Combining Stochastic Optimization and Monte-Carlo Simulation to Deal with Uncertainties in Climate Policy Assessment *

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Abstract

In this paper we explore the impact of several sources of uncertainties on the assessment of energy and climate policies when one uses in an harmonized way stochastic programming (SP) in a large scale bottom-up (BU) model and Monte-Carlo simulation (MC) in a large scale top-down (TD) model. The BU model we use is the Times Integrated Assessment Model (TIAM), which is run in a stochastic programming version to provide a hedging emission policy to cope with the uncertainty characterizing climate sensitivity. The TD model we use is the computable general equilibrium model GEMINI-E3. Through Monte-Carlo simulations of randomly generated uncertain parameter values one provides a stochastic micro- and macro-economic analysis. Through statistical analysis of the simulation results we analyze the impact of the uncertainties on the policy assessment.

1 Introduction

The purpose of this paper is to evaluate the impact of uncertainty on the economic assessment of long term energy policies designed to mitigate climate change. We identify four classes of uncertainties related to climate, technology, economy and energy prices, respectively. We propose a dual approach, based on the combined use of stochastic programming and Monte-Carlo (MC) analysis to deal with these uncertainties in a techno-economic analysis involving two complementary models. A stochastic programming approach is implemented on a bottom-up integrated assessment model, TIAM [28], to propose a hedging emission abatement policy for the time horizon 2030, followed by four typical recourse abatement policies, compatible with a target of 2.1^{o}C temperature increase in 2100, under reasonable assumptions on the uncertainty on climate sensitivity (Cs) [3]. The scenarios produced by TIAM take into account the Cs uncertainty but are based on perfect forsight assumptions for a lot of technological and economic parameters that could also impact the policy assessment.

To take into account the impact of these other sources of uncertainty on climate policy assessment we use MC analysis on a Computable General Equilibrium (CGE) model, GEMINI-E3 [9], specifically designed to assess climate policies and which is run in an harmonized way with TIAM. The CGE is a multi-country, multi-sector, dynamic model running in annual steps from the base year 2001 to 2050. We take into account several sources of uncertainty pertaining to the general economic and technological environment, using MC simulations with Latin Hypercube sampling [18] to obtain probability density functions (pdf) for the output variables of GEMINI-E3 that concern welfare gains, emissions abatement, etc.

*Acknowledgments: This work was supported by the FP7 European Research Project PLANETS and by the Swiss-NSF-NCCR climate grant. For helpful comments and discussions, we thank A. Bousquet and R. Gerlagh. Two referees comments have been most useful to improve the paper.

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Recently, MC based approaches have been successfully implemented on the EPPA model which is also a world CGE model [42].The simulations in the EPPA model use the Latin Hypercube technique for analyzing the impacts of 100 uncertain parameters, including labor productivity growth rates, energy efficiency trends, elasticities of substitution, costs of advanced technologies, fossil fuel resource availability, and trends in emissions factors for urban pollutants. These simulations served to evaluate four climate policy scenarios and showed that energy demand parameters, including elasticities of substitution and energy efficiency trends are the sources of uncertainty impacting more significantly climate policies. A previous study, also involving the EPPA model [41], focused on the uncertainty of the projections of anthropogenic emissions. It reported a range of temperature change in 2100 comprised between 0.9 and 4.0 ^{o}C. In Ref. [36] MC simulations have been also performed on the integrated assessment model MiniCAM 1.0 to analyze the sources of uncertainty and their relative importance in the decision policy process. The paper concludes that the "current targets for atmospheric stabilization appear excessively ambitious" and that "an adaptive policy of "act, then learn, then act" appears to offer better prospects for balancing uncertain costs and benefits of controlling greenhouse gas emissions than do rigid precautionary measures". More recently MC simulations have been applied to the MERGE model [23] to produce probability distribution functions (pdf) of economic and climate related variables for different possible policies. Other Refs. concerning MC simulations on global assessment models are given in [30, 34, 13].

In the present work we identify four classes of uncertainties related to technology, economy, energy and climate, respectively. The first one regroups technological parameters, i.e., cost and date of availability of carbon capture and sequestration (CCS) technology, elasticities of substitution between energy forms, elasticities of substitution between production factors and technical progress factors. The second class deals with economic drivers such as GDP growth of emerging countries. The third one focuses on energy prices. Finally, the last category, related to climate, is summarized by the climate sensitivity (Cs) parameter. Recall that Cs is loosely defined as the temperature increase that would result from a doubling of atmospheric GHG concentration, compared with preindustrial level. So, in terms of climate policies, a variation in the assumed Cs value results in a different long term GHG concentration target and, as a consequence, in a different profile for the emissions abatement schedule resulting from an adaptation of the global energy system. From a policy point of view, one has to formulate a hedging emission trajectory which will be implemented now and eventually corrected or adapted when a more precise knowledge of Cs is available. We assume that the uncertainty on Cs will be resolved in 2030, we generate emission trajectories for different climate sensitivity values using the stochastic version of the model TIAM. By so doing, we get a single trajectory of emissions until 2030 and different profiles afterward depending on the revealed climate sensitivity. GEMINI-E3 is run for an ensemble of scenarios corresponding to sampled values for all uncertain parameters. In the case of Cs, the sampled value will determine an emission profile after 2030, obtained by interpolation of the typical emissions trajectories produced by TIAM stochastic. The simulation results represented by the economic indicators, like e.g. welfare loss, energy consumption and carbon price, are statistically analysed using logit and standard regression models. This permits an identification of the most sensitive parameters and of their role in the possible infeasibility of energy/climate policies.

The paper is organized as follows. In section 2 we describe the specifications of the bottom-up TIAM and top-down GEMINI-E3 models used in this study. In section 3, we model the different sources of uncertainty taken into consideration. In section 4 we discuss the stochastic programming and MC implementation issues and in section 5 we analyse the simulation results. In conclusion we evaluate the new insights brought by this analysis of uncertainty in an harmonized use of a bottom-up model (TIAM) and a top-down model (GEMINI-E3).

2 The TIAM and GEMINI-E3 models

In this section we give an overview of the two complementary models that are used for climate policy assessment. We also present the process of harmonization that has been implemented for the combined use of the two models.

2.1 Overview of TIAM

2.1.1 Energy/technology/emissions description

The TIMES Integrated Assessment Model (TIAM) is a global technology-rich bottom-up model that represents the entire energy system of the World divided in 16 regions: Africa, Australia-New Zealand, Canada, United States, Mexico, Central and South America, China, India, Japan, South Korea, Other Developing Asia, Middle-East, EU30, Other East Europe, Russia, Central Asia & Caucasia. It covers the procurement, transformation, trade, and end-uses of all energy forms in all sectors of the economy (Figure 1)

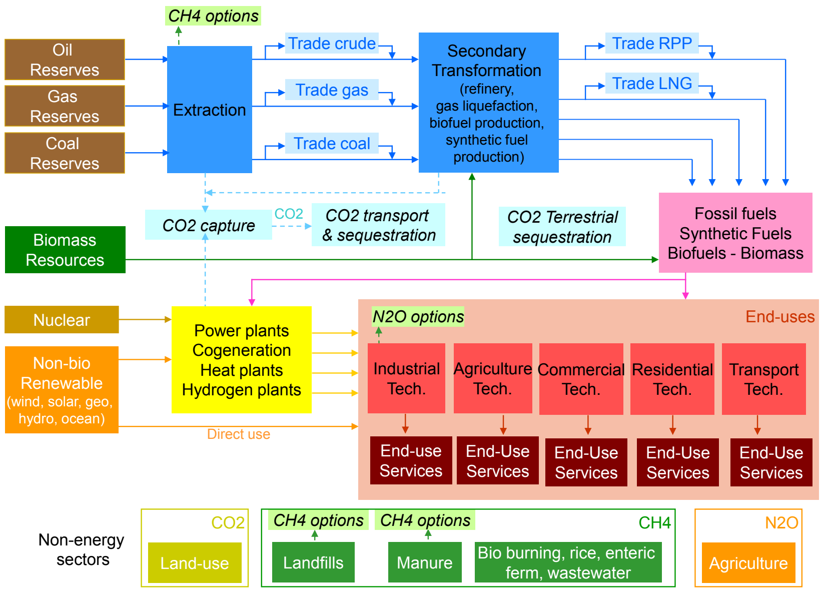

Figure 1: Reference energy system of TIAM

TIMES' economic paradigm is the computation of a dynamic inter-temporal partial equilibrium on energy/emission markets where demands for energy services are exogenously specified only in the reference case, and are sensitive to price changes in alternate scenarios via a set of own-price elasticities at each period [25]. Although TIMES does not encompass all macroeconomic variables beyond the energy sector, accounting for price elasticity of demands captures a major element of feedback effects between the energy system and the economy. Thus, the equilibrium is driven by the maximization (via linear programming) of the discounted present value of total surplus, representing the sum of surplus of producers and consumers, which acts as a proxy for welfare in each region of the model.

The time horizon of TIAM extends to 2100. The model contains explicit descriptions of more than one thousand technologies and one hundred commodities in each region, logically interrelated in a Reference Energy System [28]. Residential, commercial, industry, transport, power plants, as well as upstream (from extraction to secondary transformation) are represented in a highly detailed mode, covering the 42 different service demands such as space heating, lighting, km driven by cars, by buses, production of iron and steel, of pulp and paper, etc. Such explicitness of the representation of technologies and fuels in all sectors allows precise tracking of capital turnover, and provides a detailed description of technological competition and sectoral and cross-sectoral energy-environmental policies.

2.1.2 The climate module

TIAM includes an endogenous climate module that allows the user to impose climate targets, such as upper bounds on concentrations, on atmospheric radiative forcing, or on temperature increase, at single or multiple dates. The emissions of CO_2, CH_4 and N_2O related to the energy sector, are explicitly represented by the energy technologies included in the model. The non-energy-related CO_2, CH_4 and N_2O emissions (landfills, manure, rice paddies, enteric fermentation, wastewater, land-use) are also included in order to fully represent the radiative forcing induced by them, but they are exogenously defined. Emissions from some Kyoto gases (CFC's, HFC's, SF_6) are not explicitly modeled, but a special radiative forcing term is added in the climate module. Emissions of chemically active gases such as NOx, CO, VOCs are not modeled either, but their influence on the life cycles of GHG gases is implicitly accounted for in the concentration equations for the three main GHGs, at the calibration phase of the equations.

Greenhouse gas mitigation options available in the model are: energy substitutions, improved efficiency of installed devices, specific non-CO_2 abatement devices (e.g. suppression and/or combustion of fugitive CH_4 from landfills, thermal destruction of N_2O in the adipic acid industry, suppression of leakages at natural gas transmission level, anaerobic digestion of wastes with gas recovery, etc.), sequestration (CO_2 capture and underground storage, biological carbon sequestration), mitigation potential of up to 20% of the CO_2 and N_2O emitted by the agriculture sector, and reductions in energy service demands in reaction to increased carbon prices.

2.1.3 Stochastic TIAM

TIAM possesses a feature that allows the modeler to calculate hedging strategies in the presence of uncertainty for certain key parameters. The treatment of uncertainty is done via Stochastic Programming in extensive form. In this method, the model adopts a single hedging route in the interval of time preceding the resolution of uncertainty (act then learn), so as to be best positioned to adapt to any of the possible long term futures (after resolution of uncertainty). In a large scale model such as TIAM, due to computational considerations, the stochastic programming approach is successful when the uncertain parameters are assumed to have only a limited number of possible outcomes. The uncertainty is therefore described via an event tree with a reasonably small number of end-points. Finally, in our application, the selected maximization criterion is the expected value of the total surplus, but the approach is also valid with other criteria, such as minimizing the Savage criterion (MinMax Regret), as in [27], or a utility function consisting of a linear combination of expected surplus minus a quantity representing risk (see the TIMES documentation available at `www.etsap.org/documentation`).

The main interest of a hedging strategy resides in its description of what to do prior to the resolution date (in contrast, traditional deterministic scenario analysis computes multiple strategies even prior to the resolution date, leaving the decision maker in a quandary). Once uncertainty is resolved, the decision maker no longer faces uncertainty, and her decisions result from optimizing a deterministic problem afterward. Nevertheless, the computation of the hedging strategy must also take into account all possible outcomes after the resolution date. In other words, short term decisions are devised while taking the uncertain long term into consideration. This is the essence of decision under risk, and in particular of stochastic programming.

