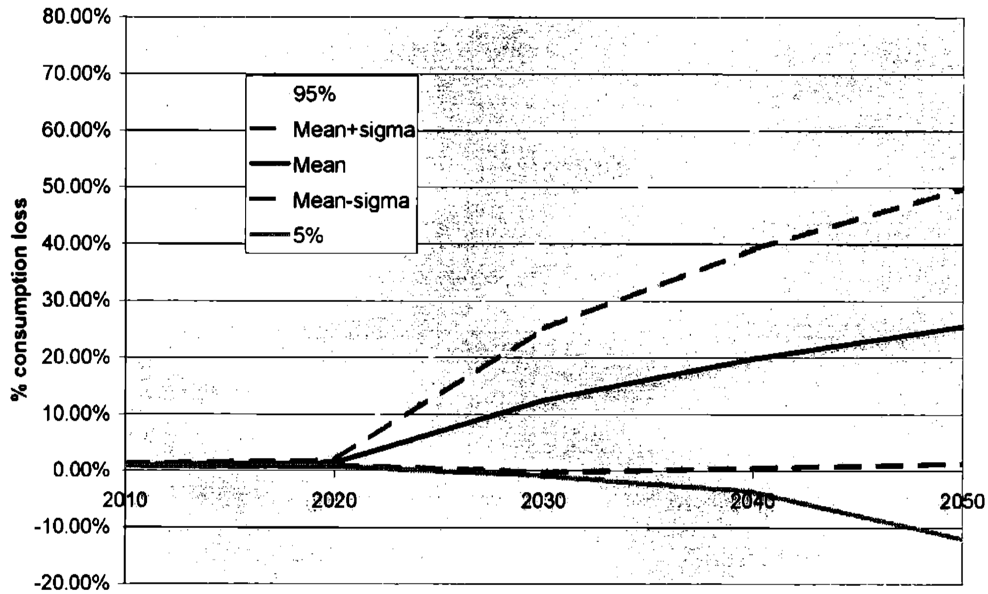


Figure 22: Uncertainty in the Chinese welfare loss

Latin America showed a standard error of approximately 6% of consumption in 2050 (71% of the average welfare loss) and in the same year the Chinese standard deviation plummeted at more than 24% of consumption (95% of the average).

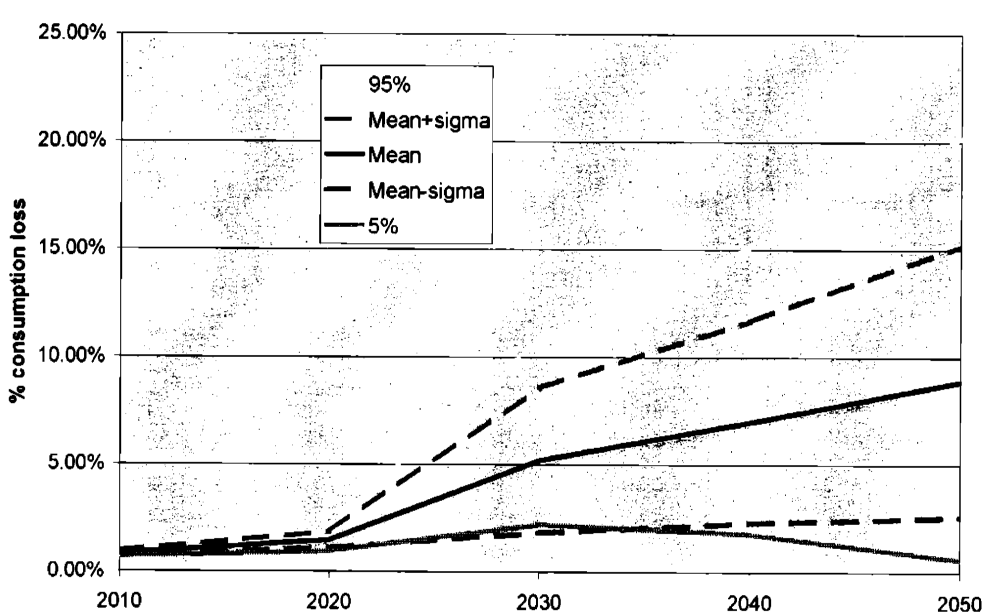


Figure 23: Uncertainty in the Latin American welfare loss

The 95% fractiles were scenarios in which consumption losses were higher than 20% for Latin America in 2050, and almost at 70% for China in the same period.

These results show that policy costs are significantly uncertain. There was an important level of variability and some extreme scenarios were showing very high costs. It seemed that this was probably a second explanation for the misalignment of stakeholders' incentives. Policy makers are in general very risk averse. The important uncertainty in the costs as well as the presence of low probability-high consequences events would surely give them fewer incentives to join any international agreement.

However our analysis also helped us understand where the uncertainty was mainly coming from. Indeed, once we had found the welfare losses associated with every scenario we had run, we could estimate the correlation between these costs and the input parameters. The following table shows the correlation coefficients between each input and the output for the United States in 2050. A negative coefficient means that the two variables are moving in opposite directions: an increase in the elasticity of substitution between the energy and non-energy bundles for example will decrease the costs of a policy, allowing an allocation of a bigger share to non-energy inputs in production functions.

	Correlation
LPG	0.68
pop	0.27
e-ne elas	-0.25
ghg-agri elas	0.22
AEEI	-0.09
ch4 indus	-0.06
bl-bk-fossil	-0.05
fixed factor	-0.02
vintaging	0.02
l-k elas	-0.02

Table 20: Correlation coefficients between inputs and policy costs in the US in 2050

We were therefore able to explain where the variability we had observed was mainly coming from: two scale variables (labor productivity growth and population) seemed to explain an important part of it. The elasticity between the energy and non-energy bundles unsurprisingly appeared also as a key factor. Elasticities with non-CO2 gases and AEEI were other significantly important sources of uncertainty. One would have expected these results to confirm exactly the order given by tornado diagrams (see Figure 29). We indeed found the same three key factors on top: LPG, population and energy non-energy elasticities. However this analysis relied on a more complete and precise elicitation of the uncertainty associated with input parameters and made it therefore possible to identify variables that we had underestimated in our sensitivity analysis (like elasticities with non-CO2 gases that seemed to be even more important than AEEI in this case) as well as inputs we had overestimated (like labor-capital elasticities).

Therefore, although policy costs appeared as highly uncertain, there seemed to be a way to reduce their variability. Scientists would need to focus their research and forecasting efforts on the key factors that this study had identified. Understanding better the way these parameters were behaving would surely help solving the uncertainty associated with the cost of climate policy.

