Project No 308329
ADVANCE
Advanced Model Development and Validation for Improved Analysis of Costs and Impacts of Mitigation Policies

FP7-Cooperation-ENV
Collaborative project

DELIVERABLE No 4.3
Policy instruments for innovation & uncertainty for mitigation, adaptation and geo-engineering technology
- The joint impact of uncertainty and innovation on climate control strategies -

Due date of deliverable: December 2015
Actual submission date: January 2016

Start date of project: 01/01/2013 Duration: 48

Organisation name of lead contractor for this deliverable: FEEM

Revision: 0

Project co-funded by the European Commission within the Seventh Framework Programme		
Dissemination level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

This project has received funding from the European Union's Seventh Programme for research, technological development and demonstration under grant agreement No. 308329 (ADVANCE)

DELIVERABLE NO. 4.3

The joint impact of uncertainty and innovation on climate control strategies

Name of all participants to the redaction of the report [a]

[a] Fondazione Eni Enrico Mattei

Table of Contents

1. Executive summary

This deliverable completes the work which has advanced the representation of uncertainty and technical progress in Integrated assessment models (IAMs). In particular, three new methodological applications have been developed and tested.

The first paper, “From Shared Socio-Economic Baseline Assumptions to CO2 Fossil Fuels Emissions”, has developed and tested a new way to represent uncertainty in IAMs. Traditionally, IAMs have represented parameter uncertainty using Monte Carlo techniques which allow to change one factor at the time. However, these methods do not allow to capture the interaction between parameters. Interactions are important because IAMs output is not a linear combination of input parameters. In order to overcome this obstacle, specific methods have been developed to carry out ‘Global Sensitivity Analysis’. However, these are computationally intensive, limiting their applicability to model comparison studies. In this paper, we have developed a new decomposition method which reduces the computational costs while allowing to compute both individual and interaction effects. We have applied this novel methodology to assess the role of key factors in determining emissions in the newly developed Shared Socio Economic scenarios (SSPs). The study involves 6 IAMs from the ADVANCED consortium, testifying to the feasibility of the approach in a large multi model assessment. All details are reported in the accompanying paper.

The other application is discussed in the paper “Modelling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models”. The technique of modelling to generate alternatives (MGA) allows to relax one key assumption of IAMs, meaning that of cost optimality. In reality, due to uncertainties in political and behavioural elements, economic optimization can be hardly achieved in reality. MGA allows to map the diversity of different energy systems that lie within its near cost minimum solution space, allowing to assess the stability of the solution outside its optimality. This technique has been applied to one IAM from the ADVANCE consortium, assessing a business as usual (BAU) case and a global CO2 reduction pathway scenario applied to SSP2. Full details are presented in the attached article.

The final example, “Decision frameworks and the investment in R&D”, has used yet another technique to incorporate uncertainty into IAMs. The paper uses importance sampling to assess how to best allocate Research&Development investments in low carbon technologies. The paper uses real data from three large expert elicitation studies and a incorporates them into an IAM. The results show that is is important to account for both the prospects for technological advancement and the interactions of the technologies in and with the economy.

All papers provide significant advancement with respect to the existing literature, and have shown that incorporating new methods to represent uncertainties is indeed feasible in large scale IAMs. This has allowed to assess the robustness of the IAMs results, and to attribute the sources of uncertainty to different fundamental policy drivers. The first two paper papers will be submitted to high impact peer review journals, while the third has been already published in the highly read journal “Energy Policy”.

RUNNING TITLE: Decomposing SSPs CO2 Fossil Fuels Emissions

From Shared Socio-Economic Baseline Assumptions to CO2 Fossil Fuels Emissions

Giacomo Marangoni[1,2*] et al.

[1]Fondazione Eni Enrico Mattei (FEEM) and Centro Euro-Mediterrano sui Cambiamenti Climatici (CMCC), Italy;
[2]Politecnico di Milano, Via Lambruschini 4b, 20156 Milan, Italy;

*__Correspondence:__
Giacomo Marangoni
Fondazione Eni Enrico Mattei
Corso Magenta 63, 20123 Milan, Italy
giacomo.marangoni@feem.it

Abstract

Climate Change Research has recently seen the introduction of five narratives, called Shared Socio-economic Pathways (SSPs), to describe alternative potential society developments with respect to the economy and the energy system. Different SSPs are distinguished by many factors, which influence the evolution of emissions as well as the ability to mitigate or adapt to them. The goal of this paper is to understand how cumulative CO2 emissions from fossil fuels, and in turn the resulting policy implications, depend on baseline assumptions. Most influential uncertain sets of inputs and their interactions are identified when moving from a middle-of-the-road scenario to either a green or a challenging world. To perform such quantification, we leverage on the results of six renowned climate-economy-energy integrated models. The sensitivity on the variable of interest is performed via discrete changes to five sets of inputs, regarding population, income per capita, energy intensity, fossil fuel availability and low-carbon energy technology development. Setups for these inputs are taken from the first three SSPs. It turns out that in the medium term, i.e. up to 2050, the top influencers of fossil CO2 emissions will be changes in energy intensity and economic growth. Different population pathways yielded the lowest impact. Resource and technology assumptions lie inbetween.

Introduction

The scientific community supporting the assessment of climate change policies with Integrated Assessment Models (IAMs) almost always rely on baselines, i.e. business-as-usual scenarios with given assumptions on future society, economy, resources availability and technology development. These generally exclude explicit measures for limiting GHGs, and serve as benchmarks when evaluting costs and benefits of such measures. Thus, these costs and benefits depend on and are at most as plausible as the baselines they refer to.

Climate Change Research has recently seen the introduction of five narratives, called Socio-economic development Pathways [7], to describe alternative potential society developments with respect to the economy and the energy system. Different SSPs are distinguished by both quantitative aspects, like specific country population and GDP, and qualitative descriptions, like high/low carbon intensity improvements or high/low energy intensity improvements, which influence the evolution of emissions as well as the ability to mitigate or adapt to them. Given the deep uncertainty of these aspects, considering a space of possible scenarios is necessary when using Integrated Assessment Models (IAMs) to robustly evalute climate policies and reliably inform the climate policy debate.

The goal of this analysis is to understand how the output of models, and in turn the resulting policy implications, depend on baseline assumptions, identifying the most influential uncertain sets of inputs and their interactions for different IAMs. Such research has several potential benefits for both modellers and policy makers: to assist in focusing modelling efforts on those inputs whose uncertainty counts the most, to direct decision making attention to the main drivers of the results, and to better understand whether only a subset of assumptions in the narratives like the SSPs would be enough to cover a similar uncertainty space. This parsimonious attitude towards inputs and assumptions becomes more and more desirable, as uncertainty can be thoroughly treated only up to few dimensions and IAMs become more advanced and computationally burdensome (i.e. curse of dimensionality).