The TIAM model in stochastic mode was used to model a number of energy and environmental issues [24, 29, 22], with uncertainty assumed on economic parameters and/or on climate parameters.

Countries or Regions		Sectors
Annex B		***Energy***
Germany	DEU	01 Coal
France	FRA	02 Crude Oil
United Kingdom	GBR	03 Natural Gas
Italy	ITA	04 Refined Petroleum
Spain	ESP	05 Electricity
Netherlands	NLD	***Non-Energy***
Belgium	BEL	06 Agriculture
Poland	POL	07 Forestry
Rest of EU-25	OEU	08 Mineral Products
Switzerland	CHE	09 Chemical Rubber Plastic
Other European Countries	XEU	10 Metal and metal products
United States of America	USA	11 Paper Products Publishing
Canada	CAN	12 Transport n.e.c.
Australia and New Zealand	AUZ	13 Sea Transport
Japan	JAP	14 Air Transport
Russia	RUS	15 Consuming goods
Rest of Former Soviet Union	XSU	16 Equipment goods
Non-Annex B		17 Services
China	CHI	18 Dwellings
Brazil	BRA	
India	IND	***Household Sector***
Mexico	MEX	
Venezuela	VEN	***Primary Factors***
Rest of Latin America	LAT	Labor
Turkey	TUR	Capital
Rest of Asia	ASI	Energy
Middle East	MID	Fixed factor (sector 01-03)
Tunisia	TUN	Other inputs
Rest of Africa	AFR	

Table 1: Dimensions of the GEMINI-E3 model.

2.2 Overview of GEMINI-E3

GEMINI-E3[1] is a multi-country, multi-sector, recursive computable general equilibrium model comparable to the other CGE models (GREEN, EPPA, MERGE, Linkage, World-Scan) built and implemented by other modeling teams and institutions, and sharing the same long experience in the design of this class of economic models. The standard model is based on the assumption of total flexibility in all markets, both macroeconomic markets such as the capital and the exchange markets (with the associated prices being the real rate of interest and the real exchange rate, which are then endogenous), and microeconomic or sector markets (goods, factors of production).

The model is built on a comprehensive energy-economy dataset, the GTAP-6 database [12], that incorporates a consistent representation of energy markets in physical units, social accounting matrices for each individualized country/region, and the whole set of bilateral trade flows. Additional statistical information accrues from OECD national accounts, IEA energy balances and energy prices/taxes and IMF Statistics (Government budget for non OECD countries). Carbon emissions are computed on the basis of fossil fuel energy consumption in physical units. For the modeling of non-CO_2 greenhouse gases emissions (CH_4, N_2O and F-gases), we employ region- and sector-specific marginal abatement cost curves and emission projections provided by the Energy Modeling Forum within the Working Group 21 [40].

For each sector the model computes the demand on the basis of household consumption,

[1] The web site `http://gemini-e3.epfl.ch/` provides all information about the model, including its complete description.

government consumption, exports, investment, and intermediate uses. Total demand is then divided between domestic production and imports, using the Armington assumption [4]. Under this convention a domestically produced good is treated as a different commodity from an imported good produced in the same industry. Production technologies are described using nested CES functions (see Figure 5).

Time periods are linked in the model through endogenous real rates of interest determined by equilibrium between savings and investment. National and regional models are linked by endogenous real exchange rates resulting from constraints on foreign trade deficits or surpluses. The main outputs of the GEMINI-E3 model are by country on an annual basis: carbon taxes, marginal abatement costs and prices of tradable permits (when relevant), effective abatement of CO_2 emissions, net sales of tradable permits (when relevant), total net welfare loss and components (net loss from terms of trade, pure deadweight loss of taxation, net purchases of tradable permits when relevant), macro-economic aggregates (e.g. production, imports and final demand), real exchange rates and real interest rates, and data at the industry-level (e.g. change in production and in factors of production, prices of goods).

Like other general equilibrium models, GEMINI-E3 assesses the welfare cost of policies through the measurement of the classical Dupuit's surplus, i.e. in its modern formulation the Equivalent Variation of Income (EVI) or the Compensating Variation of Income (CVI). It is commonly acknowledged that surplus is preferable to change in GDP or change in Households' Final Consumption because these aggregates are measured at constant prices according to the methods of National Accounting and do not capture the change in the structure of prices, a main effect of climate change policies [8]. Moreover, it is revealing to split the welfare cost between its two components, the domestic component or Deadweight Loss of Taxation (DWL) and the imported component or Gains from Terms of Trade (GTT).

2.2.1 Aggregate version of GEMINI-E3 used in this study

The classifications - breakdowns by country/region and by sector/product - are framed according to the general context and the targets of each study. An important issue applying Monte-Carlo simulations is to make the procedure consistent with respect to the uncertainty. One may produce a set of scenarios large enough to be representative of all possible realizations so that the result interpretations are well founded. Thus in order to perform a high number of Monte-Carlo simulations in a reasonable CPU time we use an aggregate version of GEMINI-E3. We use the following reduced classification:

- EUR : European Union;
- OEC : Other developed countries;
- EEC : Oil exporting countries (middle east and former soviet union);
- ASI : Asian countries;
- ROW : Rest of the world.

Using this classification the CPU time for one run of GEMINI-E3 is about 5 minutes[2].

2.2.2 Modeling power generation in GEMINI-E3

In order to reliably model the role of Carbon Capture and Sequestration (CCS) in power generation, electricity production is now represented by a nested CES function including - besides fossil fuels, nuclear and hydraulic plants - the new capacities installed in the renewable technologies, as shown in figure 2. Then power generation is separated from the other activities (transmission and distribution) that appear through their factors of production at the top of the nesting structure. Power generation involves only two factors of production, capital and fuel (only capital for renewables)[3]. Concerning CCS we suppose that this technology could only be used with coal and CCS is implemented when the cost of carbon per ton

[2]We used a Dual 2.6 GHz Intel Xeon computer for the simulations, thus we had four available CPUs.

[3]Labor in the generation activity is low compared to labor in the other activities (transport, distribution) and of a similar relative size for all plants. It is thus represented as a common factor.

sequestered is inferior to the price of carbon computed by the model at equilibrium. The cost of CCS is described in Section 3.2.1. With this new nesting structure it is possible to better take into account the power generation portfolio and to represent inter-fuel substitutability as well as substitutability between fossil and renewable power generation [43]. This representation does not distinguish between base and peak production which will be only possible by representing differentiated demands. We approximate the fact that nuclear, renewable and fossil fuel are not completely substitutable by using different elasticity parameters with the assumption that $\sigma_{fos} > \sigma_{gen}$. We assume no constraint on the deployment of nuclear and renewable due for example to political acceptability.

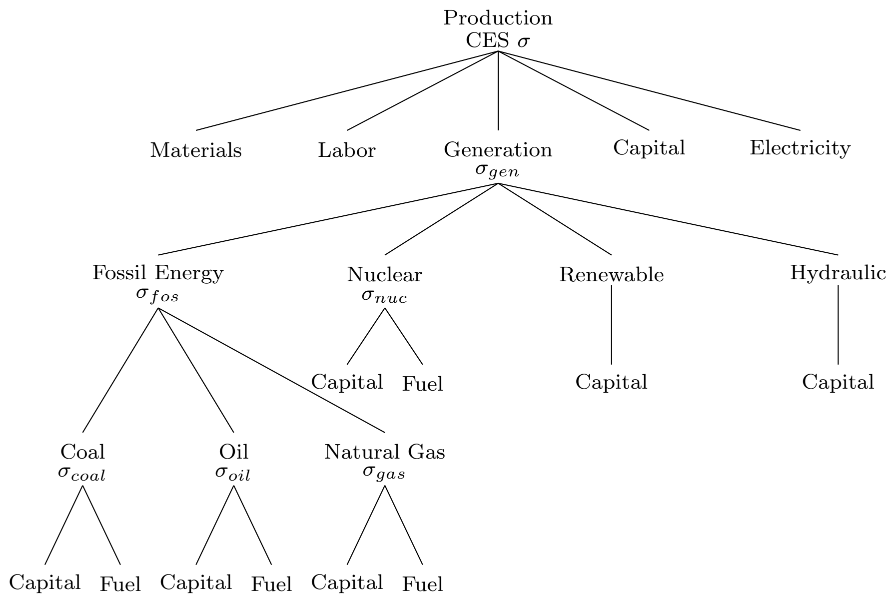

Figure 2: Nesting CES structure of electricity production

2.2.3 GDP growth assumptions

Reference scenarios in CGE models are built from forecasts or assumptions on economic growth in the various countries/regions and national (energy) policies. Assumptions concerning GDP growth are consistent with the World Energy Technology Outlook done by the European Commission[4] [15]. Table 2 summarizes the projected annual GDP growth for each region. The World GDP growth will converge in 2050 to 2.2% per year. The growth would be greater in developing and emerging countries.

	2010-2020	2020-2030	2030-2040	2040-2050
EUR	2.3%	1.8%	1.4%	1.4%
OEC	2.4%	1.9%	1.9%	2.0%
EEC	3.7%	3.0%	2.1%	1.9%
ASI	5.5%	4.3%	2.9%	3.0%
ROW	4.5%	3.4%	2.6%	2.6%
World	3.2%	2.6%	2.2%	2.2%

Table 2: GDP Growth in percentage per year.

[4]Note that these assumptions, imposed under the FP7 European project Planets, lead to lower GDP growth than those of the most recent forecasts [1] that incorporate the impact of the current economic crisis. This low GDP growth is primarily due to the conservative growth assumptions for developing countries and especially Asia. This source of uncertainty is discussed in section 3.3.

2.3 Harmonization of the two models

In this paper we used a harmonized version of the models TIAM and GEMINI-E3, both models are run independently except that in the "policy" scenarios the climate target is given by the model TIAM. Through harmonization we ensure that certain key assumptions shared between models are consistent. The first common assumption is linked to economic growth. We use the same demographic assumptions and GDP growth by region, and the energy service demands of TIAM are computed using drivers provided by GEMINI-E3. These drivers in the TIAM model are related to household consumption and industrial outputs (cement, iron and steel productions, etc.) which are directly computed by GEMINI-E3. A similar procedure is done concerning energy prices. In this paper the energy prices are given exogenously to both models (see section 3.4). Finally we use the same assumptions about the costs of CCS (which is also given exogenously see section 3.2.1) and we ensure that the costs of electricity generation are consistent across technologies. This harmonization is only done for the business as usual (BAU) scenario, whereas in the climate policy scenarios, the only link between the two models is the GHG target which is computed on the basis of TIAM simulations.

3 Uncertainties

In this section we describe the uncertain parameters taken into consideration and we give the assumptions on probability distributions that are used to generate the ensemble of scenarios via a Latin Hypercube method. We classify the uncertain parameters in four main categories: climate, technology, economy and energy prices.

3.1 Climate uncertainty

Climate modeling is based on a set of critical physical and technical parameters. Among these parameters, climate sensitivity (Cs) is one of the most important. Its assumed value influences strongly the temperature increase projections computed by climate models and at the same time Cs is highly uncertain. We suppose, as often assumed in similar studies that Cs uncertainty will be resolved in the future[5], around 2030. Therefore our approach is two-phased and combines optimal hedging computations and MC simulations.

In the first phase, we use the stochastic version of the energy-economy model TIAM to generate a hedging strategy from 2005 to 2030, followed by contingent optimal recourse strategies after 2030. The uncertainty on Cs is thus represented by a simple event tree representing a discrete approximation of the Cs probability distribution. Ideally, we would want to run TIAM under a very detailed event tree on Cs, in order to better approximate its continuous probability density function (pdf). This would produce a single hedging decision before the resolution date (e.g. until 2030) and a large number of subsequent recourse abatement scenarios on all the branches of the event tree after that date. Then, GEMINI-E3 would be run using directly the emission profiles obtained from TIAM results.

	2005	2010	2020	2030	2040	2050
Cs = 1.1	10.19	10.46	9.09	9.62	15.38	19.20
Cs = 1.7	10.19	10.46	9.09	9.62	15.11	18.60
Cs = 2.9	10.19	10.46	9.09	9.62	11.75	11.96
Cs = 4.4	10.19	10.46	9.09	9.62	5.39	3.17
Cs = 2.9 (det.)	10.19	10.46	11.62	11.99	11.22	10.55

Table 3: Emission trajectories from TIAM stochastic runs (in Gt of C-eq).