4.3 Conclusion and next steps

The purpose of this paper was double: the main goal was definitely to perform an uncertainty analysis on the cost of climate change policies. Such analysis had never been conducted with the EPPA model before and its results were extremely instructive: first, the level of uncertainty in the cost of climate policies helped us understand why an international agreement was the only way to deal with the climate issue. The differences we found then in both the level of and the uncertainty associated with the burden each country would have to bear showed clearly why any multilateral climate change agreement was intrinsically bounded by the misalignment of stakeholders' incentives. Finally, our analysis showed that although regions would react very differently from an international climate policy, their misalignment could actually be minimized by two particularities: first it seemed that allowing developing countries to trade permits in the first commitment period would give them incentives to join any further agreement and then, our study helped identifying the main sources of uncertainty responsible for the high variability in policy costs allowing further research to focus on these sources in order to reduce uncertainty.

The other purpose of this study was to test the sensitivity of the EPPA model to its numerous parameters, understanding how EPPA reacted to changes in its inputs and if some of the reference values adopted in the model ought to be changed. Our work towards these two purposes could be extended. I see the following steps for future studies.

4.3.1 Next steps for an uncertainty analysis

The uncertainty analysis we performed in this paper could definitely be improved: we were constrained by the short period we had to elicit all relevant parameters and run our model. The main suggestions I would make as a follow-up on this work would be, by the order in which they would appear in the study:

- Conduct expert elicitation on LPG and AEEI, conditioned to the historical analysis used here.
- Conduct the elicitation on more than ten parameters to capture more of the dynamics of the model
- Ask more experts on the uncertainty in some key input parameters such as the fixed factor elasticity or population
- Try to go from a path-dependant way of modeling uncertainty (typically what we did for LPG, changing the two end-points and keeping the same trends) to a time-dependant method (each year is treated as a separate variable)
- Set up policy cases in which quotas depend on the no-policy case emissions of each scenario
- Run the model with different policy scenarios and compare their costs

4.3.2 Next steps for the EPPA model

When we performed the expert elicitations we always abstracted from the actual values in the EPPA model in order not to anchor experts' judgments. Once elicitations have been performed it is time to compare the results of the compilation of experts with the reference values in EPPA and to see whether the results forecasted by EPPA are consistent with what our analysis predicted.

The following table presents the result of our expert elicitation (median and standard error) and the reference value in EPPA 4:

		Median	Standard error	EPPA
energy/non energy elasticity	EINT	0.3	0.1	0.5
	OTHR	0.4	0.2	0.5
	ELEC	0.2	0.1	0.1
	SERV	0.4	0.2	0.5
	AGRI	0.2	0.1	0.3
	CONS	0.4	0.2	0.25
	TRANS	0.4	0.2	0.3
Labor Capital elasticity	AGRI	0.3	0.4	1
	ENOE	0.8	0.1	1
	ELEC	1.0	0.2	1
	EINT	1.1	0.2	1
	SERV	1.5	0.3	1
	OTHR	1.2	0.4	1
	TRANS	0.9	0.1	1
	CGD	1.5	0.3	1
Fixed factor elasticity	OIL-GAS	0.5	0.1	0.6
Population (millions)	World 2100	9937	1442	9937
CH4 emissions	mmt	144.5	65.3	138.9
Vintaging		52%	16%	30%

		Median	Standard error	EPPA
CH4 elasticity in AGRI	us	2%	1.2%	5%
	jpn	1%	0.4%	7%
	eur	1%	0.3%	7%
	anz	2%	0.5%	4%
	fsu	1%	0.5%	5%
	eet	2%	0.5%	8%
	chn	3%	1.9%	5%
	ind	1%	0.5%	4%
	mes	1%	0.4%	2%
	lam	1%	0.5%	2%
	asi	4%	2.6%	5%
	row	1%	0.4%	3%
N20 elasticity in AGRI	oecd	2%	0.3%	4%
	ldc	2%	0.3%	2%
	fsu	1%	0.1%	4%
	eet	1%	0.4%	4%
Backstop factors	synf-oil	4.0	1.0	2.8
	gas. Coal	4.4	1.1	3.5
	IGCAP	1.2	0.1	1.11
	NGCAP	1.2	0.1	1.15
	NGCC	0.9	0.04	0.88

Table 21: Expert elicitation results and EPPA reference values

The first impression when we look at the previous table is that hopefully most of EPPA reference values are close to what the experts predicted (in a range of one standard error). This suggests that most parameters can be left at their reference value. Some of them however are out of the one sigma-range and should be the subject of our future attention. This is first the case for the labor-capital elasticity in the agricultural sector modeled as being equal to 1 (Cobb-Douglas production function) and thought by the experts as being around 0.3 with a standard error of 0.4. Vintaging seems also a little bit too low in EPPA (30% compared to a mean of 52% for the expert elicitation). Finally elasticities with CH_4 and N_2O seem to be much too high in EPPA: experts thought that they should be lower in the short term and gradually increase to a value close to EPPA at the end of the century.

Since most parameters were close to EPPA reference values, we should expect EPPA estimates of the cost of climate change policies to be also in a standard deviation range from the mean. This was indeed the case as we can see on the following graph showing for each region the mean predicted by the uncertainty analysis and the reference value given by the EPPA model:

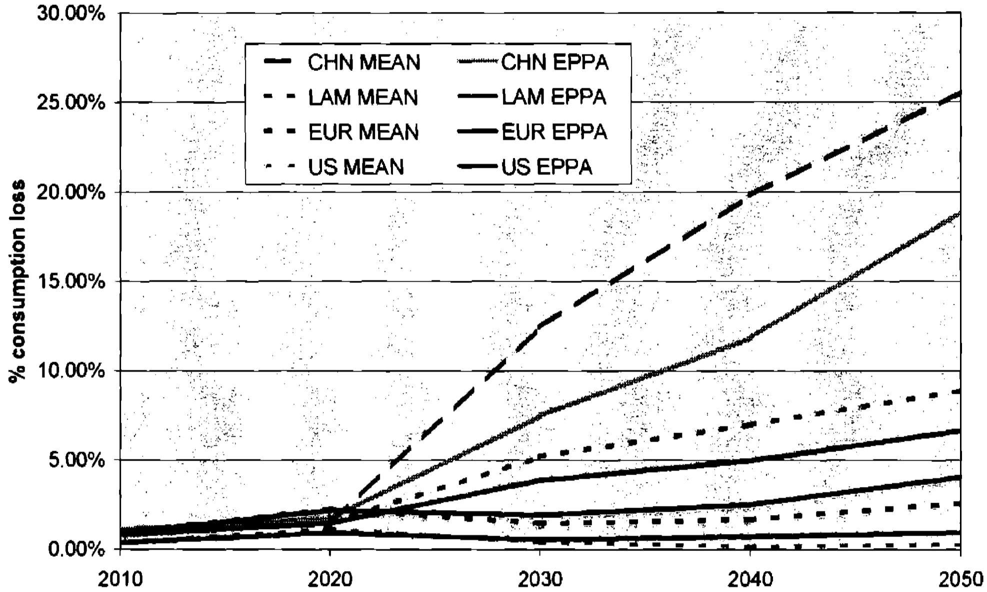


Figure 24: Comparison of mean and reference values in the uncertainty analysis

These results were extremely important because they showed that the EPPA model was consistent with what an independent elicitation had found. It therefore brought even more credibility to EPPA.