Literature review

Several sensitivity exercises were performed in the past on IAMs. Nordhaus [6], by varying one factor at a time (OFAT) in a 1-6 standard deviation range, assessed the sensitivity of the social cost of carbon and GHG emissions of DICE, one of the most popular IAM, to 8 exogenous inputs. The ranking of key drivers simply depended on the distance of the factors from their mean values. The same sensitivity exercise was later expanded in different ways. Anderson et al. [1] did not limit the analysis to preselected inputs. Their sensitivity rankings also accounted for the whole sampled distributions, comparing the relative importance of all the parameters of DICE with respect to SCC, emissions and temperature. A similar study was performed by Butler et al. [3], providing a comprehensive model diagnostic evaluation that explicitly accounts for the parametric interactions and dependencies between DICE coupled climate and economic components. They find that uncertainties in population estimates, future technology efficiency, carbon intensity of production, and the emergence of replacements for carbon-based energy sources are the most critical to several relevant cost metrics.

The space of scenarios envisioned by SSPs framework was already taken into consideration for sensitivity purposes in Rozenberg et al. [9], who questioned the definition of SSPs and identified energy sobriety, equity and convergence as the most important factors in explaining future differences in challenges to adaptation and mitigation. In a way the present paper continues along this line of research, using different methods and employing multiple models.

Methods

Among the five scenarios defined in the SSP framework, we focus on the middle-of-the-road baseline, named SSP2, and two alternative ones, namely SSP1 and SSP3, towards either smaller or greater mitigation and adaptation challenges respectively. A partial but important proxy for such challenges is given by the level of cumulative CO_2 emissions from fossil fuels and industry over the next decades (CO2FFI in short). Six IAMs (GEM-E3, IMAGE, IMACLIM, MESSAGE, TIAM-UCL and WITCH) implemented the assumptions behind these scenarios (see SI for details), and reported this output of interest. It turns out that different scenarios yield different CO2FFI levels, with SSP1 and SSP3 on the lower and upper ends respectively (Supplementary Fig. **??**).

SSPs differ under many regards, so it is hard to say a priori what is really driving the observed changes. We assume that the output comes from specific choices on socio-economic and energy-related inputs and parameters, which we group in 5 main categories: population (POP), GDP per capita (GDPPC), energy efficiency improvements (END), fossil fuels availability (FF) and low carbon energy technology development (LC). Each of these macro inputs can take either SSP1, SSP2 or SSP3 level, and when all five groups are referring to the same SSP, they provide the corresponding SSP scenario implementation, net of neglected input features like land use, which only marginally affect our output of interest, i.e. CO2FFI.

Given this setup, we are able to design a scenario protocol to attribute the observed change in output to changes in these five groups of inputs when deviating from the middle SSP2 case to either one of its two variants here considered. We use in particular the scenario decomposition scheme by [2], illustrated in Figure 1, which provides information on the sensitivity to the single scenario features and their interactions with a linear computational cost in the number of inputs.

The 3 base SSP scenarios and their sensitivity counterparts are implemented either under a business as usual case (BAU), i.e. no coordinated climate policy enforced, or under a mild global carbon tax (CTAX30), for a total of 46 scenarios provided by each of the 6 models.

Results

Sensitivity of CO2FFI in 2050 can be visualized with the aid of a generalized tornado plot (see Figure **??**). When moving from SSP2 to SSP1, we observe a reduction in CO2FFI of 19.5% on average (left panel, BASE row). Thick transparent bars show the effects of moving individually each input category. For example, population alone on average brought emissions down by 3%, ranking last in affecting output. Fossil resources and low-carbon technology related assumptions rank inbetween the others, with a highly model-dependent effect. FF ranges from a 20% decrease to a null effect, while LC has a milder extreme effect of 10%, with even a small positive impact on the other side of the spectrum. Economic and energy intensity assumptions drive most of the change, at least individually, with a CO2FFI effect range of 8-25% and 6-25% in absolute value for END and GDP respectively. While similar in average magnitude, these two factors have exactly opposite sign, due to the SSP1 design. It turns out high income per capita counterbalances the low energy intensity with a potentially uncertain net effect, driven eventually down by a general predominance of END, with the help of the other factors pushing in the same direction.

The sum of the individual effects does not yield the observed BASE change across SSPs. This is due to the fact that by changing simultaneously we may have interaction effect, either amplifying or dampening the changes obtained by individual actions. LC and FF, for example, show a mild attentuation when interacting with the other inputs, with few exceptions. Again, the factors playing a major role are found in the END and GDP categories. And again, two opposite behaviors are found. Consistently across all models, GDP reduces its effect, going from an average of 18% to 11%. On the other side, END exhibits a heterogenous behavior: GEM-E3, IMACLIM and MESSAGE foresee no significant interactions; for IMAGE and WITCH it behaves like GDP, reducing its magnitude of impact; in TIAM-UCL it amplifies with the other inputs. Averaging across models the effect ranks first in magnitude.

Let us now move back to a middle-of-the-road situation and transition towards the more challenging world of SSP3 (right panel of Figure **??**). The change in output is more diverse and model-dependent: the less-green component counterbalances the less-growth one with different net results. CO2FFI does increase, but in a range from 1% to 35%. Compared to the previous case, impacts have opposite signs, making the tornado plot in figure look quite symmetrical. Rankings of magnitudes are also similar. One important difference is due to the role of interactions, which this time amplify the negative effect of GDP and dampen the positive effect of END. Here, the average total effect of GDPPC turns out to be greater than the one of END.

In Table 1 we can see how the ranking of CO2FFI drivers change over time and across climate policies. For each model, year and climate policy, a total effect without sign is estimated and normalized across factors, so that the most influential one is equal to 100. Ranges are obtained by bootstrapping the average across the available estimates by the 6 models, repeating the process for each factor, year and climate policy. In the medium term, i.e. up to 2050, a carbon tax leaves the ranking on average unaltered. Model uncertainty becomes more relevant though, as ranges generally widen. In the long term, few things change first in the BAU. POP becomes more relevant. LC is becoming on average more relevant in SSP1 and much less relevant in SSP3. The opposite happens for FF. GDPPC is pushed further down in SSP1, while getting full agreement across models for the first place in SSP3. END loses ranking points while widening its range. Adding the CTAX30 on the long run, rankings are further blurred, with notable exceptions of a clear lower ranking for LC in SSP1, GDPPC in SSP1, and END in SSP3, with GDPPC keeping a full ranking in SSP3.