[5]Some recent publications [2, 35] tend to affirm that it might be impossible to resolve uncertainty about Cs in the foreseeable future. If this is the case, the decision in 2030 should be based on the worst case alternative.

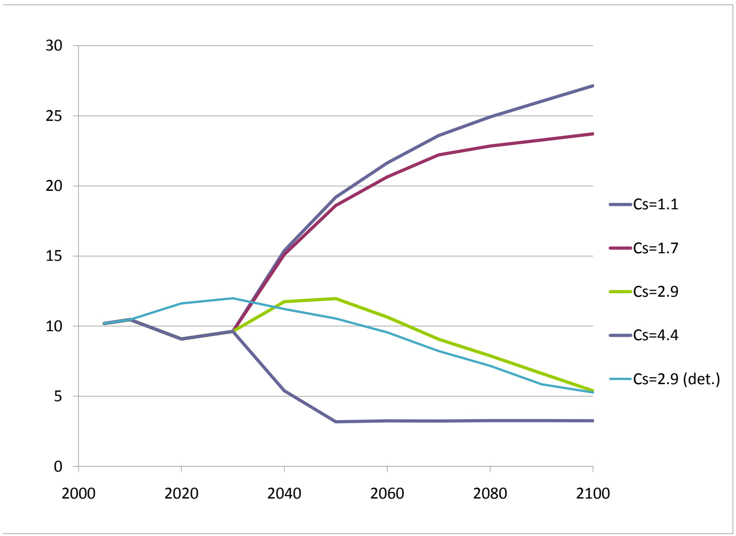

Figure 3: Emission trajectories from TIAM stochastic runs (in Gt of C-eq).

In practice, this approach is not computationally feasible since the stochastic program resulting from a very detailed event tree would create too large an instance of TIAM, the model becoming then computationally intractable. Therefore, we discretized the pdf of Cs, and created an event tree with four branches corresponding to Cs values 1.1, 1.7, 2.9 and 4.4 ^{o}C. The choice of the continuous distribution and the discretization issue are detailed in subsection 4.1. By running TIAM in its stochastic programming version with this reduced event tree, we obtain a single hedging emission profile until 2030, and four recourse policies after 2030, each one corresponding to a typical Cs value. The four resulting emission trajectories (in Gt of carbon-equivalent) are reported in Table 3 and plotted in Figure 3. We also indicate in Table 3 and in Figure 3 the emission trajectories resulting from the deterministic version of TIAM with a Cs value[6] of 2.9.

In the second phase, we exploit those four emission trajectories obtained from TIAM in the Monte-Carlo simulations. Using latin-hypercube technique we generate a large random sample of 2000 values for the driving parameters of GEMINI-E3. Among these parameters are Cs values which are sampled from a triangular distribution in the interval [1.1, 4.4] with mode 2.9 (see Figure 4). For each sampled Cs value we use linear interpolation of the two adjacent typical values treated in TIAM to get a sample emission trajectory. In the corresponding simulation, GEMINI-E3 uses this emission trajectory as the imposed climate policy after 2030.

[6]Note that the IPCC AR4 best estimate is 3.

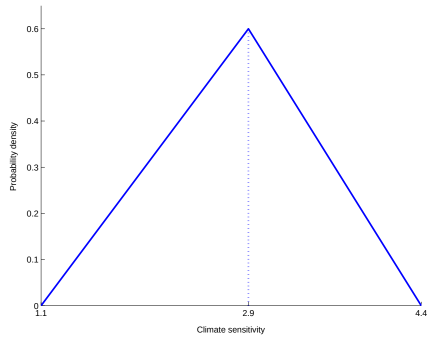

Figure 4: Triangular probability density function.

The comparison of the emission trajectories of the deterministic and the stochastic scenarios assuming the same Cs value of 2.9, is quite instructive. In the deterministic case, the planner acts as if one knows with certainty that the Cs value is 2.9. This is a relatively low value, and therefore, the emissions need not decrease rapidly until around 2030. In the stochastic case, the policy maker does not have this knowledge until year 2030, and therefore must hedge against all possible values of Cs, including the large value Cs=4.4, and this induces the model to decrease emissions much earlier (i.e. before the resolution date of 2030), in order to be positioned for any future possibility. At year 2030, still in the stochastic scenario, the true value of Cs is revealed, and if Cs happens to be equal to 2.9, the future emissions need not be as small as in the deterministic case. This crossing over of the two trajectories is quite evident in Figure 3 for CO_2 emissions, and less pronounced for the other two greenhouse gases. In the experiments, we use this determisnitic run to contrast and discuss the stochastic results.

3.2 Technological uncertainties

3.2.1 Carbon Capture and Sequestration

In several recent studies (e.g. [32, 31]), the implementation of CCS technologies appears as a key element of cost-effective GHG abatement policies. In [31], the authors show that it is possible for the European electricity generation system to cut 85% of CO_2 emissions by 2050 when CCS penetrates significantly after 2020. In TIAM scenarios corresponding to severe climate constraints CCS technologies are used for electricity production and transport fuel production (hydrogen, biodiesel, alcohols, Fischer-Tropps, from coal or biomass).

However, the deployment and the commercial availability of these technologies are still uncertain. As in [31, 32], we assume in the CGE that CCS technologies will be available in the future (e.g. between 2020 and 2050) only in the electricity production sector (coal based production) with uncertain parameters concerning capture, transportation and sequestration costs, and date of commercial availability.

As discussed in the technical report[7] [20], we retained two contrasted scenarios for the CCS deployment, combined with high-cost *vs* low-cost scenario. In the first deployment scenario, CCS is available in 2020 and we assume the costs as reported in Table 4. In the second scenario, CCS is commercially available in 2030 only and the costs are the same as in the previous scenario, but with year shifted 10 years on. To simulate CCS cost trajectories for the stochastic analysis, we first assume that the two above cost-development scenarios are equiprobable and for each time period, we straightforwardly deduce from the figures in Table 4 a range of possible realizations for the total CCS costs that is the sum of transport, storage and capture costs. For example, the total cost in 2020 for the first scenario will take values within the interval [15+10+25, 20+10+50] = [50, 80]. Finally we generate a cost

[7] [20] has been prepared by the working group on the technology assessment of the PLANETS EU-project.

Year	Transport (high/low)	Storage	Capture (high/low)	Total (high/low)
2020	20/15	10	50/25	80/50
2025	10/7	7	40/20	57/34
2030	5/5	5	37.5/17.5	47.5/27.5
2035	3.5/3	3.5	35/15	42/21.5

Table 4: Cost-development scenario for transport, storage and capture in €/ton of CO_2.

trajectory by sampling uniformly a unique random factor between 0 and 1 that will be used for all periods to make linear interpolation in the above defined cost intervals.

3.2.2 Energy efficiency improvement

As most models used to assess climate change policies GEMINI-E3 assumes an exogenous rate of energy efficiency improvement called "Autonomous Energy Efficiency Improvement" (AEEI) [17, 6]. This AEEI handles the historical trend of efficiency improvement that is independent of economic changes such that e.g. energy prices or economic growth. In GEMINI-E3, the AEEI lies in the range of 1% to 2.2% per year depending on time periods, regions and sectors. We assume a normal distribution, normalized to a mean of 1.0 and a standard deviation of 0.4, and apply the positive sampled value as a multiplicative factor for the regionally and time varying AEEIs as specified in GEMINI-E3. Note that this standard deviation is similar to that retained by [42].

3.2.3 Elasticities of substitution

Production is represented in GEMINI-E3 through nested CES functions as shown in Figure 5. We assume that the possibilities of substitution are identical between countries for a given sector, but differ between sectors. We focus our analysis on three elasticities which play a central role in energy consumption in the GEMINI-E3 model:

- The elasticity between aggregate inputs (i.e. the elasticity between materials, energy, labor and capital, represented in Figure 5 by σ);
- The elasticity between electricity and fossil fuel energy (σ_e);
- The elasticity between fossil fuel energies (σ_{ef}).

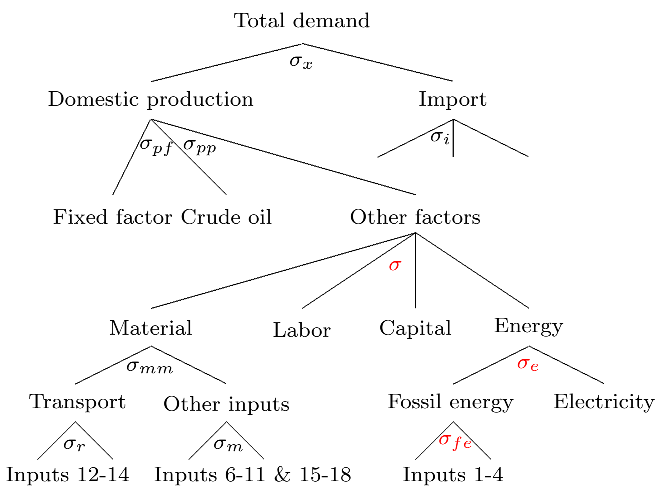

Figure 5: Nesting CES structure of production in GEMINI-E3

In a certain sense, the elasticity of substitution can serve as an indicator of technological "flexibility". For these three parameters we retain two multiplicative random factors, one for σ and the other for σ_e and σ_{ef}. The two factors have a normal distribution, normalized to a mean of 1.0 and a standard deviation of 0.3. This assumption is in line with the standard deviation estimated in [39] and used in simulations of the EPPA model [42].

3.3 Economic growth uncertainty

On the basis of the historical per-capita GDP growth rates computed by [42] (see Table 5), we find that the variance of this variable is greater in developing countries and lower in developed countries. Moreover, the per-capita GDP growth is much higher in developing countries, the implications of this uncertainty are in consequence particularly important on the World GDP growth. In contrary the uncertainty concerning the population growth seems not really different between these two regions, if we compare the World population prospects done by the United Nation [38] among the different assumptions used (i.e. fertility, mortality and international migration). Consequently we suppose that the main uncertainty concerning the GDP growth is located in developing countries, this means in our regional classification Asian countries (ASI) and the rest of the World (ROW). In a CGE like GEMINI-E3 the economic growth is derived from the growth of production factors (labor, capital, energy) and from the technical progress associated to each factor[8]. Among them the most important factors are the growth of labor force and the evolution of labor productivity. The technical progress associated to each factor is calibrated in this study in order to reproduce an economic growth and energy consumptions consistent with the World Energy Technology Outlook done by the European Commission [15]. We retain the same assumption concerning the growth of labor force in all scenarios (i.e. stochastic runs) based on the median variant of the United Nation, but we use different technical progress associated to labor in ASI and ROW to represent the uncertainty surrounding the economic growth of these two regions. For these productivity factors we use two different multiplicative random factors having a normal distribution, normalized to a mean of 1 and with a standard deviation equal to 30%. We suppose also that these two technical progress are correlated with a correlation ratio equal to 0.5, a similar assumption is also adopted in [42].

Region	Mean	Standard Deviation
USA	2.2	2.3%
Canada	2.3	2.3%
Mexico	2.2	5.2%
Japan	4.9	3.5%
Australia & New Zealand	2.0	1.8%
European Union	2.8	1.6%
Eastern Europe	1.1	3.9%
Former Soviet Union	1.1	5.3%
East Asia	4.3	4.7%
China	4.3	3.7%
India	2.3	2.7%
Indonesia	2.7	5.0%
Africa	1.0	1.8%
Middle East	2.3	3.3%
Central & South America	1.7	2.0%
Rest of the World	2.2	3.5%

Table 5: Mean and Standard Deviation of Historical Per-Capita GDP Growth Rates 1950 - 2000 (source: [42])

[8]Note that we take an uncertainty on the technical progress associated to energy, see Section 3.2.2.

3.4 Oil and gas price uncertainty

Oil price is highly volatile and has an important impact on economy [33]. (For example, it varied quickly between $40 and $140 between July 2008 and December 2008.) The uncertainty related to oil price raises thus a challenging issue. In the long term, oil price will be affected by several factors, among which are: the development of oil reserves, the arrival of new extraction techniques, the behavior of oil producers (OPEC), the emergence of unconventional oil, changes in demand, etc. In the last International Energy Outlook [14], the US Department of Energy summarized this uncertainty by choosing three alternative oil price cases which are displayed on Figure 6:

- in the reference case, world oil price (in real 2007 dollars) rises from $68 per barrel in 2006 to $130 per barrel in 2030;
- in the high price case, world oil price climbs to $200 per barrel in 2030;
- in the low price case, it declines to $50 per barrel in 2015 and remains at that level through 2030.