Annex

1) **Tornado diagrams**

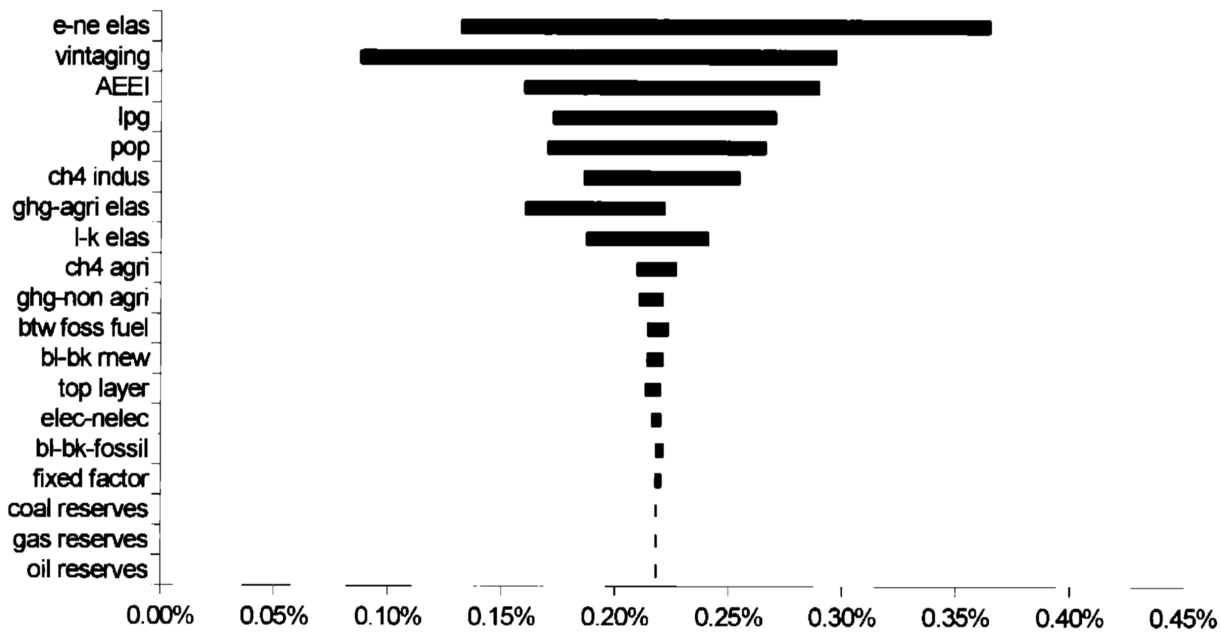


Figure 25: Welfare loss for the US in 2010

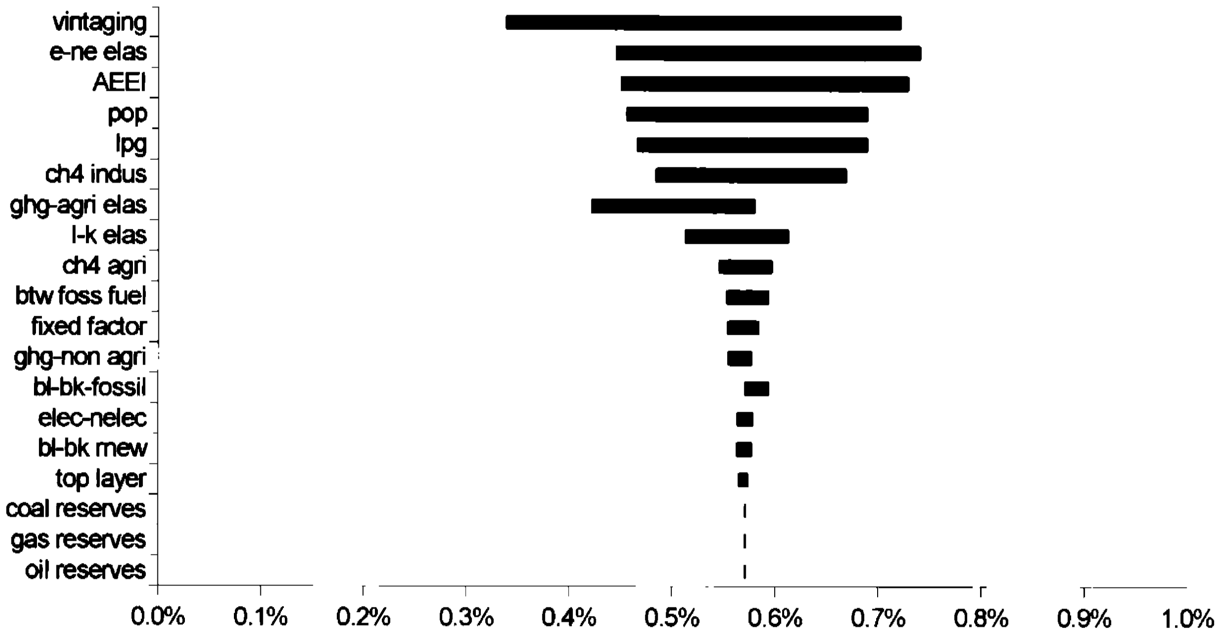


Figure 26: Welfare loss for Europe in 2010

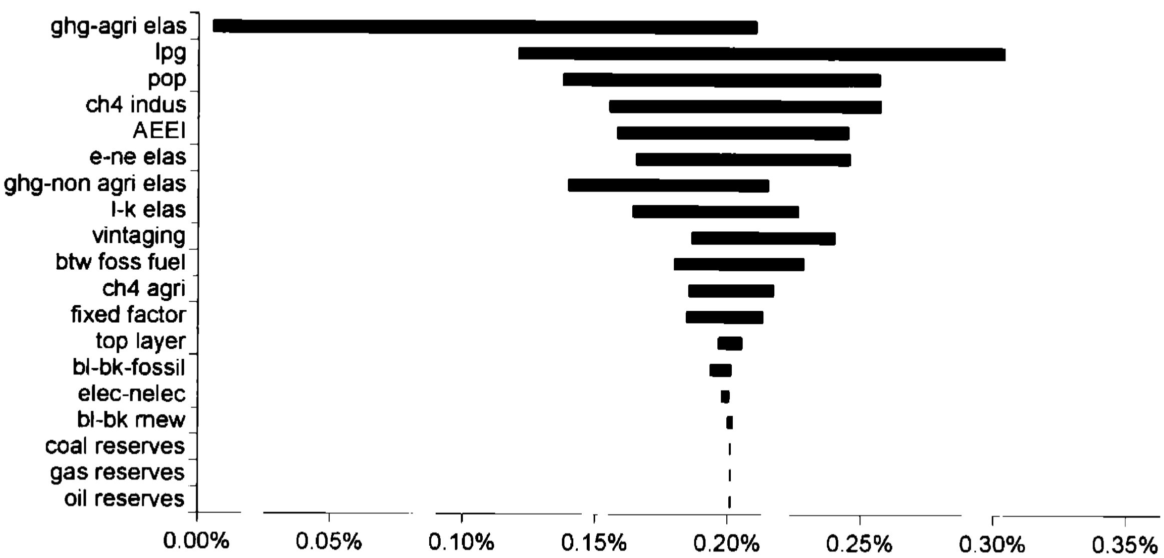


Figure 27: Welfare loss for Latin America in 2010

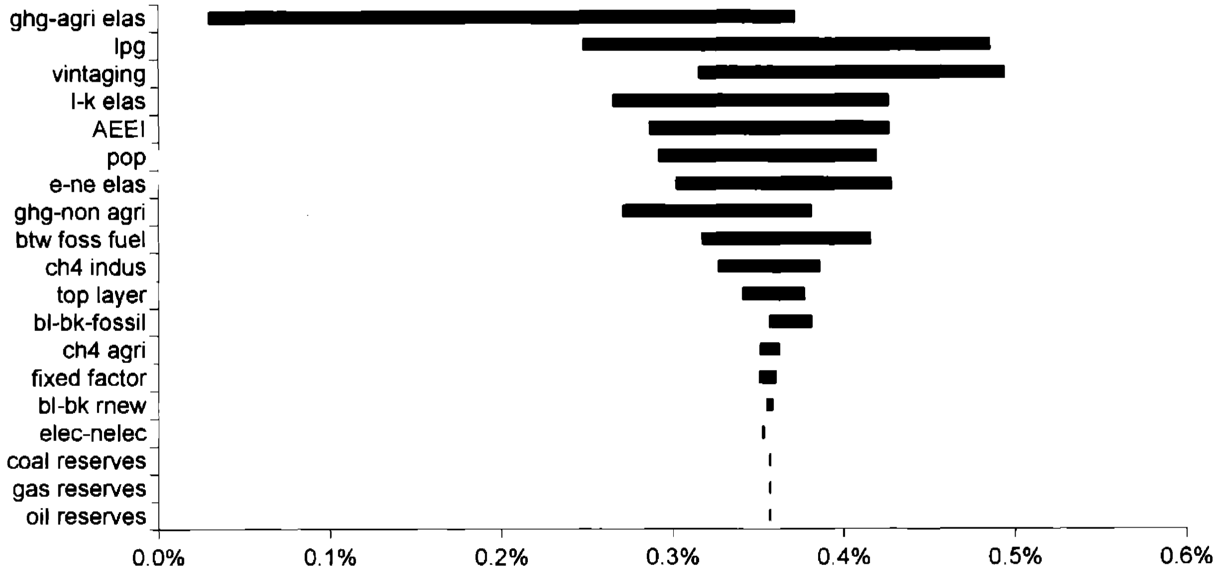


Figure 28: Welfare loss for China in 2010

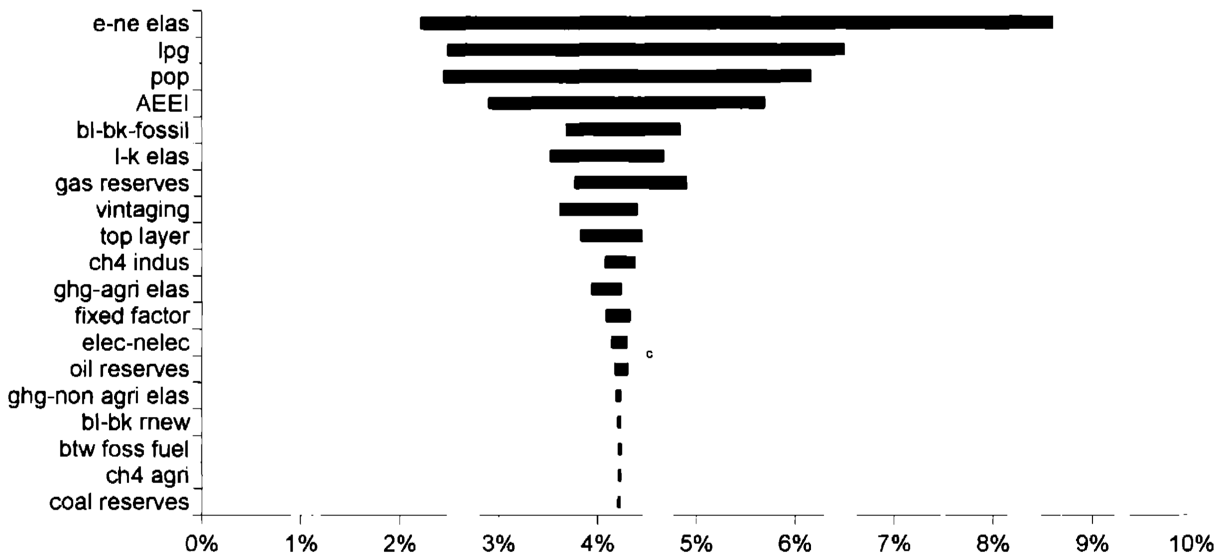


Figure 29: Welfare loss for the US in 2050

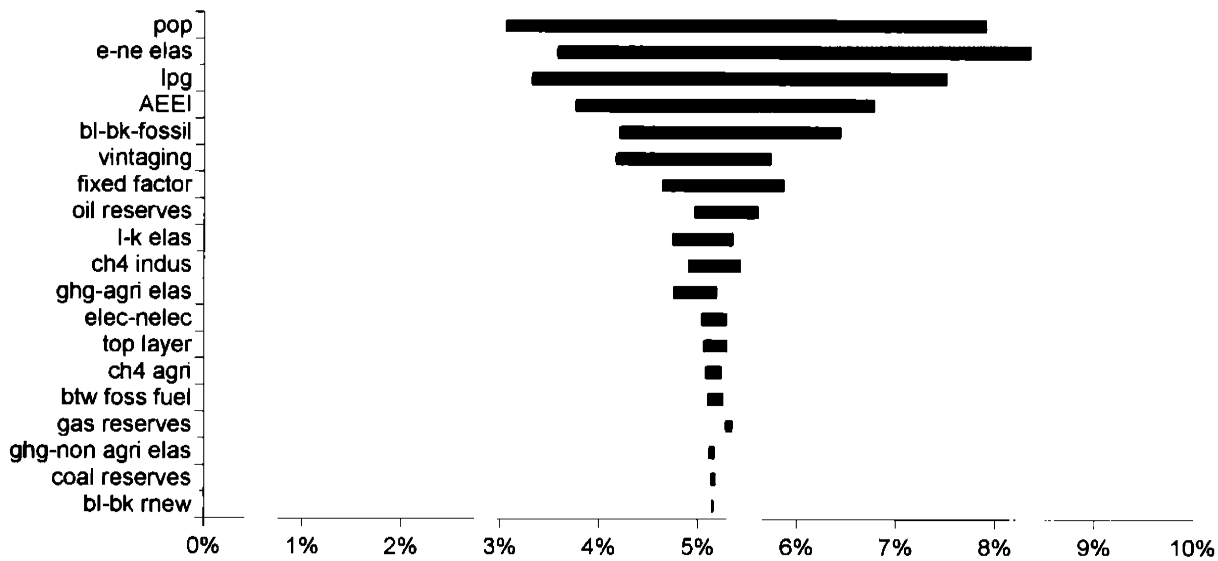


Figure 30: Welfare loss for Europe in 2050

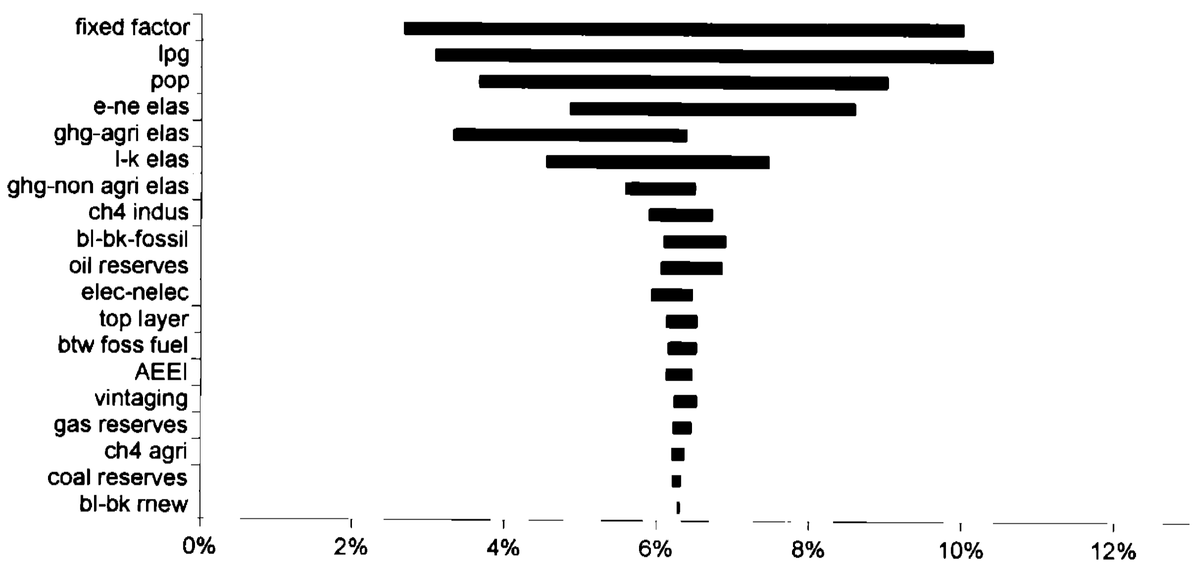


Figure 31: Welfare loss for Latin America in 2050

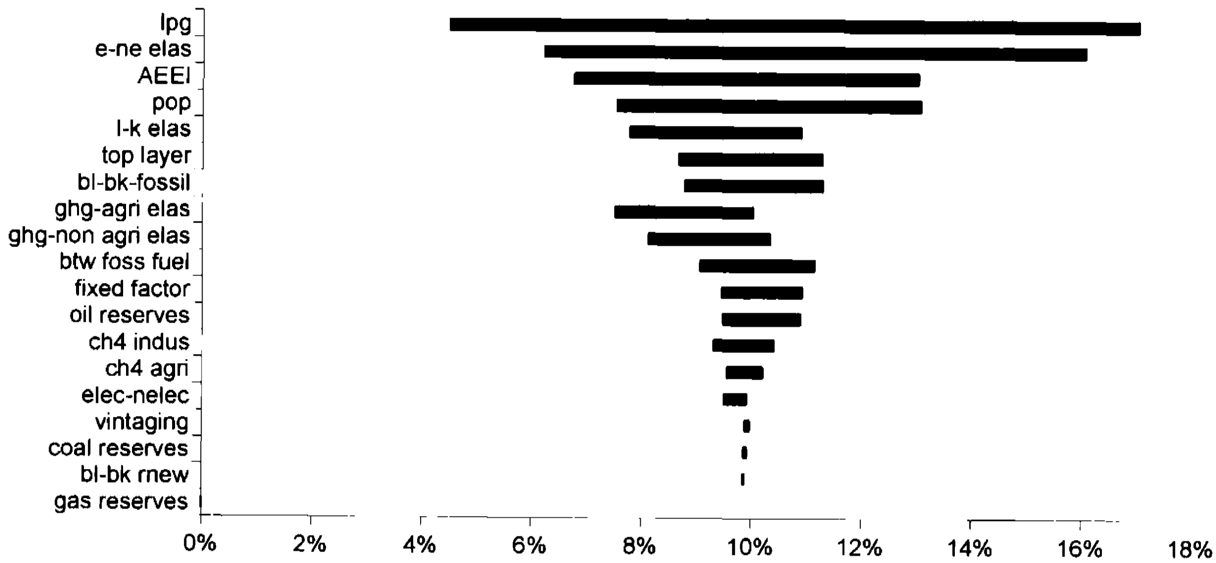


Figure 32: Welfare loss for China in 2050

2) C programs

a. Transforming the excel spreadsheet into "coll" files

```
#include <stdio.h>
#include <string.h>
#define MAXBUF 500

void makegams(FILE *, int, int *);
main()
{
 char modelname[MAXBUF];
 char infile[MAXBUF];
 char command[MAXBUF];
 int numparams;
 int loop, i, j;
 int lines1, lines2;
 FILE *fin1, *ftmp;
 char c;
 sprintf(infile, "essai-1000.txt");
 if ((fin1 = fopen(infile, "r")) == NULL){
  printf("Can't open solution input file %s\n", infile);
  exit(1);
 }
 /* translate from solution file */
 loop = 1;
 lines1 = 500;
 makegams(fin1, lines1, &loop);
 fclose(fin1);
}
```

```
void makegams(fin, lines, loop)
FILE *fin;
int lines;
int *loop;
{
 int i, j;
 FILE *fout;
 double ENE[7], LK[8], FXF[1], VINT[1], CH4[13], N2O[4], BLBK[2], POP[16], EM[1], LPG[16], AEEI[16], CAP[3];
 int ptime;
 char outfilename[MAXBUF];

 for(j=0; j<lines; j++){

  /* open output file */
  sprintf(outfilename, "coll%d.gms", *loop);
  if ((fout = fopen(outfilename, "w")) == NULL){
   printf("Can't open output file %s\n", outfilename);
   exit(1);
  }
  printf("Creating coll%d.gms\n", *loop);

  /* Read in all values for this line */
  for (i=0; i<7; i++)
   fscanf(fin, "%lf", &ENE[i]);
  for (i=0; i<8; i++)
   fscanf(fin, "%lf", &LK[i]);
  for (i=0; i<1; i++)
   fscanf(fin, "%lf", &FXF[i]);
  for (i=0; i<1; i++)
   fscanf(fin, "%lf", &VINT[i]);
  for (i=0; i<13; i++)
   fscanf(fin, "%lf", &CH4[i]);
  for (i=0; i<4; i++)
   fscanf(fin, "%lf", &N2O[i]);
  for (i=0; i<2; i++)
   fscanf(fin, "%lf", &BLBK[i]);
  for (i=0; i<16; i++)
   fscanf(fin, "%lf", &POP[i]);
  for (i=0; i<1; i++)
   fscanf(fin, "%lf", &EM[i]);
		for (i=0; i<16; i++)
				fscanf(fin, "%lf", &LPG[i]);
		for (i=0; i<16; i++)
				fscanf(fin, "%lf", &AEEI[i]);
		for (i=0; i<3; i++)
				fscanf(fin, "%lf", &CAP[i]);

  /* print energy value added elasticity  */
  fprintf(fout, "PARAMETER\tUNCEVA(G);\n");