Conclusions

Averaging results over models, END and GDPPC occur to be the most influential factors in explaining the observed change in cumulative fossil fuels CO2 emissions. FF and LC play an intermediate role, while POP scored last. Results are conditional to the width of uncertainty span by SSPs storylines (e.g. limited variation in population up to 2050 induces a minor role for population), the specific modelling choices in implementing the storylines and the different modelling responses. The ranking is also affected by the fact that individual impacts of input groups can be dampened or reinforced when these are varied together, which is the case for GDPPC for example, leading it behind END in SSP1 and above END in SSP3 in the ranking. Results exhibit similarities over time and with the addition of a mild carbon tax, even though they generally blur the rankings.

Further research would be needed to cast more light on the mechanics of interactions and on the correlations between deviations from means and models characteristics. It would be also useful to separate model response differences from model implementation differences. Such efforts, along with those undertaken in this paper, can provide important insights in a yet lacking and far from conclusive literature on IAMs sensitivity to baseline assumptions uncertainty.

Methods

Socio-economic pathways. The narratives behind the SSP scenarios are explained qualitatively in [8]. In particular, this work focuses just on the first 3 SSPs, which, if they were to be located in a mitigation vs adaptation challange space, would belong to the main diagonal. Here we assume that SSP scenarios are implemented by changing model inputs belonging to one of 5 categories, described below. Differences between SSP1 and SSP3 choices are highlighted, assuming that SSP2 lies somewhere in the middle.

- **POP**: refers to assumptions on regional population over the century. Estimates have been developed by the International Institute for Applied Systems Analysis (IIASA) at country level[5]. SSP1 has lower global population growth, while in SSP3 the latter is low in industrialized and high in developing countries.
- **GDPPC**: refers to assumptions on regional income per capita over the century. These are obtained by dividing the GDP level projections obtained with the `ENV-Growth` model by OECD specialists for the SSP scenarios[4] with the population levels above. SSP1 features a favorable economic growth, while SSP3 economy is weakened by international fragmentation.
- **END**: refers to assumptions on energy intensity. Qualitatively, SSP1 features a fast phase-out of traditional fuels, modest service demands and low energy intensity of services due to improved resource efficiency. SSP3 goes in the opposite direction,

with continued reliance on traditional fuels, high service demands and high energy intensity of services. Quantitatively, levels of world final energy demand per unit of GDP were harmonized across models and scenarios with the same END assumptions.

- **FF**: refers to assumptions on fossil fuels availability. Qualitatively, SSP1 features a fast decrease in fossil fuel dependency, reluctance to use unconventional fossil resources, slow extraction technology improvements and no trade barriers. SSP3 instead involves supportive policies to both conventional and non-conventional fossil fuels, with a medium to high development of extraction technology, partially counterbalanced by high trade barriers and support of energy security goals. Quantitatively, levels of world fossil primary energy per unit of primary energy were harmonized across models and scenarios with the same FF assumptions.
- **LC**: refers to assumptions on low-carbon energy technologies availability. Qualitatively, SSP1 features high development and high social acceptance of non-biomass renewables, along with a medium development and low social acceptance of nuclear. On the other side, SSP3 involves low development and medium social acceptance of non-biomass renewables, along with low to medium development and high social acceptance of nuclear. Quantitatively, levels of world renewables and nuclear primary energy per unit of primary energy were harmonized across models and scenarios with the same LC assumptions.

Elements related to land use and CCS are left out from this analysis. The assumption is to leave them unchanged at their SSP2 levels. Thus, in principle a scenario with all 5 input categories at level 1 is different from an SSP1 scenario with its comprehensive implementation. Nonetheless, we expect the listed categories to cover most of the driving factors behind our main output variable of interest (i.e. baseline CO2 from fossil fuels emissions).

Scenario decomposition. Let focus on a single model output $y \in \mathbb{R}$, e.g. global cumulative fossil fuels and industry CO_2 emissions in the period 2010-2050. We assume that each model $m \in 1, \ldots, M$ provides y for each vector $\boldsymbol{z}$ belonging to its feasible parameter space χ_m via a response function $f_m(\cdot) : \chi_m \mapsto \mathbb{R}$.

Each model in principle has its own parameter space and response function. To find a common ground, we identify a scenario space, i.e. a space with setups implementable across models in a consistent way. We describe such scenario space by discrete vectors $\boldsymbol{x} = [x_1, \ldots, x_n] \in \{0, 1\}^n$. Each component x_i is a scenario feature, which is model-independent, and can be either at its nominal value (i.e. 0) or deviate to an alternative value (i.e. 1). Here, the scenario features are POP, GDPPC, END, FF and LC. Nominal levels correspond to SSP2 assumptions, while alternative levels correspond to either SSP1 or SSP3 assumptions.

Second, a map is needed to translate these common scenarios to implementable parameters combinations, i.e. a function $g_m(\cdot) : 0, 1^N \mapsto \chi_m$ for each model. Hence, we can associate each scenario $\boldsymbol{x}$ with a model response $y_m = f_m(g_m(\boldsymbol{x})) = h_m(\boldsymbol{x})$.

When moving from the nominal scenario $\boldsymbol{x}^0 = [0, \dots, 0]$ to its alternative counterpart $\boldsymbol{x}^1 = [1, \dots, 1]$, we observe a finite change in the output $\Delta y = h_m(\boldsymbol{x}^1) - h_m(\boldsymbol{x}^0)$. To understand the contributions of the i-th scenario feature x_i in determining this change, we express the latter as the following finite sum of terms[2], dropping the model index m for brevity:

$$\Delta y = h(\boldsymbol{x}^1) - h(\boldsymbol{x}^0) = \sum_{i=1}^{n} \Delta_i h + \sum_{i<j}^{n} \Delta_{i,j} h + \dots + \Delta_{1,2,\dots,n} h \quad (1)$$

where:

- $\Delta_i h = h([x_1^0, x_2^0, \dots, x_{i-1}^0, x_i^1, x_{i+1}^0, \dots, x_n^0] - h(\boldsymbol{x}^0)$ is the observed change in output due to the individual change in the i-th scenario input;
- $\Delta_{i,j} h = h([x_1^0, x_2^0, \dots, x_{i-1}^0, x_i^1, x_{i+1}^0, \dots, x_{j-1}^0, x_j^1, x_{j+1}^0, \dots, x_n^0] - \Delta_i h - \Delta_j h - h(\boldsymbol{x}^0)$ is the change in output due to the simultaneous change in scenario inputs i and j net of the sum of the individual effects of i and j;
- and likewise for longer indices.