To model the uncertainty of oil price we use a normal distribution with average value of 100$ and a coefficient of variation of 25% to ensure a 95% confidence interval [50, 150]. We assume that this price is reached in 2015 and then remains constant throughout the duration of the simulation in real value. This assumption is in line with the DOE scenarios and based on a panel experts review of the FP7 EU Project PLANETS.

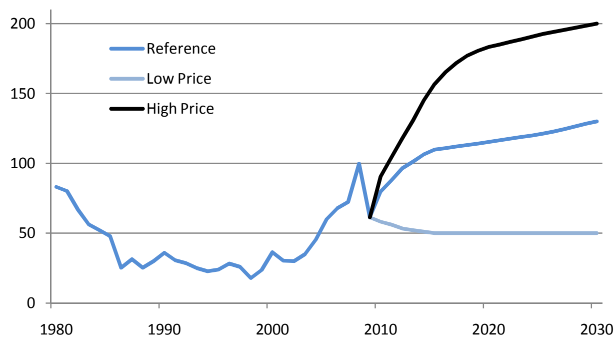

Figure 6: World oil price in International Energy Outlook 2009 in 2007 dollars per barrel [14].

Natural gas price is strongly related to oil price and several studies point out this relation. Siliverstovs et al. [37] analyze the market integration for natural gas and the link between oil price and gas price, their conclusions differ according regions. They find that following the liberalization of the US market a decoupling of natural gas prices and oil prices occurred. For the European market there is in contrary a strong evidence for cointegration between the oil price brent and European gas price. In Asia, the price indexation of natural gas refers to blend of different crude oils. Awerbuch and Sauter [5] have estimated the oil-gas price correlation for the 1973-2003. They find that the long-term oil-gas correlations for the US and EU are in range of 0.7 and that this indexation becomes higher for more recent periods. Several factors explain this relationship. At the demand side, natural gas and oil products are substitutes in consumption (especially for electricity generation and industrial process), and an increase of crude oil price will increase the gas demand and so its price. At the supply side natural gas is often produced as a co-product of oil, and long-term contracts of imported gas retain indexation rules on oil price. According to these studies we assume an indexation of gas prices to the price of oil at 0.75 (i.e. the price of gas increases by 7.5% when the oil price increases by 10%). For coal prices we do not introduce any uncertainty parameter, the price is based on the figures computed by the TIAM for the BAU scenario. Note that these assumptions concerning energy prices are only introduced in the BAU scenarios, in practical terms we calibrate the supply curves of the energy sector (oil, natural gas and coal) in order to reproduce these energy prices. In the climate policy scenarios we let the GEMINI-E3 model compute these energy prices endogenously on the basis of supply-demand equilibrium. Thus in the case of ambitious climate policy, the decline in fossil fuel consumption leads to a decrease of energy prices.

There is an extensive theoretical and empirical literature on the macroeconomic effects of oil price shocks [21]. Barsky and Kilian [7] identify a number of mechanisms that might provide a causal link from oil prices to recessions, inflation, and economic growth. However in a more recent paper Blanchard and Gali [10] find that the impacts of oil price shocks have changed over time, with steadily smaller effects on output. For the sake of simplicity we do not consider in this paper any correlation between energy price and economic growth, the two uncertainties are assumed to be independent.

4 Implementation issues

4.1 TIAM Stochastic for generating optimal hedging strategies

The stochastic version of the energy-economy model TIAM [24] is used in the first phase of the procedure described in subsection 3.1 for generating hedging strategies for different Cs factors. The first concern of this phase is the choice of an appropriate continuous probability distribution to represent the uncertainty of Cs. We have selected a triangular distribution on the interval [1,5] and with mode 2.9. This choice is motivated by the observations that the mode 2.9 and the minimum value of 1 are generally accepted in the literature [19]. Its maximum value is a controversial matter in the literature. The proposed values are often between 4 and 9, some studies proposing even larger maximum values. In the present study, we choose the value 5 for technical considerations, since we have observed that GEMINI-E3 does not produce reasonable solutions for larger values. Given those parameters (mode and range), we also have observed that the impacts of the distribution on the TIAM results are negligible.

The second issue to be resolved concerns the discretization of the triangular distribution. To limit the size of the stochastic programming model we shall use a four branch event-tree. The choice of the discrete values for Cs must satisfy two conflicting conditions. First, the discrete probability distribution must be an unbiased approximation of the continuous pdf, but second, the discrete Cs values must encompass most (or all) the true range of possible Cs values. These two conditions are indeed conflicting, because if we choose a broad range for the discrete Cs values (so as to satisfy the second condition), the two extreme values (the lowest and the largest) will not be representative of the continuous pdf, thus violating the first condition.

In conclusion, we should choose the lowest discrete value to be sufficiently larger than 1, in order to attribute to it a non-zero probability. We propose Cs=1.1 (see Figure 7). In Figure 7, the discrete value Cs=1.1 is an unbiased representative of the range extending from 1 to approximately 1.4. The four discrete probabilities to be used are also indicated in Figure 7 and Table 6.

Finally we still have to motivate the use of different ranges for the triangular distributions in the two-phase procedure : [1,5] with TIAM in stochastic programming and [1.1,4.4] with GEMINI-E3 in the MC approach. When we perform the MC simulations with GEMINI-E3 the emission path corresponding to a particular Cs value will be obtained by linear interpolation of the paths that have been computed by TIAM for the four possible branches of the event tree. Hence the sampled Cs values must be contained in the range of the discretized probability distribution used in TIAM. Adjusting the triangular distribution to this range of the Cs pdf thus does the trick.

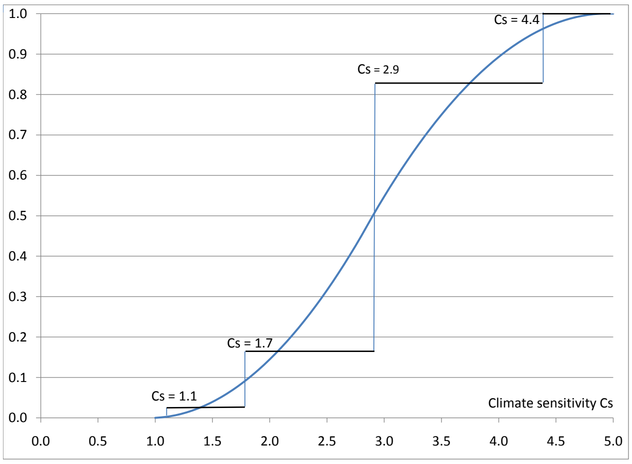

Figure 7: Unbiased discrete pdf of Cs.

Cs	Probability
1.1	0.01
1.7	0.15
2.9	0.66
4.4	0.18

Table 6: Discrete distribution of probability for climate sensitivity

4.2 Monte-Carlo analysis with GEMINI-E3

We perform Monte-Carlo (MC) simulations of the aggregate GEMINI-E3 model, using Latin Hypercube sampling [18] from the parameter distributions described in Section 3. MC methods rely on repeated random sampling to generate values for key uncertain input parameters defining scenarios and then identify a probability distribution for some output parameters and/or performance criteria. An experimental design is adopted ensuring that the set of sample values for the uncertain parameters defining the scenarios is randomly generated according to the probability laws governing these processes. If one wishes to ensure that each of the input parameter components has all portions of its distribution represented by input values one can divide the range of each parameter component into N strata of equal marginal probability $1/N$ and sample once from each stratum. These samples for each component are then matched at random. This is called the Latin Hypercube sampling [18]. This is one of several possible "space-filling" experimental designs. The output parameters are then computed optimally for each scenario. In the final step, these results are analyzed through an identification of their probability distributions. In the E^3 case one obtains indicators of the likelihood of different long-term output parameters related to climate, economy and energy prices.

The advantages of this method are twofold. First, its simplicity; It does not require any specific modifications of the model. The user only needs to sample judiciously the set of scenarios and then simulations can be run straightforwardly. Second the model size does not increase with the sample size and so a large enough sample set and scenario computations can be obtained to identify the probability distributions of the output parameters of interest.

The simulations presented here are based on 2000-member ensembles, and each sample is simulated under a reference case scenario and under a climate policy scenario. The latter one has an objective in 2100 in global temperature increase of 2.1 ^oC degrees above pre-industrial levels. We suppose that the climate change target is implemented through a worldwide CO_2 emission market which begins in 2011, the quotas of each region are defined in respect to the rules proposed in the second best scenario 2 (SC2) of the FP7 European Research Project PLANETS (see [26]). In this SC2 scenario, it is assumed that the set of emissions quotas (commitments) is defined, by specifying the starting date of the commitment (before that date, emissions are assumed to be those in the reference case) and the percentage emission reduction in 2050 with respect to emissions in 2005. It is also assumed that the reductions occur linearly from start date to 2050. Concerning European Union we supposed that its objective of 20% emission reduction w.r.t. 1990 by 2020 [16] is also implemented from 2008. On the basis of these rules we compute on the period 2005 to 2050, the share of each region in the cumulative CO_2 allocation which gives the weight applied to compute for each year the allocation of quota by region in the climate policy scenario. Table 7 summarizes these assumptions and gives the computed weight.

Regions	Starting date of quotas	quotas in 2050 wrt 2005 (reduction in brackets)	Share of quotas
EUR	2015	10% (reduction=90%)	7%
OEC	2015	10% (reduction=90%)	16%
ASI	2025	100% (reduction=0%)	40%
EEC	2025	100% (reduction=0%)	16%
ROW	2025	200% (reduction=100%)	21%
			100%

Table 7: The set of quotas used for the policy scenario.

4.3 Summary on uncertain parameters

We summarize in Table 8 the uncertain parameters under study and the probability distributions used in the Latin Hypercube procedure.

Uncertainty	Probability distribution
Elasticity between aggregate inputs	$\sigma \sim N(\bar{x}, 0.3 \cdot \bar{x})$
Elasticity between energy inputs	$\sigma_e, \sigma_{ef} \sim N(\bar{x}, 0.3 \cdot \bar{x})$
Autonomous energy efficiency improvement	$aeei \sim N(\bar{x}, 0.4 \cdot \bar{x})$
Economic growth of ASI	$gasi \sim N(\bar{x}, 0.15 \cdot \bar{x})$
Economic growth of ROW	$grow \sim N(\bar{x}, 0.15 \cdot \bar{x})$
Oil price	$poil \sim N(\bar{x}, 0.25 \cdot \bar{x})$
Year of commercial availability of CCS	$yccs \sim Bernoulli(0.5)$
Cost of CCS	$ccs \sim U(0, 1)$
Climate sensitivity	$Cs \sim Triangular(1.1, 2.9, 4.4)$

Table 8: Summarized stochastic parameters.

5 Numerical results

In the numerical study, we draw 2000 samples with Latin Hypercube technique from the parameter distributions described in Table 8. For each sample we proceed in two steps:

- In step one, we run a Business As Usual (BAU) scenario, without any climate policy;
- In step two, we perform a climate policy scenario as it was described in section 4.2.

At the end we have performed 4000 runs. We give below our analyses on both types of runs, respectively.

We have also performed a deterministic run that will be used in the stochastic analysis to compare the output of this "average deterministic" run and the average of the output in the MC analysis.

5.1 Average deterministic results

In this section, we report the main results from the average deterministic run for both BAU and climate policy scenario. We give to all stochastic parameters their mean values and we assume the optimistic date of availability of CCS in 2020.

5.1.1 BAU scenario analysis

Figure 8 shows the resulting energy consumption in the five parts of the world that we distinguish. The world energy consumption would increase by 1.6% per year, the key driver of energy consumption is the GDP growth: the growth of energy consumption would be sustained in Asia and in the rest of the World (respectively +2.3% and 2.2% per year), and moderate in the OECD countries (0.7% in EUR and 1% in OEC). In 2050, DCs (EEC, ASI and ROW) represent 66% of energy consumption against 56% in 2010. The energy mix of the economy is mainly driven by the change of the relative energy prices and by technological change. As in this scenario we do not assume different trend in fossil energy prices and technological breakthrough, the energy mix remains almost unchanged over the period. In 2050, oil would continue to remain the dominant energy: oil represents 32% of World energy consumption, the transport sector would remain the main user of oil without significant penetration of biofuels and other potential substitutes. Electricity and coal contribute to 25% each of the energy balance, gas equals only 18% of energy consumption.