  fprintf(fout, "UNCEVA(\"EINT\") = %le;\n", ENE[0]);
  fprintf(fout, "UNCEVA(\"OTHR\") = %le;\n", ENE[1]);
  fprintf(fout, "UNCEVA(\"ELEC\") = %le;\n", ENE[2]);
  fprintf(fout, "UNCEVA(\"SERV\") = %le;\n", ENE[3]);
  fprintf(fout, "UNCEVA(\"AGRI\") = %le;\n", ENE[4]);
  fprintf(fout, "UNCEVA(\"CGD\") = %le;\n", ENE[5]);
  fprintf(fout, "UNCEVA(\"TRAN\") = %le;\n", ENE[6]);
  fprintf(fout, "\n\n");

  /* print lk elasticity */
  fprintf(fout, "PARAMETER\tUNCLK(G) / \n");
  fprintf(fout, "AGRI\t%le\n",LK[0]);
  fprintf(fout, "OIL\t%le\n",LK[1]);
  fprintf(fout, "ROIL\t%le\n",LK[1]);
  fprintf(fout, "COAL\t%le\n",LK[1]);
  fprintf(fout, "GAS\t%le\n",LK[1]);
  fprintf(fout, "ELEC\t%le\n",LK[2]);
  fprintf(fout, "EINT\t%le\n",LK[3]);
  fprintf(fout, "SERV\t%le\n",LK[4]);
  fprintf(fout, "OTHR\t%le\n",LK[5]);
  fprintf(fout, "TRAN\t%le\n",LK[6]);
```

```
fprintf(fout, "CGD\t%le\n",LK[7]);
fprintf(fout, "/;\n\n");

/* print fixed factor elasticity */
fprintf(fout, "PARAMETER\tUNCFXF;\n");
fprintf(fout, "UNCFXF = %le;\n", FXF[0]);
fprintf(fout, "\n\n");

/* print vintaging */
fprintf(fout, "PARAMETER\tUNCVINT;\n");
fprintf(fout, "UNCVINT = %le;\n", VINT[0]);
fprintf(fout, "\n\n");

/* print ch4 elas */
fprintf(fout, "PARAMETER\tUNCCH4(R) / \n");
        fprintf(fout, "USA\t%le\n",CH4[0]);
        fprintf(fout, "JPN\t%le\n",CH4[1]);
        fprintf(fout, "EUR\t%le\n",CH4[2]);
        fprintf(fout, "ANZ\t%le\n",CH4[3]);
        fprintf(fout, "FSU\t%le\n",CH4[4]);
        fprintf(fout, "EET\t%le\n",CH4[5]);
fprintf(fout, "CHN\t%le\n",CH4[6]);
fprintf(fout, "IND\t%le\n",CH4[7]);
fprintf(fout, "MES\t%le\n",CH4[8]);
fprintf(fout, "LAM\t%le\n",CH4[9]);
fprintf(fout, "ASI\t%le\n",CH4[10]);
fprintf(fout, "ROW\t%le\n",CH4[11]);
        fprintf(fout, "MEX\t%le\n",CH4[12]);
fprintf(fout, "/;\n\n");

/* print n20 elas */
        fprintf(fout, "PARAMETER\tUNCN2O(R);\n");
        fprintf(fout, "UNCN2O(oecd) = %le;\n", N2O[0]);
        fprintf(fout, "UNCN2O(ldc) = %le;\n", N2O[1]);
        fprintf(fout, "UNCN2O(\"FSU\") = %le;\n", N2O[2]);
        fprintf(fout, "UNCN2O(\"EET\") = %le;\n", N2O[3]);
        fprintf(fout, "/;\n\n");

/* print backstop factors */
fprintf(fout, "PARAMETER\tUNCBLBK(BT);\n");
fprintf(fout, "UNCBLBK(\"SYNF-OIL\") = %le;\n", BLBK[0]);
fprintf(fout, "UNCBLBK(\"SYNF-GAS\") = %le;\n", BLBK[1]);
fprintf(fout, "\n\n");

/* print population */
fprintf(fout, "PARAMETER\tUNCPOP(R) / \n");
fprintf(fout, "USA\t%le\n",POP[0]);
fprintf(fout, "CAN\t%le\n",POP[1]);
fprintf(fout, "MEX\t%le\n",POP[2]);
fprintf(fout, "JPN\t%le\n",POP[3]);
fprintf(fout, "ANZ\t%le\n",POP[4]);
fprintf(fout, "EUR\t%le\n",POP[5]);
fprintf(fout, "EET\t%le\n",POP[6]);