We then introduce the following finite change sensitivity indices:

- $\phi_l^I = \Delta_l h$ and its normalized version $\Phi_l^I = \dfrac{\phi_l^I}{\Delta y}$ will be referred to as the *individual effect* of input l;

- $\phi_i^T = \sum_{k=1}^{n} \sum_{i \in i_1, i_2, \ldots, i_k; i_1 < \ldots < i_k} \Delta_{i_1, \ldots, i_k} h$ and its normalized version $\Phi_i = \dfrac{\phi_i^T}{\Delta y}$ will be referred to as the *total effect* of input i, including all the finite changes terms involving that input;

- $\phi_l^T - \phi_l^I$ will be referred to as the *interaction effect* of input i, and will be equal to the sum of all contributions to Δy involving a change in input i plus changes for some other inputs.

The number of interacting terms determinig the total effect is exponential in the number of inputs. Nonetheless, a shortcut exists to evaluate the total effects with a number of evaluations of y (and thus runs of a model) linear in the number of inputs. This depends on the fact that total effects can be also calculated as[2]:

$$\phi_i^T = h(\boldsymbol{x}^1) - h([x_1^1, x_2^1, \ldots, x_{i-1}^1, x_i^0, x_{i+1}^1, \ldots, x_n^1]) \tag{2}$$

This motivates the table of runs asked to be run by each model (see Supplementary Table 1).

Integrated Assessment Models. The sensitivity analysis was repeated with six renowned global climate-energy-economy models. This provides useful information on high robust the results are to model uncertainty. The six models considered are briefly described below.

- **GEM-E3** (National Technical University of Athens, Greece) is a general equilibrium model that puts emphasis on: i) the analysis of market instruments for energy-related environmental policy, such as taxes, subsidies, regulations, emission permits etc., at a degree of detail that is sufficient for national, sectoral and World-wide policy evaluation; ii) the assessment of distributional consequences of programmes and policies, including social equity, employment and cohesion for less developed regions.
- **IMACLIM** (CIRED, France) is a recursive dynamics hybrid model, combining a general equilibrium approach with technology explicit modules. It is intended to study the interactions between energy systems and the economy, to assess the feasibility of low carbon development strategies and the transition pathway towards low carbon future.
- **IMAGE** (PBL, The Netherlands) is a recursive dynamics model that can be described as a geographically explicit assessment, integrated assessment simulation model, focusing a detailed representation of relevant processes with respect to human use of energy, land and water in relation to relevant environmental processes. The model aims 1) to analyse interactions between human development and the natural environment to gain better insight into the

processes of global environmental change; 2) to identify response strategies to global environmental change based on assessment of options and 3) to indicate key interlinkages and associated levels of uncertainty in processes of global environmental change.

- **MESSAGE** (IIASA, Austria) is an energy engineering partial equilibrium model soft-linked to general equilibrium model. At its core it is a technology-detailed energy-engineering optimization model used for energy planning. Through linkage to macro-economic, land-use and climate models it is capable of taking into account important feedbacks and limitations in these areas outside of the energy system.

- **TIAM-UCL** (University College London, England) is an energy systems partial equilibrium model. It uses the TIMES modelling platform (formerly MARKAL), and was originally intended to analyse energy systems. Scenario based simulations maximize the total discounted sum of consumer and supplier surplus over the model horizon, while taking into account the constraints (e.g. energy demand to be fulfilled, availability of energy resources etc).

- **WITCH** (FEEM, Italy) is a hybrid economic optimal growth model, including a bottom-up energy sector and a simple climate model, embedded in a game theoretic setup. It evaluates the impacts of climate policies on global and regional economic systems and provides information on the optimal responses of these economies to climate change. It also considers the positive externalities from learning-by-doing and learning-by-researching in the energy-related technological change.

Climate policies. The sensitivity analysis is performed twice, one for each of the following climate policy.

- **BAU**: no specific climate policy;
- **CTAX30**: carbon tax, starting in 2020, increasing at 5%/yr, and equal to 30 US$2005/tCO2eq in 2040.

End Notes

Acknowledgements The research leading to these results has received funding from the European Union's Seventh Framework Programme [FP7/2007-2013] under grant agreement n^{o}30832.

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Figures

Figure 1 | Logic behind the scenario protocol design for decomposition analysis. Each input is moved from a reference level (i.e. the one used in SSP2) to an alternative level (i.e. the one used either in SSP1 or SSP3). This gives information on the individual effect of the input on the output. An opposite scheme is used to infer information on the total effect of the input.

Figure 2 | Generalized tornado plot of the CO2FFI variable in 2050, BAU case, against the 5 inputs changing from SSP2 to either SSP1 or SSP3. The BASE row shows the relative response change for each model in CO2FFI when moving from SSP2 to either SSP1 (on the left) or SSP3 (on the right). The rows below instead reports the normalized sensitivity indicators relative to each scenario input. Individual effects are reported with transparent thicker bars, total effects with solid thinner bars and interaction effects with striped bars.