Figure 9 gives the electricity generation by fuel, World electricity generation rises from 22 600 TWh in 2010 to 38 000 TWh by 2030 and to 46 000 TWh by 2050. Without any constraint on the deployment of power plants (such as a nuclear phase out) and taking into account the fact that the hierarchy among energy prices remains unchanged, the new installed capacities do not modified the structure of electricity generation within each region. Coal remains the dominant energy in electricity generation in Asia, and in less extent in OEC, electricity generation from nuclear is mainly located in developed countries, energy exporting countries continue to use mainly oil and natural gas to produce electricity. Without any climate change policy or environmental constraint (such as local air pollution control or EU target on the penetration of renewable energy by 2020) there is no strong penetration of renewable in the energy mix. Finally in Figure 10 we show the resulting evolution of GHG emissions levels from the five groups of countries under consideration.

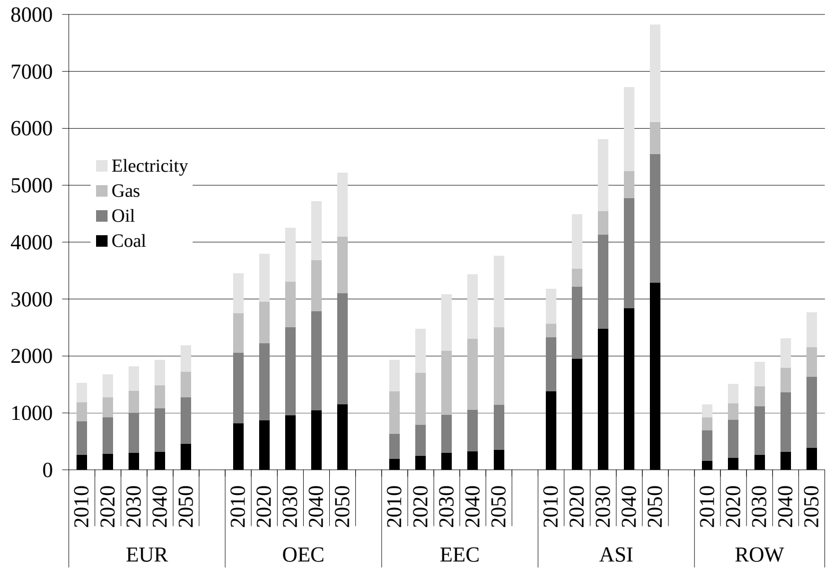

Figure 8: Energy Consumption in Mtoe in the BAU deterministic scenario.

5.1.2 Climate policy scenario analysis

In the average deterministic case the emission trajectory is obtained from the deterministic run of TIAM with 2.9^{o}C value for Cs (see Table 3). Table 9 shows the price of CO_2, in 2030 the permit price would be equal to 11 US $ and in 2050 to 87 US $. Mitigation opportunities are comparable between regions, even if they are significantly higher in Asia and energy exporting countries. The exchange of tradable permits results from the abatement opportunities and the initial endowments of permits, as it can be seen in Table 9 industrialized countries would be net buyers and other countries net seller. Figure 11 shows the change in energy consumption by fuel in % with respect to baseline in 2050. The changes in consumption depend on the energy mix in the baseline, the possibilities of substitution, the CO_2 content of each energy and the existing energy taxation. Electricity consumption is less affected, the possibilities to produce electricity from non CO_2 energy sources (nuclear, renewable) and to use CCS with coal power generation, limit the impact of the CO_2 price on the price of electricity. At the world level, 74% of electricty generation done with coal power plan uses CCS in 2050. The use of CCS limits the drop in coal consumption which remains important, this decrease is mainly due to the declining use of coal in the economy (excluding electricity generation) and to the decrease of electricity consumption, which impacts the production of coal power plant. The decrease of oil and natural gas consumption are also important and comparable in magnitude.

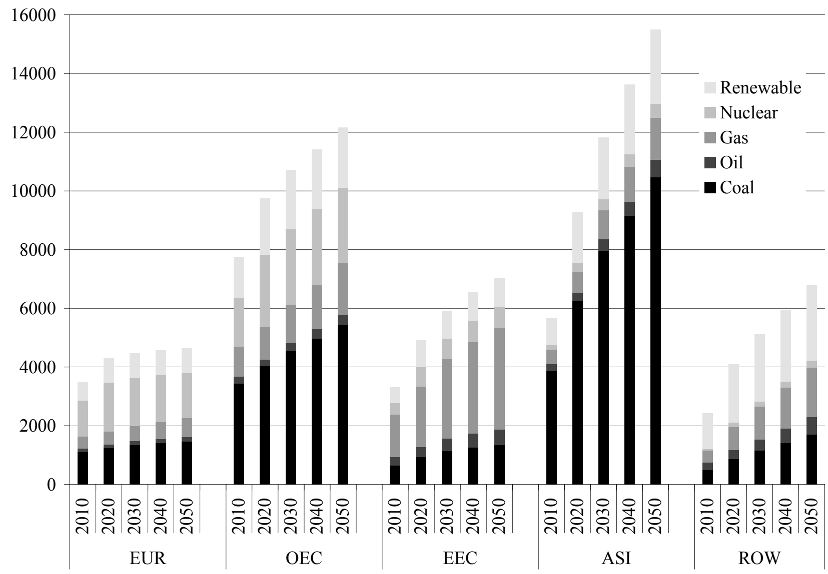

Figure 9: Electricity Generation in Twh in the BAU deterministic scenario.

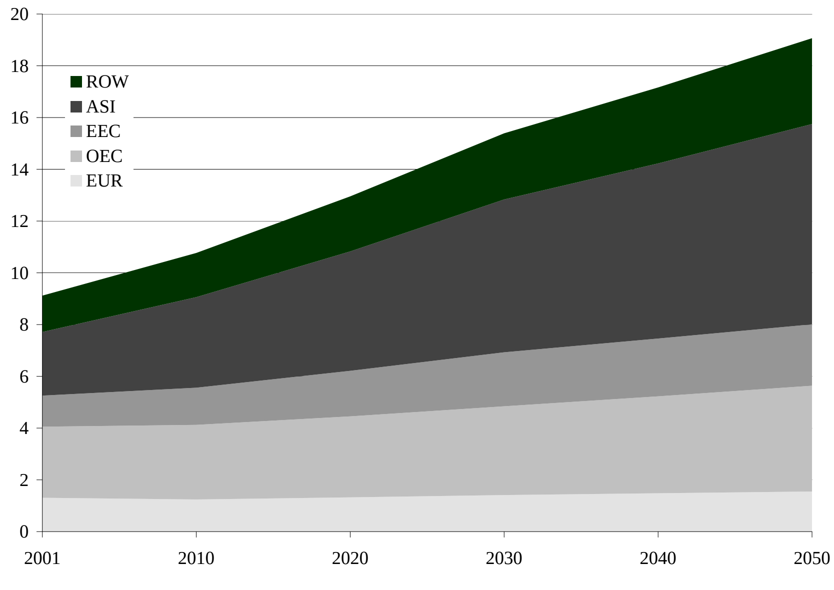

Figure 10: GHG emissions in Gt CO_2-eq in the BAU deterministic scenario.

	2020	2030	2040	2050
CO_2 price in US $	11	17	44	87
GHG Abatement in % wrt BAU				
EUR	-7.7%	-11.3%	-22.0%	-30.0%
OEC	-9.8%	-15.0%	-29.1%	-40.4%
ASI	-18.2%	-29.9%	-42.8%	-52.2%
EEC	-12.6%	-21.9%	-33.9%	-45.1%
ROW	-12.0%	-19.7%	-29.7%	-39.0%
World	-13.3%	-22.1%	-34.6%	-44.7%
Exchange of permits in MtC-eq (-):buying				
EUR	-437	-414	-371	-347
OEC	-1026	-996	-859	-748
ASI	+717	+657	+619	+515
EEC	+259	+289	+318	+387
ROW	+488	+465	+293	+193
Sum	0	0	0	0

Table 9: CO_2 price, GHG abatement & tradable permits in the deterministic scenario.

Table 10 presents the welfare cost, at the world level this cost reaches 1.2% of the households consumption in 2050. The welfare cost by regions are quite different, they depend mainly on three factors:

- The cost of mitigation (i.e. deadweight loss of taxation);
- The initial endowment of GHG permits;
- The gains or loss coming from terms of trade.

Asia benefits from the selling of permits and gains coming from terms of trade, its surplus is positive and equals to 3.7% of the household consumption in 2050. On the contrary, despite sales of permits, energy exporting countries is severely penalized by a drop in its revenue coming energy exports, ist welfare cost reaches 16% of its household consumption in 2050. The ROW is in a situation comparable to that of energy exporting countries because this region includes substantial energy exporting countries such as Venezuela, Nigeria, Algeria and Libya, the cost is evaluated at 4.2% of the household consumption. Finally, the cost for industrialized countries is rather limited, theses countries benefitting from gains related to terms of trade and to low abatement since GHG emissions do not increase much over the period of simulation. This is particularly the case in European countries where weak GDP growth combined with low energy intensity leads to a GHG emissions increase at the end of the simulation in the baseline scenario which is half of that concerning the OEC region. The cost for EUR is equal to 0.5% of the household consumption, to be compared with the cost for OEC (1.2% of the household consumption).

	2020	2030	2040	2050
EUR	-0.07%	-0.01%	-0.13%	-0.55%
OEC	-0.29%	-0.31%	-0.65%	-1.20%
ASI	1.73%	2.05%	3.42%	3.69%
EEC	-2.76%	-4.30%	-10.22%	-16.45%
ROW	-0.16%	-0.38%	-1.98%	-4.21%
World	-0.03%	-0.01%	-0.37%	-1.16%

Table 10: Welfare cost (Surplus in % of household consumption) in the deterministic scenario.

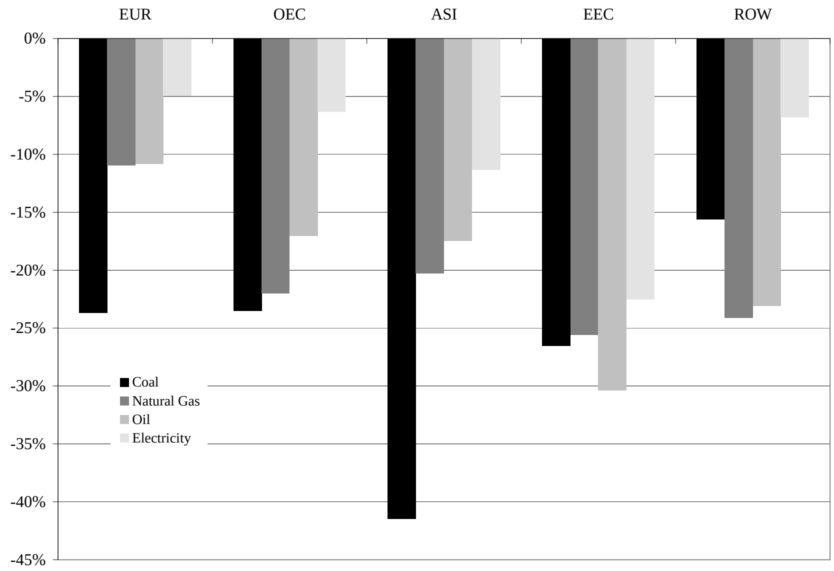

Figure 11: Change in energy consumption in 2050 in % wrt BAU in the deterministic scenario.

5.2 Analysing uncertainty on BAU scenarios

We report, in the section, the main results from the BAU scenarios. We also have noticed that the output of the deterministic BAU scenario corresponds approximately to the average of the stochastic output. This results was expected as no climate policy constraint is imposed on the BAU scenarios.