fprintf(fout, "FSU\t%le\n",POP[7]);
fprintf(fout, "ASI\t%le\n",POP[8]);
fprintf(fout, "CHN\t%le\n",POP[9]);
fprintf(fout, "IND\t%le\n",POP[10]);
fprintf(fout, "IDZ\t%le\n",POP[11]);
fprintf(fout, "AFR\t%le\n",POP[12]);
fprintf(fout, "MES\t%le\n",POP[13]);
fprintf(fout, "LAM\t%le\n",POP[14]);
fprintf(fout, "ROW\t%le\n",POP[15]);
fprintf(fout, "/;\n\n");

/* print emissions */
fprintf(fout, "PARAMETER\tUNCGHG;\n");
fprintf(fout, "UNCGHG = %le;\n", EM[0]);
        fprintf(fout, "/;\n\n");

        /* print lpg */
```

```
            fprintf(fout, "PARAMETER\tUNCLPG(R) / \n");
            fprintf(fout, "USA\t%le\n",LPG[0]);
            fprintf(fout, "CAN\t%le\n",LPG[1]);
            fprintf(fout, "MEX\t%le\n",LPG[2]);
            fprintf(fout, "JPN\t%le\n",LPG[3]);
            fprintf(fout, "ANZ\t%le\n",LPG[4]);
            fprintf(fout, "EUR\t%le\n",LPG[5]);
            fprintf(fout, "EET\t%le\n",LPG[6]);
            fprintf(fout, "FSU\t%le\n",LPG[7]);
            fprintf(fout, "ASI\t%le\n",LPG[8]);
            fprintf(fout, "CHN\t%le\n",LPG[9]);
            fprintf(fout, "IND\t%le\n",LPG[10]);
            fprintf(fout, "IDZ\t%le\n",LPG[11]);
            fprintf(fout, "AFR\t%le\n",LPG[12]);
            fprintf(fout, "MES\t%le\n",LPG[13]);
            fprintf(fout, "LAM\t%le\n",LPG[14]);
            fprintf(fout, "ROW\t%le\n",LPG[15]);
            fprintf(fout, "/;\n\n");

            /* print aeei */
            fprintf(fout, "PARAMETER\tUNCAEEI(R) / \n");
            fprintf(fout, "USA\t%le\n",AEEI[0]);
            fprintf(fout, "CAN\t%le\n",AEEI[1]);
            fprintf(fout, "MEX\t%le\n",AEEI[2]);
            fprintf(fout, "JPN\t%le\n",AEEI[3]);
            fprintf(fout, "ANZ\t%le\n",AEEI[4]);
            fprintf(fout, "EUR\t%le\n",AEEI[5]);
            fprintf(fout, "EET\t%le\n",AEEI[6]);
            fprintf(fout, "FSU\t%le\n",AEEI[7]);
            fprintf(fout, "ASI\t%le\n",AEEI[8]);
            fprintf(fout, "CHN\t%le\n",AEEI[9]);
            fprintf(fout, "IND\t%le\n",AEEI[10]);
            fprintf(fout, "IDZ\t%le\n",AEEI[11]);
            fprintf(fout, "AFR\t%le\n",AEEI[12]);
            fprintf(fout, "MES\t%le\n",AEEI[13]);
            fprintf(fout, "LAM\t%le\n",AEEI[14]);
            fprintf(fout, "ROW\t%le\n",AEEI[15]);
            fprintf(fout, "/;\n\n");

            /* print carbon capture markups */
            fprintf(fout, "PARAMETER\tUNCCAP(BT) / \n");
            fprintf(fout, "IGCAP\t%le\n",CAP[0]);
            fprintf(fout, "NGCAP\t%le\n",CAP[1]);
            fprintf(fout, "NGCC\t%le\n",CAP[2]);
            fprintf(fout, "/;\n\n");

  (*loop)++;
  fclose(fout);
 }
}
```