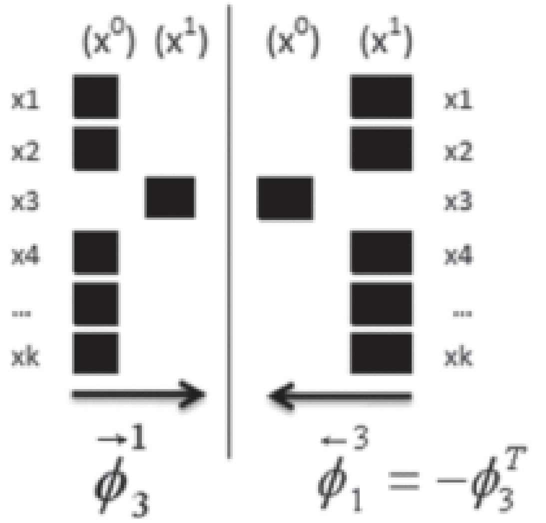
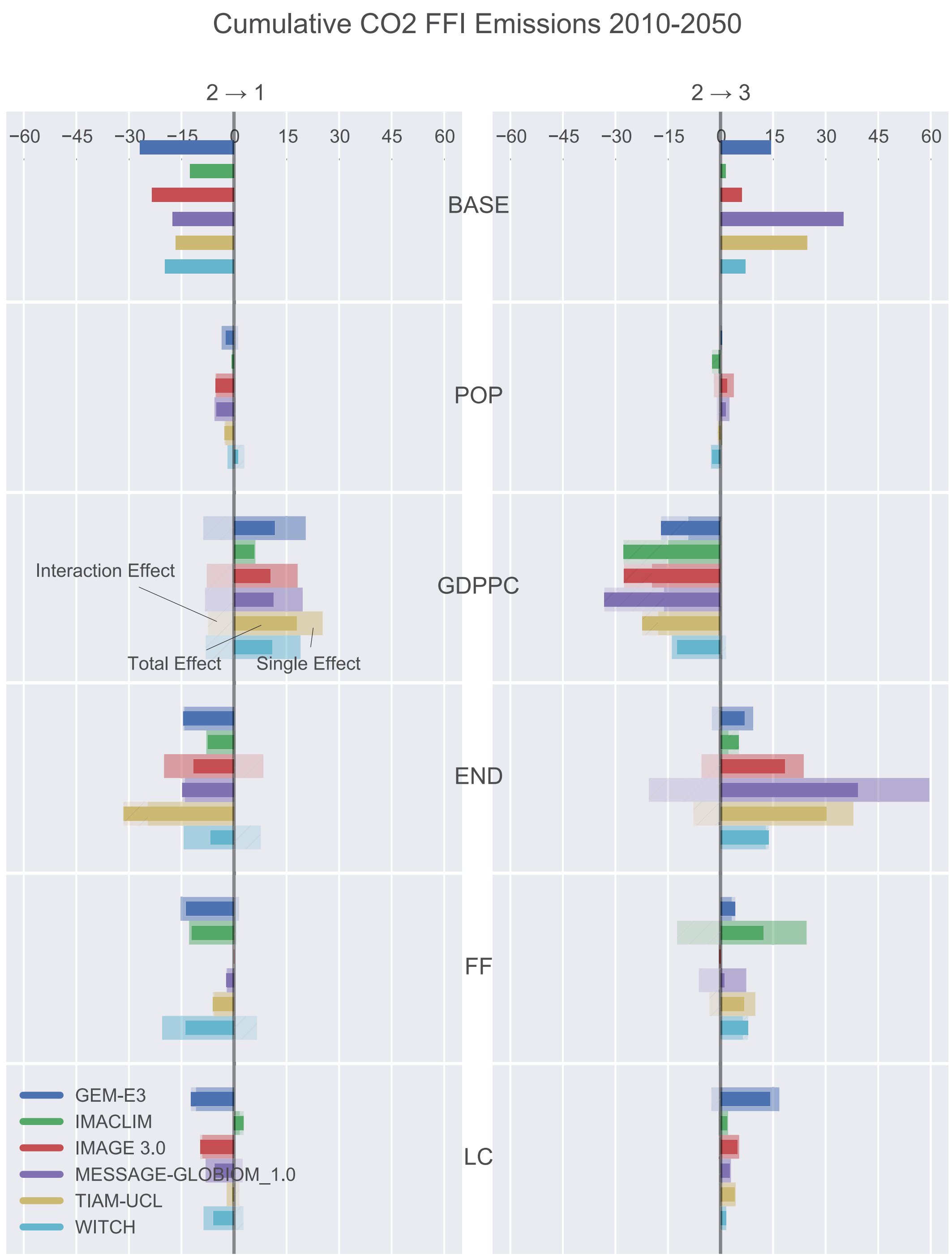

(x0) (x1)
(x0) (x1)
x1
x2
x3
x4
...
xk
x1
x2
x3
x4
...
xk
$\overrightarrow{\phi}_3^{1}$
$\overleftarrow{\phi}_1^{3} = -\phi_3^T$

Figure 1



Cumulative CO2 FFI Emissions 2010-2050
2 → 1
2 → 3
−60 −45 −30 −15 0 15 30 45 60
−60 −45 −30 −15 0 15 30 45 60
BASE
POP
GDPPC
END
FF
LC
Interaction Effect
Total Effect
Single Effect
GEM-E3
IMACLIM
IMAGE 3.0
MESSAGE-GLOBIOM_1.0
TIAM-UCL
WITCH

Figure 2

Tables

Table 1 | Ranges of normalized total effects of inputs on CO2FFI over time and under two different climate policies. For each model, year and climate policy, a total effect without sign is estimated and normalized across factors, so that the most influential one is equal to 100. Ranges are obtained by bootstrapping the average across the available estimates by the 6 models, repeating the process for each factor, year and climate policy.

Deviation	SSP1 ← SSP2				SSP2 → SSP3			
Year	2050		2090		2050		2090	
Policy	BAU	CTAX30	BAU	CTAX30	BAU	CTAX30	BAU	CTAX30
Input								
END	59-94	62-92	34-96	28-88	40-90	25-89	19-61	15-31
GDPPC	59-82	60-93	25-43	20-37	81-97	89-100	100-100	100-100
FF	20-85	11-81	18-86	6-81	10-42	9-47	8-67	3-78
LC	22-69	22-69	5-81	15-28	10-60	5-49	5-15	6-54
POP	9-34	9-42	18-57	21-84	4-13	5-22	7-16	12-57

Table 1

Supplementary Information |

From Shared Socio-Economic Baseline Assumptions to CO2 Fossil Fuels Emissions

Giacomo Marangoni et al.

Supplementary Figures

Supplementary Figure 1 | CO2 emissions from Fossil Fuel and Industry with potential drivers. First line: yearly CO2 emissions from fossil fuels and industry throughout the century. Second line: yearly world population, yearly GDP (PPP) per capita, yearly final energy per unit of GDP (PPP), yearly share of primary oil, coal and gas supply over all primary energy supply, and yearly share of primary renewables (including biomass) and nuclear supply over all primary energy supply. All values taken as reported in the SSP database (SSPDB) by the 5 SSP marker models. In grey: SSPDB results by each marker model. In pale red: min-max range. In blue: average.

Supplementary Figure 2 | CO2 emissions from Fossil Fuel and Industry across BAU SSP1, SSP2, SSP3 scenarios, as implemented in this exercise. With solid lines: results from the 6 models. In pale red: min-max range for the SSPDB.