5.2.1 Economic flexibility and convergence

In 17% of BAU scenarios, GEMINI-E3 does not converge, these runs are infeasible. To interpret this result we use a logit model where the dependent variable is equal to one if the run is infeasible, and 0 otherwise and where the explanatory variables are the uncertain parameters. In Table 11 one observes that only one parameter is significant, namely σ which is related[9] to the elasticity of substitution between aggregate inputs (labor, capital, energy and other materials); this is a measure of flexibility of the economy. When the value of the σ parameter is small, the economic flexibility is too weak, and GEMINI-E3 could not find any solution, and does not converge.

	Estimate	Std. Error	z value	$\Pr(>\|z\|)$
Intercept	11.86	1.37	8.669	<2e-16
aeei	0.00	0.26	-0.004	0.996
σ	-15.69	0.93	**-16.911**	<2e-16
σ_e, σ_{ef}	-0.06	0.33	-0.185	0.854
gasi	-0.88	0.67	-1.315	0.189
grow	0.38	0.68	0.568	0.57
poil	-0.36	0.41	-0.867	0.386

Table 11: Logit model on the BAU scenario convergence (0 if convergence; 1 otherwise).

Figure 12 gives the probability of non-convergence of a scenario as a function of the σ

[9]Because the elasticities are different among sectors we use here the parameter σ which is used as a multiplier to the nominal elasticities (i.e. when GEMINI-E3 is used without uncertainties).

values. All σ values simulated in the experiments are plotted (in small diamonds) either at the top or at the bottom of the figure depending on non-convergence or convergence of the scenario, respectively. One observes that the critical value of the elasticity multiplier σ for convergence with probability $\frac{1}{2}$ is around 0.7. This means that when the value of the elasticities is reduced by 30% the probability of convergence is equal to $\frac{1}{2}$.

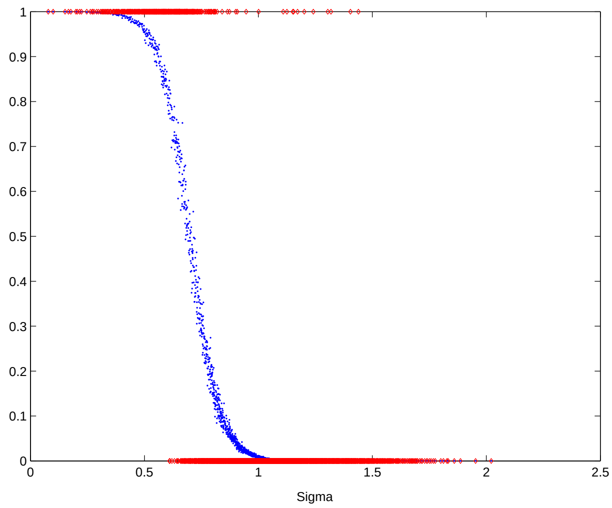

Figure 12: Probability of convergence in function of σ.

5.2.2 Impact of energy consumption uncertainty on GHG emissions

If we consider the runs that have converged (1660 runs out of a sample of size 2000), it is interesting to take a look at the uncertainty regarding greenhouse gas emissions. Figure 13 presents the GHG emissions of the BAU scenarios and gives the 50% (doted lines) and 100% (bold doted lines) probability bounds of these emissions. In 2050, the median value of GHG emissions is located at 19.1 Gt of C-eq, the higher value is equal to 27.3 and the lowest value is less than 13.6. Our scenarios overlap the range of emissions covered by the SRES scenarios published by the IPCC [19], except the scenario A1FI in which the GHG emissions reach more than 30 Gt of C-eq in 2050. We draw on Figure 13 (dotted line with asterisk marker) the emission trajectories coming from the TIAM stochastic climate constraint runs and we observe that when the climate sensitivity is low there are some runs which would not be constrained in 2050. On contrary it should be noted that all runs are constrained in 2030.

We estimate a Log-linear model concerning the GHG emissions and energy consumption by fuels in 2050 with uncertain parameters as explanatory variables, Tables 12 and 13 present these estimations at the World level and by regions. The results of these estimations are always statistically significant, as can be easily seen from the adjusted R^2 which are never below 0.87. GHG Emissions are of course negatively related to technical progress on energy (aeei). At the world level the impact of economic growth in Asia is crucial to global emissions (0.295), the economic growth of ROW is of secondary importance (0.065). This is due to the weight of Asia in global energy consumption and its energy mix based largely on coal. We find also that the economic growths of ASI and ROW increase the emissions of the other regions due to the trade effect, again the impact of Asia is more important than the rest of the world (ROW). An increase in oil prices reduces emissions of greenhouse gas emissions (-0.131) and despite its positive impact on coal consumption, but this negative impact is much more important in industrialized countries and quite less important in Asia; again the explanation comes from the energy mix of each region. The effects of elasticities (σ and σ_e - σ_{ef}) are weaker and more ambiguous, and must be connected to energy mix and industrial structure of each region. The effect of the elasticity directly related to substitution within energy (σ_e - σ_{ef}) is more clear on energy consumption. Coal and electricity consumption are

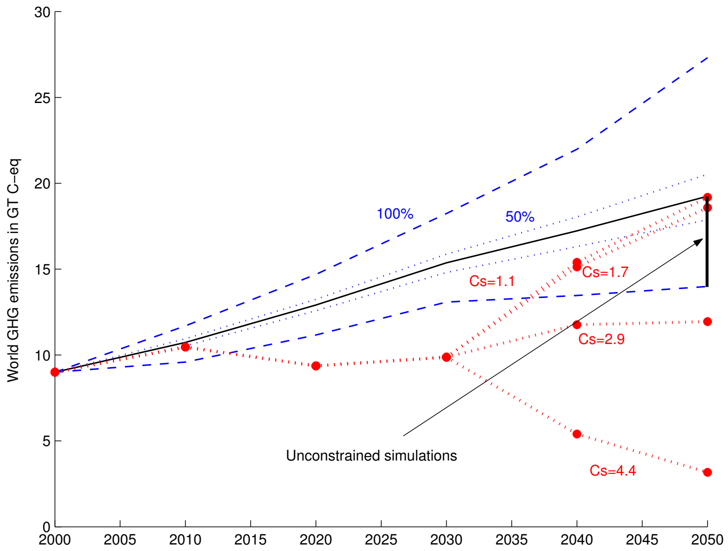

Figure 13: Uncertainty in emissions projections.

positively related to the parameters σ_e and σ_{ef}, in contrary oil and natural gas are negatively related. When these elasticities increase it is more easy to replace oil and natural gas when the oil price increase[10] by electricity and coal, all other things held constant.

	World	EUR	OEC	ASI	EEC	ROW
Intercept	9.848	7.336	8.305	8.946	7.753	8.101
	(11710.3)	(9025.7)	(11771.3)	(8445.5)	(8266.3)	(15911.1)
log(aeei)	-0.168	-0.178	-0.143	-0.201	-0.192	-0.096
	(-102.8)	(-112.7)	(-104.7)	(-98.1)	(-105.6)	(-97.2)
log(σ)	-0.012	0.033	-0.012	-0.012	0.036	-0.064
	(-3.3)	(9.4)	(-3.9)	(-2.6)	(8.9)	(-29.3)
log(σ_e)	0.003	0.001	-0.003	0.017	-0.014	-0.008
	(1.3)	(0.3)	(-1.7)	(6.0)	(-5.8)	(-6.3)
log(poil)	-0.131	-0.203	-0.210	-0.072	-0.132	-0.131
	(-40.3)	(-64.9)	(-77.3)	(-17.8)	(-36.6)	(-66.7)
log(gasi)	0.295	0.029	0.006	0.688	0.076	0.026
	(58.3)	(-64.9)	(1.5)	(107.8)	(13.5)	(8.5)
log(grow)	0.065	0.010	0.007	0.011	0.010	0.332
	(13.0)	(5.9)	(1.7)	(1.8)	(1.8)	(109.6)
Adjusted R^2	0.90	0.91	0.91	0.93	0.89	0.94

Table 12: Estimate of the log(Emission) in 2050.

Figures 14 and 15 present the uncertainties on energy consumption and electricity generation by fuels in the form of Tukey box plots in which the box indicates the 50% probability range, the line within the box gives the median value and the whiskers indicate the 95% range. When a climate constraint is taken into account this induces a decrease of energy consumption in average, but the uncertainty range is more important. In the case of electricity generation, the climate policy scenarios result in a large increase of generation from renewable with a quite important range of uncertainty. The nuclear generation increases also but in a smaller proportion. The case of generation from coal is interesting, the figures between climate policy scenarios and the BAU scenarios are comparable showing that the use of CCS allows to continue to burn coal for electricity generation.

[10] Note that we suppose that the natural gas price is indexed on oil price, see Section 3.4.

	Coal						Refined Oil					
	World	EUR	OEC	ASI	EEC	ROW	World	EUR	OEC	ASI	EEC	ROW
Intercept	8.605	5.797	7.040	8.086	5.857	5.945	8.851	6.692	7.558	7.709	6.668	7.118
	(6931.1)	(5386.4)	(8054.5)	(5562.4)	(5758.6)	(6179.4)	(8451.8)	(7165.8)	(9753.8)	(5494.9)	(5564.7)	(8118.3)
log(aeei)	-0.232	-0.218	-0.169	-0.266	-0.197	-0.170	-0.205	-0.200	-0.152	-0.262	-0.239	-0.162
	(-96.2)	(-104.5)	(-99.7)	(-94.3)	(-99.7)	(-91.1)	(-100.8)	(-110.4)	(-101.1)	(-96.4)	(-103)	(-95.1)
log(σ)	-0.001	0.088	0.027	-0.015	0.027	-0.057	-0.056	0.001	-0.059	-0.066	0.028	-0.121
	(-0.1)	(19.2)	(7.2)	(-2.5)	(6.3)	(-14)	(-12.5)	(0.2)	(-17.8)	(-11.1)	(5.5)	(-32.2)
log(σ_e)	0.062	0.057	0.047	0.070	0.047	0.060	-0.046	-0.023	-0.028	-0.065	-0.063	-0.042
	(18.9)	(20)	(20.3)	(18.2)	(17.5)	(23.5)	(-16.4)	(-9.5)	(-13.6)	(-17.3)	(-19.8)	(-17.8)
log(poil)	0.177	0.127	0.117	0.162	0.500	0.247	-0.405	-0.320	-0.394	-0.486	-0.292	-0.399
	(37.1)	(30.7)	(34.8)	(29)	(127.7)	(66.7)	(-100.4)	(-89.1)	(-132.1)	(-89.9)	(-63.4)	(-118.2)
log(gasi)	0.430	0.021	0.002	0.711	0.075	0.020	0.245	0.051	0.016	0.684	0.085	0.036
	(57.4)	(3.3)	(0.4)	(81.1)	(12.2)	(3.4)	(38.8)	(9.1)	(3.5)	(80.9)	(11.7)	(6.8)
log(grow)	0.039	0.016	0.010	0.016	0.011	0.384	0.068	0.016	0.010	0.017	0.013	0.326
	(5.3)	(2.5)	(1.9)	(1.8)	(1.9)	(67.1)	(10.9)	(3)	(2.3)	(2)	(1.8)	(62.4)
Adjusted R^2	0.89	0.88	0.87	0.91	0.94	0.91	0.93	0.93	0.95	0.94	0.90	0.95
	Natural Gas						Electricity					
	World	EUR	OEC	ASI	EEC	ROW	World	EUR	OEC	ASI	EEC	ROW
Intercept	8.247	6.073	6.889	6.316	7.196	6.228	8.538	6.122	7.012	7.432	7.117	6.411
	(8191.2)	(7103.6)	(7671.1)	(4608.5)	(6927)	(6312.8)	(8593.5)	(6856.9)	(9584.4)	(5357.4)	(8328.4)	(7581.4)
log(aeei)	-0.198	-0.184	-0.172	-0.257	-0.206	-0.178	-0.198	-0.194	-0.150	-0.266	-0.166	-0.160
	(-101.7)	(-111)	(-98.9)	(-96.6)	(-102.4)	(-92.9)	(-102.7)	(-111.9)	(-105.9)	(-98.9)	(-100.2)	(-97.4)
log(σ)	-0.018	0.050	-0.008	-0.058	0.023	-0.163	-0.014	0.038	0.020	-0.030	-0.028	-0.042
	(-4.3)	(13.6)	(-2.1)	(-9.9)	(5.2)	(-38.8)	(-3.4)	(9.9)	(6.5)	(-5)	(-7.7)	(-11.8)
log(σ_e)	-0.028	-0.018	-0.049	-0.028	-0.012	-0.033	0.060	0.051	0.045	0.092	0.033	0.060
	(-10.3)	(-8)	(-20.6)	(-7.7)	(-4.4)	(-12.7)	(22.7)	(21.5)	(23)	(25.1)	(14.4)	(26.6)
log(poil)	-0.472	-0.507	-0.540	-0.588	-0.365	-0.459	-0.032	-0.001	-0.032	-0.095	0.028	-0.001
	(-121.8)	(-154.1)	(-156.3)	(-111.4)	(-91.2)	(-120.9)	(-8.5)	(-0.2)	(-11.3)	(-17.8)	(8.5)	(-0.2)
log(gasi)	0.139	0.014	-0.003	0.725	0.082	0.036	0.265	0.013	0.008	0.729	0.080	0.017
	(22.9)	(2.6)	(-0.6)	(87.7)	(13)	(6.1)	(44.2)	(2.4)	(1.9)	(87.1)	(15.5)	(3.4)
log(grow)	0.054	0.010	0.006	0.014	0.010	0.355	0.051	0.011	0.009	0.014	0.010	0.354
	(9.1)	(1.9)	(1.1)	(1.7)	(1.6)	(60.4)	(8.6)	(2)	(2.1)	(1.7)	(1.9)	(70.2)
Adjusted R^2	0.94	0.96	0.96	0.95	0.92	0.95	0.89	0.89	0.88	0.92	0.87	0.90

Table 13: Estimate of the log(Energy) in 2050.