b. <u>Reading the output files and computing welfare loss</u>

```
#include <stdio.h>
#include <string.h>

main(argc, argv)
int argc;
char *argv[];
{
          int i, startnum, endnum;

          printf("Enter first sample to consider\n");
          scanf("%d", &startnum);

          printf("Enter last sample to consider\n");
```

```
        scanf("%d", &endnum);

  for (i=startnum; i<=endnum; i++)
    net(i);
}

net(num)
int num;
{
  int i, j, k, dummy;
  double var1, var2, var3, var4;
  double invar1, invar2, invar3;
  double cost;
  double welfloss[22][16];
  char dfilename[80];
  FILE *dfile;
  FILE *infile;
  FILE *fin1, *fin2, *fout;
  char fname1[80];
  char fname2[80];
  char foutname[80];
  char firstline[80];

  printf("Processing case %d\n", num);

 /* open ref file */
  sprintf(fname1, "nlsfiles/ref%d.nls", num);
  if ((fin1 = fopen(fname1, "r")) == NULL){
    printf("Cannot open file %s\n", fname1);
    /* exit(0); */
    return;
  }

  /* open eppa file */
  sprintf(fname2, "nlsfiles/eppa%d.nls", num);
  if ((fin2 = fopen(fname2, "r")) == NULL){
    printf("Cannot open file %s\n", fname2);
    /* exit(0); */
    return;
  }

  /*  Welfare Changes by Region */
  sprintf(foutname, "WELF/welf%d.nls", num);
  if ((fout = fopen(foutname, "w")) == NULL){
    printf("Cannot open file %s\n", foutname);
    exit(0);
  }

 for (k=0; k<10; k++){
   fgets(firstline, 80, fin1);
   fgets(firstline, 80, fin2);
 }
   fscanf(fin1, "%lf", &dummy);
   fscanf(fin2, "%lf", &dummy);
   for (j=0; j<22; j++){
     for (i=0; i<16; i++){
       fscanf(fin1, "%lf", &var1);
       fscanf(fin2, "%lf", &var2);
            var1=(var1-var2)/var1;
       fprintf(fout, "%lf\n", var1);
     }
     fscanf(fin1, "%lf", &dummy);
     fscanf(fin2, "%lf", &dummy);
     fprintf(fout, "\n");
     }

  fprintf(fout, "\n\n");
  fclose(fout);
}
```