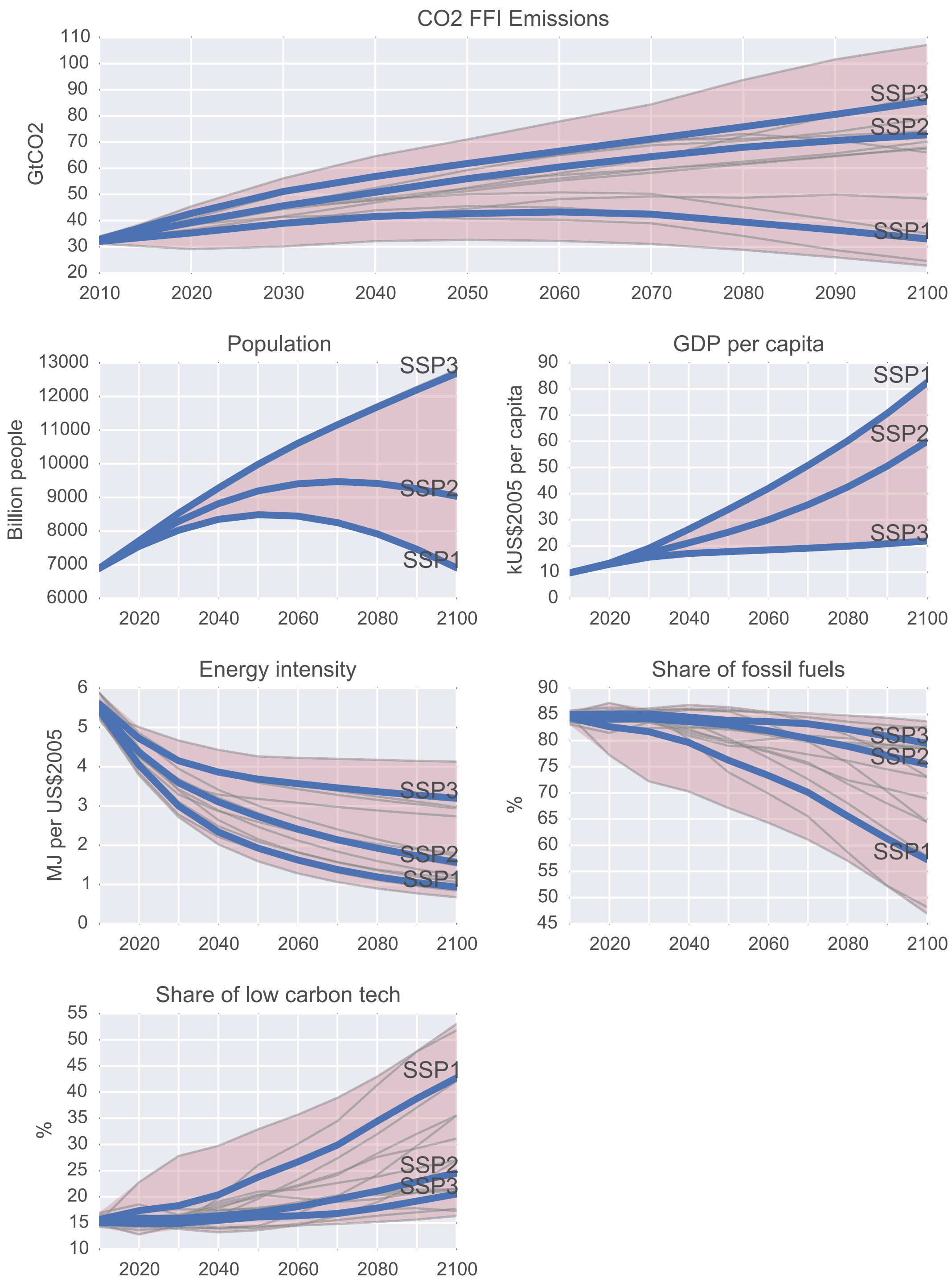
Supplementary Figure 3 | CO2 emissions from Fossil Fuel and Industry difference between BAU SSP2 and either SSP1 or SSP3 scenarios, as implemented in this exercise. With solid colored lines: results from the 6 models. Black line: 0 difference with SSP2. In pale red: min-max range for the SSPDB.

Supplementary Figure 4 | Time series of representative variables for the 5 considered scenario inputs, plotted across scenarios sharing similar assumptions for that input in

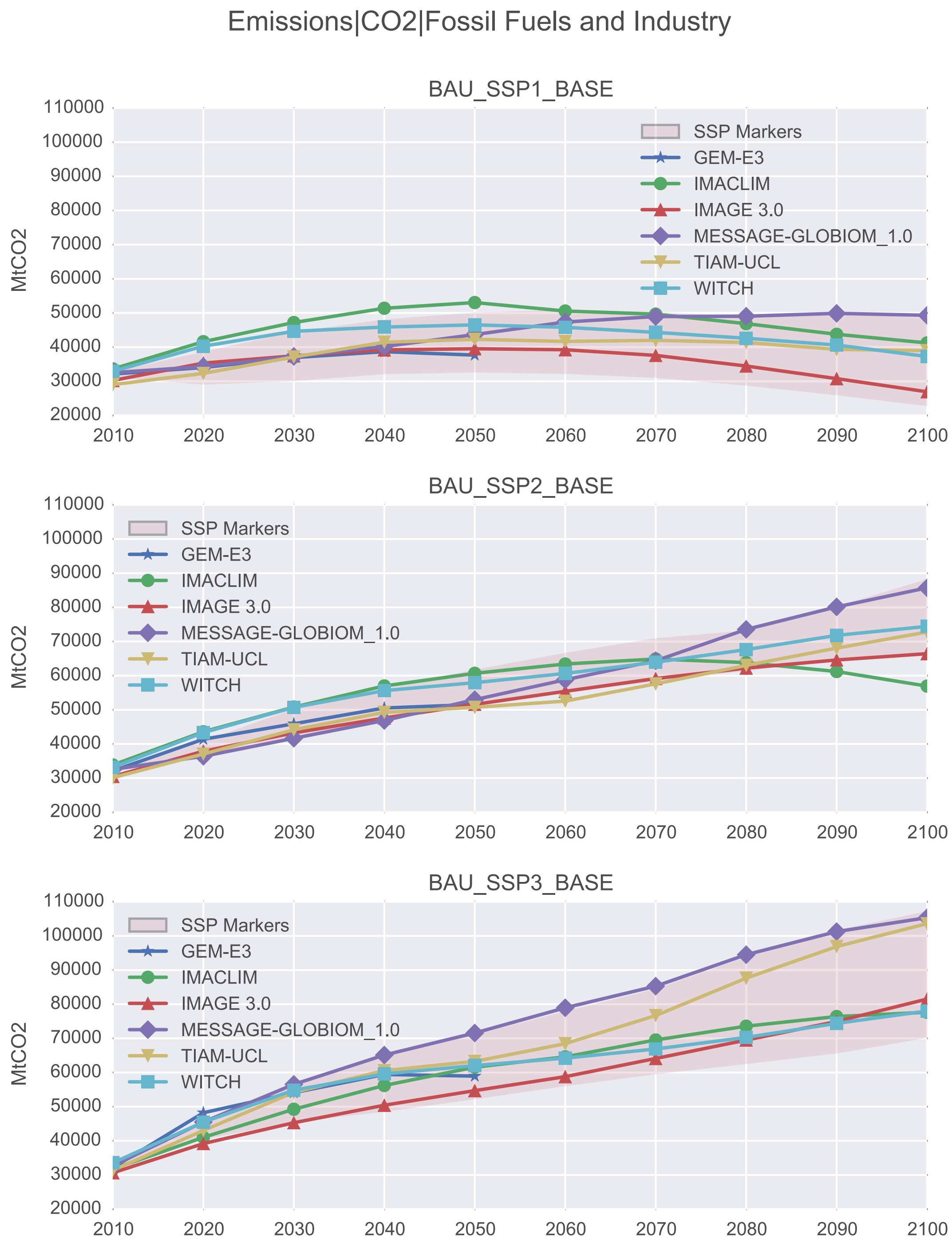
the BAU case. Plot shows proxy variables used to check agreement between SSPDB ranges (shaded in red) and results collected in the sensitivity scenarios of this exercise. The closer the line to the red shade, the close the implementation to its SSP definition. 5 variables were chosen as proxy for implementation proximity with respect to the 5 main input categories explored in the text (the same listed in Supplementary Figure 1): global population size for POP, GDP (PPP) per capita for GDPPC, final energy per unit of GDP PPP for END, share of fossil fuels (i.e. oil, coal, gas) per unit of primary energy for FF, and share of low-carbon energy (biomass, non-biomass renewables and nuclear) per unit of primary energy. Each subplot contains results for the ensemble of scenarios sharing the input setup expressed in the title, e.g. under "Population SSP1" we find BAU_SSP1_BASE, BAU_SSP1_GDPPC2, BAU_SSP1_END2, BAU_SSP1_FF2, BAU_SSP1_LC2, BAU_SSP2_POP1.