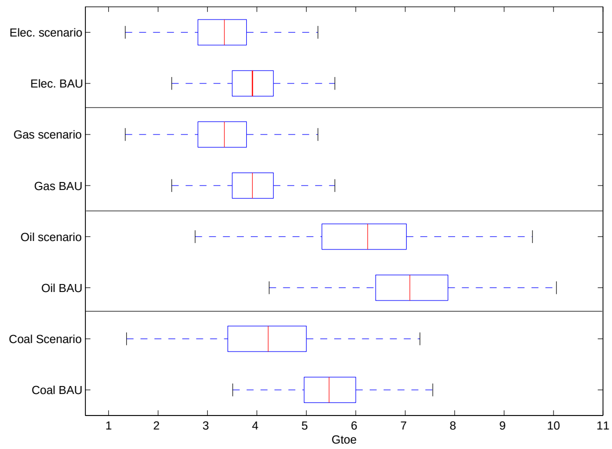

Figure 14: Energy consumption in 2050.

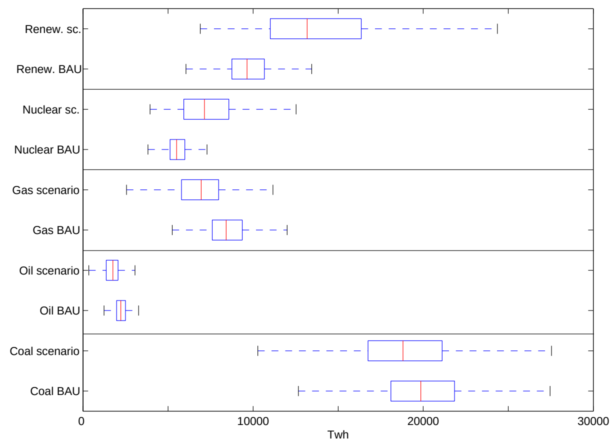

Figure 15: Electricity generation in 2050.

5.3 Analysing uncertainty in climate policy scenarios

On the basis of the 1660 BAU scenarios which have converged we run the climate policy scenarios. Among these 1660 runs, 9% become infeasible under a climate policy. Therefore we estimate a new logit model where the dependent variable is equal to one if the run is infeasible, and 0 otherwise with uncertain parameters as explanatory variables. Table 14 gives the estimation. Compared to the estimation done for the BAU scenarios we add three variables: the cost of CCS (ccs), the year of CCS availability (2020 or 2030, yccs) and the GHG target in 2050 (obj2050). Three factors explain this infeasibility:

- The first factor is related to the "state of technology" which is represented in a CGE by the value of the elasticities (σ, σ_e, σ_{ef}). The probability of achieving the climate target is increasing with the value of these elasticities. The parameter aeei may also be included in this category because it represents the technical progress associated to energy consumption;
- The second factor is of course linked to the climate target itself (obj2050), if the climate sensitivity is too high (which means that obj2050 is too low) the model could not reach this target. This impossibility to meet stringent (ambitious) climate target has been highlighted recently in the study done by the Energy Modeling Forum [11]. This study shows that the 450 ppmv CO_2-eq concentration target is infeasible for 12 of 14 models used if concentrations are not allowed to temporarily exceed their long-term

targets. If overshooting is allowed 8 of 14 models were able to produce a 450 ppmv CO_2-eq case. Remember that with a climate sensitivity equal to 3, the 450 ppmv CO_2-eq concentration target will result in a temperature change relative to preindustrial around 1.9 to 2.2 ^oC.

- Finally the oil price also affects the possibility of reaching a target climate, when it increases the probability decreases. This result is counter-intuitive because we see that GHG emissions are related negatively to oil price in the BAU scenarios. We interpret this result by the fact that high oil prices led to a more intensive use of coal (see Table 13) and ex-post to an economy in which all decarbonization becomes more difficult.

The uncertainties related to the other parameters do not seem to affect the probability of achieving the climate target, especially the variables related to the CCS (yccs and ccs). The analysis that follows below focuses now on the runs that have converged both in the BAU scenarios and in the climate policy scenarios, that is to say 1508 runs.

	Estimate	Std. Error	z value	$Pr(>\|z\|)$
Intercept	9.64	27.29	0.353	0.72383
yccs	0.00	0.01	-0.046	0.96307
ccs	-0.07	0.23	-0.293	0.76941
aeei	-1.51	0.20	**-7.601**	2.95E-14
σ	-9.88	0.75	**-13.17**	< 2e-16
σ_e, σ_{ef}	-0.73	0.23	**-3.105**	0.0019
gasi	0.68	0.47	1.456	0.14542
grow	-0.83	0.45	-1.839	6.60E-02
poil	3.64	0.39	**9.347**	< 2e-16
obj2050	-0.05	0.01	**-9.254**	< 2e-16

Table 14: Logit model on the climate policy scenario convergence (0 if convergence; 1 otherwise).

5.3.1 Impact of uncertainty on CO_2 price

Figure 16 shows the probability distributions of carbon prices in 2030 and 2050. We estimate these carbon prices on the uncertain parameters and these estimates are presented in Table 15. The results of these estimations are statistically satisfactory, all the explanatory variables are significant and have the expected sign.

In 2030, there is no uncertainty in the GHG emissions target due to the used hedging strategy (we find a single hedging emission profile until 2030, see Section 3.1), the variable related to uncertainty on GHG emissions target could not be used. The CO_2 price follows a distribution similar to a log normal, the probability range is 15 US\$ to 126 US\$ and the mean of the distribution is 63 US \$. The most important factors which explain the uncertainty related to CO_2 price are in order of decreasing importance the σ parameter elasticity of substitution between aggregate inputs), the economic growth of Asian countries, the oil price and the aeei coefficient. Based on these estimates, we compute the relationship between the CO_2 price and the σ parameter and the rate of growth in Asia. Figure 17 presents these links. The elasticity between σ and the CO_2 price is equal to 0.7. The relation between the GDP growth of Asian countries and the CO_2 price could not be directly computed on the basis of the estimation presented in Table 15 because the coefficient gasi represents the technical progress on labor which is one of the determinants of the growth rate of the GDP. We proceed in two steps: first we estimate the impact of the technical progress on the GDP, and secondly we compute the relationship between the GDP growth and the CO_2 price based on the estimation of the CO_2 price on the uncertain parameters. As it can be seen in Figure 17 when the annual growth rate of Asia on the period 2010 to 2030 increases by one point, the CO_2 increases by 16 US\$.

In 2050, the probability density of the CO_2 price appears quite different from that of 2030. Firstly the shape of the probability distributions is clearly asymmetric which comes from the climate constraint in which low climate sensitivities lead to weakly binding emission levels. These low emission constraints in 2050 combined with carbon free investments made before the revelation of uncertainty in climate sensitivity in 2030, led to a zero CO_2 price in 19% of cases. Again in contrary to the year 2030, the probability range of the CO_2 price is much more important (0 US$ to 1112 US$) even if the mean of the distribution is quite close (84 US $). If we remove observations in which the price is equal to zero, and estimate the CO_2 price on the uncertain parameters we obtain the estimate presented in Table 15 for the year 2050. The parameters σ, gasi, poil and aeei remain significant but the variable which is the most important is the climate target (obj2050). Figure 18 shows the relation between the climate target (obj2050) and the CO_2 price; when the GHG emission constraint is below 7 GtC-eq, the price increases very rapidly reflecting the difficulty in reaching the climate target.

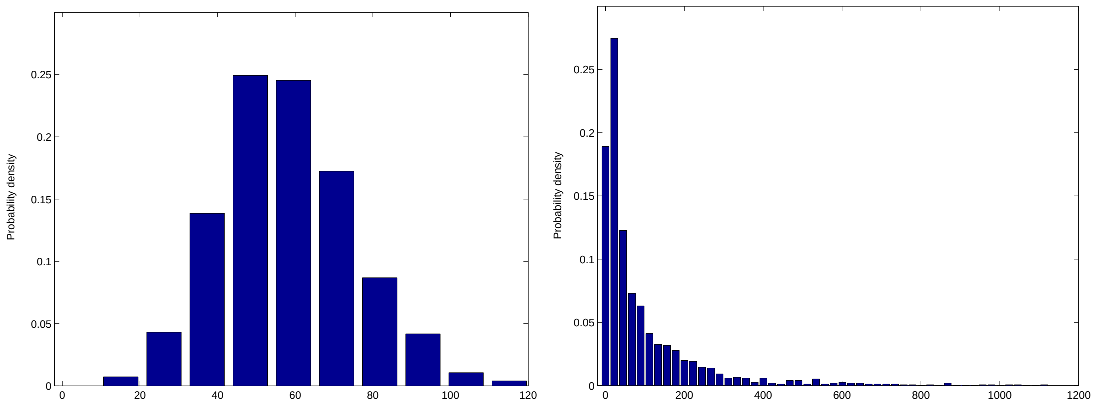

Figure 16: CO_2 price in US $ in 2030 (left) and 2050 (right).

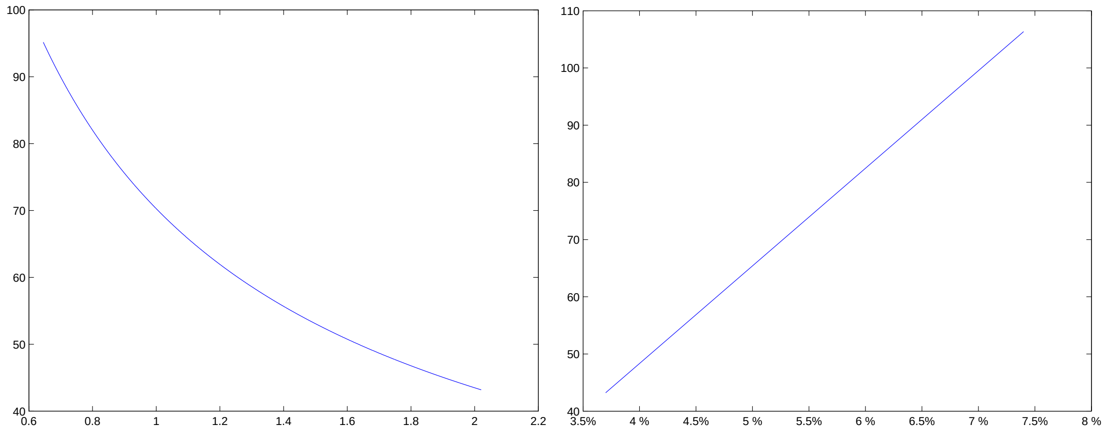

Figure 17: Relation in 2030 between σ and the CO_2 price (left) – annual GDP growth of ASI and the CO_2 price (right).