c. <u>Gathering welfare loss outputs for one region at a specific date</u>

```
#include <stdio.h>
#include <string.h>

double welfloss[1000];

main()

{
        char outname[80];
        FILE *fout;
        int i;
        int year, reg, samples;

        printf("Enter number of samples\n");
        scanf("%d", &samples);

        printf("Enter year (1-22)\n");
        scanf("%d", &year);

        printf("Enter region (1-16)\n");
        scanf("%d", &reg);

        printf("Enter output filename\n");
        scanf("%s", outname);

        if ((fout = fopen(outname, "w")) == NULL){
                printf("Cannot open file %s\n", outname);
                return;
        }

        for (i=1; i<=samples; i++){
                readfile(i, year, reg);
                fprintf(fout, "%lf", welfloss[i]);
                fprintf(fout, "\n");
        }
fclose(fout);
}

readfile(int num, int year, int reg)
{
        char fname[80];
        FILE *fin;
        int j, k, l, n, m;
        double dummy;
sprintf(fname, "WELF/welf%d.nls", num);
        if ((fin = fopen(fname, "r")) == NULL){
                printf("Cannot open file %s\n", fname);
                /* exit(0); */
                return;
        }

if (year == 1) {
/*      if (reg == 1) {


        }
        */

        if (reg > 1) {
                for (k=1; k<reg; k++){
                        fscanf(fin, "%lf", &dummy);
                }

        }
}
```

```
if(year > 1) {

if (reg == 1) {
	for (k=1; k<year; k++){
		for (j=0; j<16; j++){
			fscanf(fin, "%lf", &dummy);
		}
	}

}

if (reg > 1) {
	for (l=1; l<year; l++){
		for (n=0; n<16; n++){
			fscanf(fin, "%lf", &dummy);
		}
	}

	for (m=1; m<reg; m++){
		fscanf(fin, "%lf", &dummy);
		}
	}

}
fscanf(fin, "%lf", &welfloss[num]);
fclose(fin);
}
```

References

[Babiker, Reilly, Mayer, Eckaus, Sue Wing & Hyman, February 2001] "The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Revisions, Sensitivities, and Comparisons of Results", MIT Joint Program on the Science and Policy of Global Change, report #71, Feb 2001

[Balistreri, 2002] "An Estimation of the US Industry Level Capital-Labor Substitution Elasticity: Cobb-Douglas as a Reasonable Starting Point?" US International Trade Commission, Sept. 2002

[Dalkey, 1967] "Delphi" Rand Corporation paper P-3704, Rand Co., Santa Monica, CA, 1967

[Dimaranan, Mc Dougall, 2003] "Global Trade Analysis, Modeling and Applications: Database Summary, Sectorial Data", http://www.gtap.agecon.purdue.edu/resources/download/902.pdf

[Edmonds, Reilly 1983]. "Global Energy Production and Use to the Year 2050." Energy 8(6): 419-32, 1983

[Environmental Protection Agency, 1999] "Inventory of US Greenhouse Gas Emissions and Sinks 1990-1999", 1999

[Genest, Zidek, 1986] "Likelihood Dominance and Group Belief Formation", UBC Statistic Department #29, 1986

[Hertel, 1997] "Global Trade Analysis, Modeling and Applications", Cambridge University Press, 1997

[Iman, Helton, 1988] "An investigation of uncertainty and sensitivity analysis techniques for computer models" Risk Analysis, 8(1):71–90

[Lee, 1998] "Probabilistic approaches to Population forecasting", Population and Development review vol. 24, 1998

[Manne, Richels, 1990]: ' CO_2 Emission Limits: An Economic Cost Analysis for the USA', *The Energy Journal*, Vol. 11, No. 2, pp. 75-84 , 1990

[Meyers, 1984] "Handbook of Synfuels technologies", McGraw-Hill Book Company, 1984

[Morgan, July 1993] "Risk Analysis and management, Inadequate approaches to handling risks may result in bad policy. Fortunately, rational techniques for assessment now exist", Scientific American, July 1993

[Morgan, Henrion, 1990] "Uncertainty, A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis", Cambridge University Press, 1990

[Morgan, Keith, 1995] "Subjective Judgments by Climate Experts", *Environ. Sci. Technol.* **29**, 468-476, 1995

[Olson, 1971] "The Logic of Collective Action: Public Goods and the Theory of Groups", Harvard University Press, Cambridge Mass., 1971

[Tversky, Kahneman, 1974] "Judgment under uncertainty: Heuristics and biases," Science, vol.185, pp.1124-1131, 1974

[United Nations Framework Convention on Climate Change, 1997] "Kyoto Protocol to the UNFCCC", http://unfccc.int/resource/convkp.html

[United Nations Framework Convention on Climate Change, 1992] "Text of the Convention", http://unfccc.int/resource/convkp.html

[Webster et al., 2001] "Uncertainty in Emissions Projections for Climate Models." Atmospheric Environment (in review), 2001

[Webster, February 2000] "Uncertainty and Learning in Sequential Decision-Making: The Case of Climate Policy", MIT Joint Program on the Science and Policy of Global Change, February 2000

[Webster et al., 2000] "The Curious Role of Learning: Should We Wait for More Data?" MIT Joint Program on the Science and Policy of Global Change, The Energy Journal, (in review), 2000

[Winkler, 1986] "Record Linkage of Business Lists," unpublished report, Washington DC: Energy Information Administration Technical Report, U. S. Dept. of Energy, 1986

[Yang, Eckaus, Ellerman & Jacoby, May 1996] "The MIT Emissions Prediction and Policy Analysis (EPPA) Model", MIT Joint Program on the Science and Policy of Global Change, report #6, May 1996

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