Supplementary Figure 5 | Boxplot across models of total and interaction effects on CO2FFI till 2050 vs 2090, BAU case.

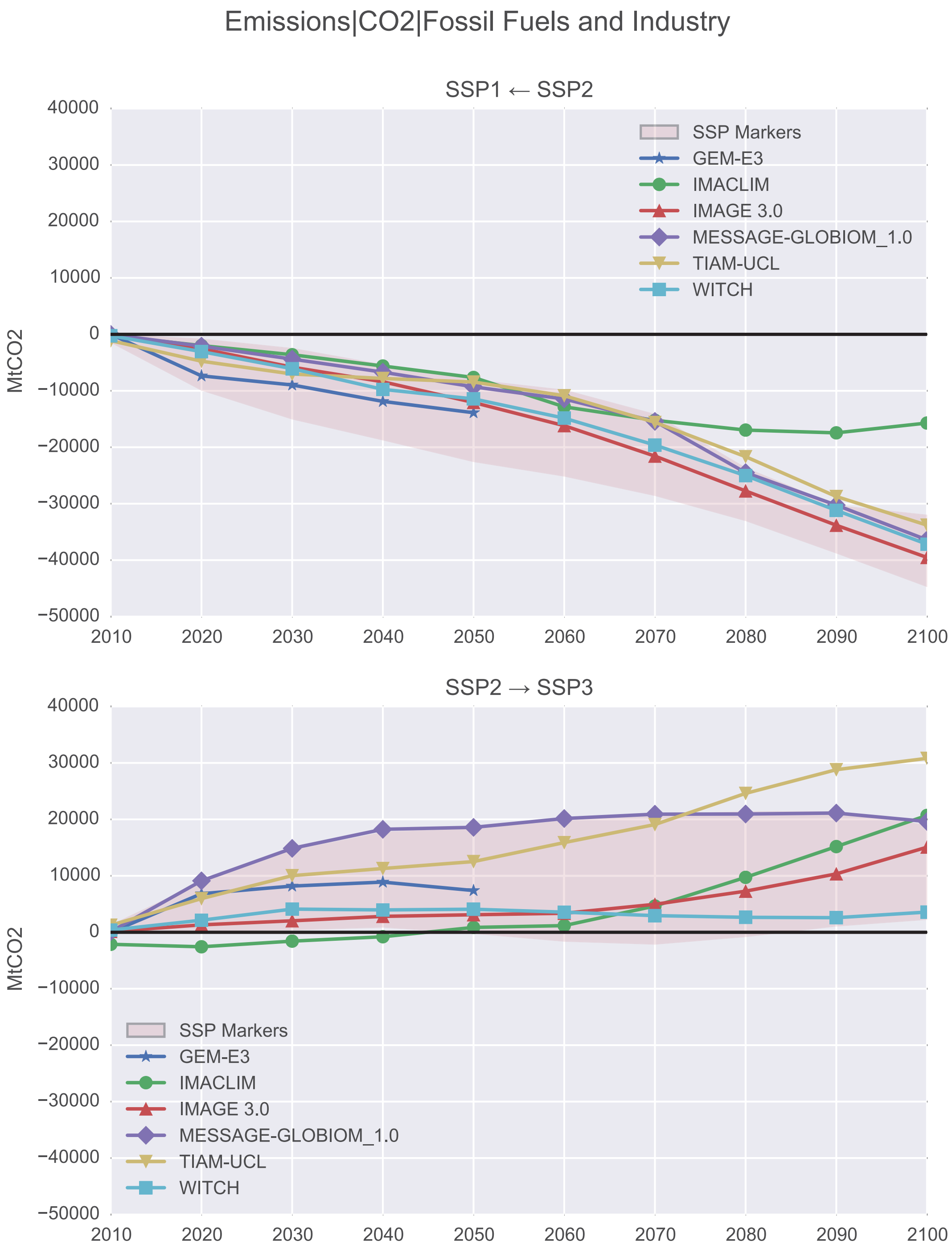
Supplementary Figure 6 | Boxplot across models of total and interaction effects on CO2FFI till 2050, BAU vs CTAX30 case.