5.3.2 Welfare loss indicator

Figure 19 presents the world welfare loss expressed by an indicator which consists of the discounted world surplus (compensative variation of income) divided by the discounted house-

	In 2030	In 2050
Intercept	4.261	23.211
	(1015.5)	(101.2)
log(aeei)	**-0.313**	**-0.849**
	(-58.8)	(-22.9)
log(σ)	**-0.692**	**-0.507**
	(-58.9)	(-6.0)
log(σ_e, σ_{ef})	-0.194	-0.261
	(-28.5)	(-5.5)
log(poil)	**-0.406**	**-0.577**
	(-40.7)	(-8.3)
log(gasi)	**0.566**	**1.190**
	(36.4)	(10.8)
log(grow)	0.140	0.432
	(9.2)	(4.1)
log(ccs)	0.022	0.068
	(9.1)	(4.0)
yccs	-0.203	-0.099
	(-42.3)	(-2.9)
log(obj2050)	–	**-5.266**
	–	(-86.0)
Adjusted R^2	0.90	0.86

Table 15: Estimate of the log(CO_2 price).

hold consumption. Its density distribution is similar to the one of the CO_2 price for the year 2050 (see Figure 16). The world welfare loss ranges from -14 trillion of US$ to 89 trillion with a mean of 8 trillion of US$. These figures are comparable to those found in [11]. In some very few cases the world cost is negative (i.e. the climate policy scenario lead to a welfare increase). These are situations in which the climate sensitivity is low and the increase of oil prices high. In these cases, investments made before 2030, leading to lower energy consumption, coincide with a situation of high energy prices, resulting in a way of a perfect foresight in energy prices. Of course, this result must be related to the structure of GEMINI-E3 which assumes adaptive anticipation. Table 16 presents the estimate of the welfare cost on the uncertain parameters. Because we use the logarithm of this welfare cost as an explanatory variable, we remove the negative values of the sample. The results of these estimates are consistent with those of the CO_2 price. The most important parameter is the climate target, after come at the world level, the oil price, the growth of Asia and the autonomous energy efficiency improvement. At regional level we find the same effects with minor differences

5.3.3 Uncertainty in CCS

One objective of this paper was to study the role of technology and especially the CCS in climate policies. A cursory reading of our results might suggest that this technology has a limited impact in our scenarios. Indeed it is true that the parameters linked to CCS (ccs and ycss) have limited impacts and the estimates related to them are not always significant. This does not mean that this technology does not contribute to GHG abatement, but rather that the uncertainty surrounding its costs is of limited scope particularly in respect to the CO_2 price. Indeed, in 2030, in 74% of cases the cost of CCS is lower than the carbon price, the use of this technology is a viable proposition. Is it interesting to look at the percentage of effective GHG emission reduction via CCS in Figure 20. When the climate sensitivity becomes high the contribution of the CCS to the GHG abatement converges to 20%. The figure also shows that when the climate constraint is low, this share is much higher and may even exceed 100%. This result must be related to the hedging strategy that we have taken into account, when the climate sensitivity is very low, the investment in CCS done

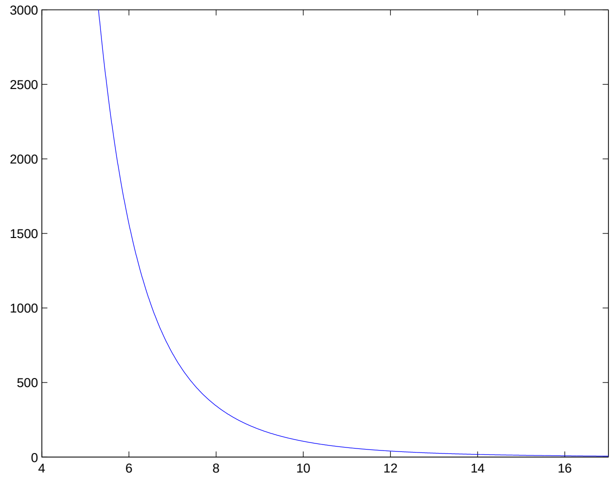

Figure 18: Relation between GHG emissions target (in GtC-eq) and the CO_2 price in 2050.

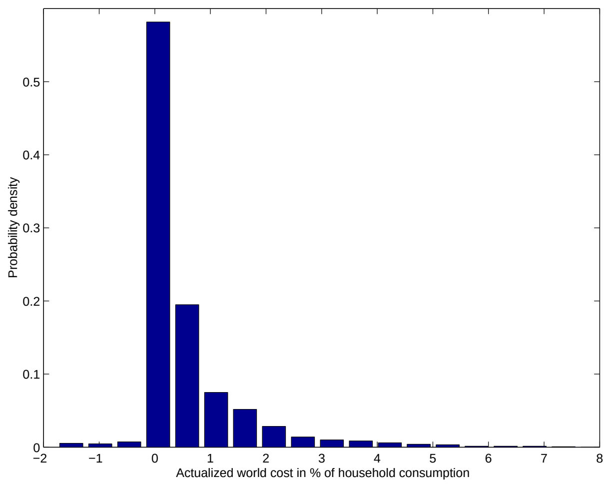

Figure 19: World welfare loss indicator pdf.

before 2030 lead to an amount of CO_2 sequestration above the GHG abatement required in 2050. We suppose in GEMINI-E3 that the CCS installed would not be removed, it might be more realistic to assume that in these situations the sequestration facilities are disconnected from the power plant. This result also shows that sequestration is used first, then when the abatement increases the potential for sequestration is used to its maximum and peaks at 20% to the total reduction. We compared the results of GEMINI-E3 concerning the share of emissions sequestered with four other models in the case of a scenario in which we assume that the total atmospheric radiative forcing resulting from long lived greenhouse gases would not exceed 3.5 W/m^2 at any time during the 21^{st} century[11]. Table 17 indicates the percentages of CO_2 emission reductions that are done via CCS in 2050. CCS appears to play a major role in the TIAM approach to CO_2 abatement, an important role for TIAMEC and DEMETER, and a more modest role for GEMINI-E3 and WITCH. These wide differences come from widely different assumptions on the potential for sequestration allowed in each model, but also from the fact that TIAM is the only model having technological options for producing electricity, hydrogen and synthetic fuels from biomass with CCS, which result in negative

[11]This corresponds roughly to a mean surface temperature increases between 2.23 ^{o}C and 2.52 ^{o}C with a climate sensitivity equal to 3 according to the TIAM model.

	World	EUR	OEC	ASI	EEC	ROW
Intercept	8.418	8.872	6.533	21.442	7.208	9.617
	(107.4)	(37.5)	(90.1)	(12.1)	(87.9)	(109.2)
log(aeei)	**-0.681**	**-0.863**	**-0.509**	**-1.785**	**-0.440**	**-0.585**
	(-48.7)	(-20.1)	(-39.4)	(-6.9)	(-30.1)	(-37.3)
log(σ)	-0.448	-0.805	-0.876	-1.484	-0.448	-0.374
	(-14.2)	(-8.1)	(-30.1)	(-3.1)	(-13.9)	(-10.8)
log(σ_e, σ_{ef})	-0.293	-0.307	-0.202	-1.194	-0.217	-0.340
	(-16.4)	(-5.6)	(-12.2)	(-5.1)	(-11.6)	(-16.9)
log(poil)	**-1.405**	**-3.621**	**-1.390**	**-1.343**	**-0.588**	**-0.511**
	(-53.9)	(-41.9)	(-57.7)	(-3.2)	(-21.6)	(-17.5)
log(gasi)	**1.051**	**0.638**	**0.638**	**7.049**	**0.457**	**0.399**
	(25.8)	(5.1)	(16.9)	(8.9)	(10.8)	(8.7)
log(grow)	0.209	0.077	0.060	-0.332	0.062	0.880
	(5.2)	(0.6)	(1.6)	(-0.6)	(1.5)	(19.6)
log(ccs)	0.017	0.001	0.025	0.039	0.021	0.010
	(2.7)	(0)	(4.3)	(0.3)	(3.3)	(1.4)
log(obj2050)	**-2.407**	**-2.817**	**-1.847**	**-6.943**	**-1.354**	**-2.519**
	(-117.4)	(-45.2)	(-97.4)	(-11.6)	(-63.1)	(-109.4)
yccs	-0.031	0.135	-0.074	-0.354	-0.121	0.052
	(-2.5)	(3.5)	(-6.4)	(-2)	(-9.3)	(3.7)
Adjusted R^2	0.93	0.76	0.91	0.76	0.79	0.90

Table 16: Estimate of the welfare cost.

emissions of CO_2. Such technologies are powerful ones when strong reductions are needed, and they are heavily adopted by the TIAM model. They go a long way in lowering the cost of abatement and thus the price of carbon as we saw in previous sections.

DEMETER	38%
GEMINI-E3	19%
TIAM	75%
TIAMEC	43%
WITCH	11%

Table 17: Percentage of emission reductions effected via CCS in 2050.

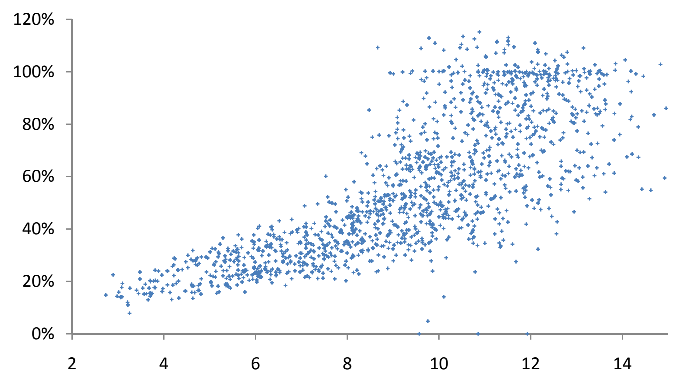

Figure 20: Percentage of emission reductions effected via CCS in 2050 in respect to the GHG emissions in Gt C-eq.

5.3.4 Deterministic equivalent solution vs. MC simulations

To conclude this analysis on climate policy scenarios we compare the results in the "average deterministic" run and the average of these results in the MC analysis runs. The most significant results are shown in Table 18.

	Deterministic equiv. sol.	Averages of MC simulations
CO_2 price in 2030	\$17	\$63
CO_2 price in 2050	\$87	\$84
Discounted world cost (trillion \$)	-3.8	-8.0
% of electricity generation done by coal using CCS	74%	66%

Table 18: Deterministic equivalent solution vs. MC simulations.

These output values are remarkably different. We notice that the average deterministic run underestimates the carbon price in 2030 and the total cost. This shows how misleading could be an analysis based only on the use of average values in a deterministic model and this demonstrates the added insight on policy analysis that is brought by a stochastic analysis of these two models.

6 Conclusion

The purpose of this paper was to show the impact of uncertainty on the integrated assessment of climate policies. We identified four classes of uncertainties related to climate, technology, economy and energy prices, respectively. Several conclusions emerge from this work:

The main uncertainty is related to the climate sensitivity, and it is necessary to determine its value as soon as possible. Indeed we showed that if the climate sensitivity is too high, simply, the climate target cannot be achieved in the CGE model. This impossibility to meet stringent climate target has been also highlighted in the study done by the Energy Modeling Forum [11]. We also showed that the cost of climate policy is very dependent on the climate sensitivity, when the GHG emission constraint is below 7 GtC-eq in 2050, the cost increases very rapidly reflecting the difficulty in reaching the climate target.

Concerning the technological aspects of climate policy, we found that the availability of carbon free technologies is also determinant and that there is no single silver-bullet to combat carbon emissions. Thus, according to the model, CCS alone cannot provide the solution to the problem of GHG emissions increase and we must promote the development of a basket of carbon free technologies. From this perspective, we must encourage the development of substitution among energy forms but also between energy and other inputs. This means also that we must encourage all substitutions, and that the transition to a carbon free economy asked to modify our production process but also our way of life itself.

Our simulations have shown however that other factors are liable to affect the success and the cost of climate policy. The price of oil and behind it the behaviour of OPEC affects the possibility of reaching a target climate. The climate negotiation must therefore incorporate the specificities of these countries. Note that the oil exporting countries have always conditioned their participation in such an agreement to financial compensation transfers. The economic development of Asia is also a decisive factor in the cost and the success of a climate policy. China and India have to be integrated as soon as possible in the climate agreement.

Finally, we found that in 9% of runs the climate target cannot be reached, this means that if mitigation policies should be implemented, climate change adaptation policies must also be set up in parallel in case it would be simply impossible to achieve the target.

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