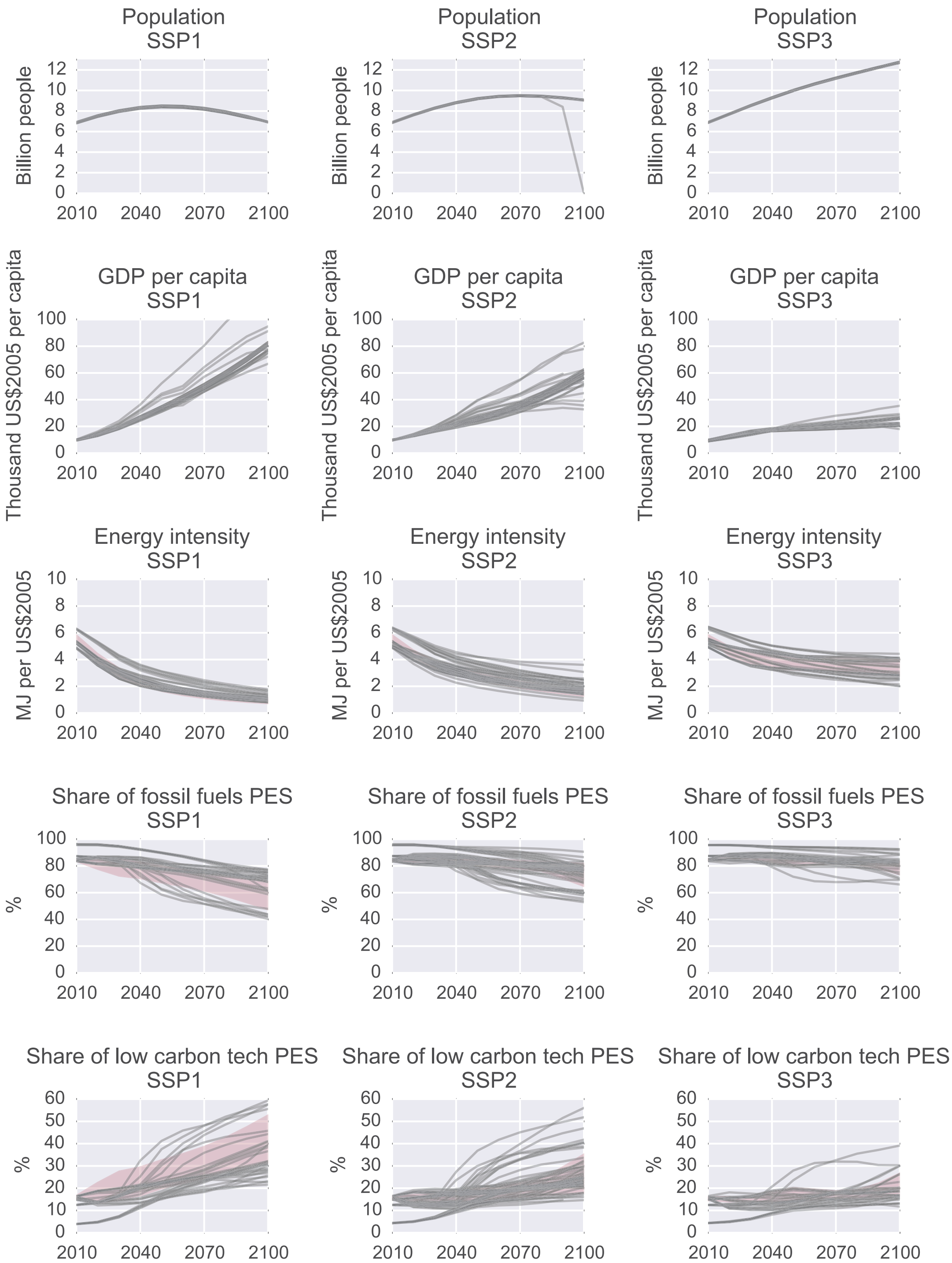
Supplementary Figure 1 | CO2 emissions from Fossil Fuel and Industry with potential drivers.



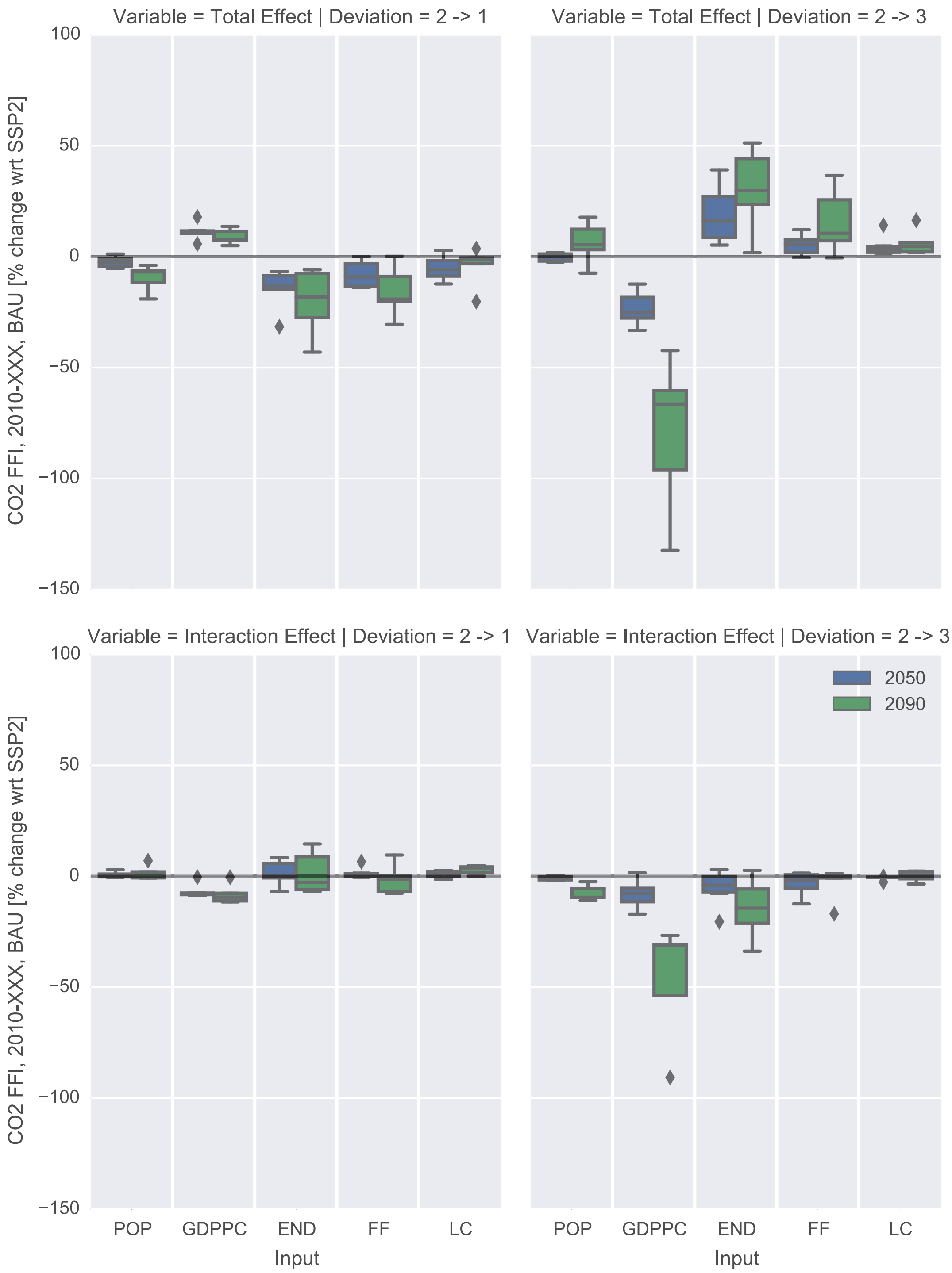
Supplementary Figure 2 | CO2 emissions from Fossil Fuel and Industry across BAU SSP1, SSP2, SSP3 scenarios, as implemented in this exercise.



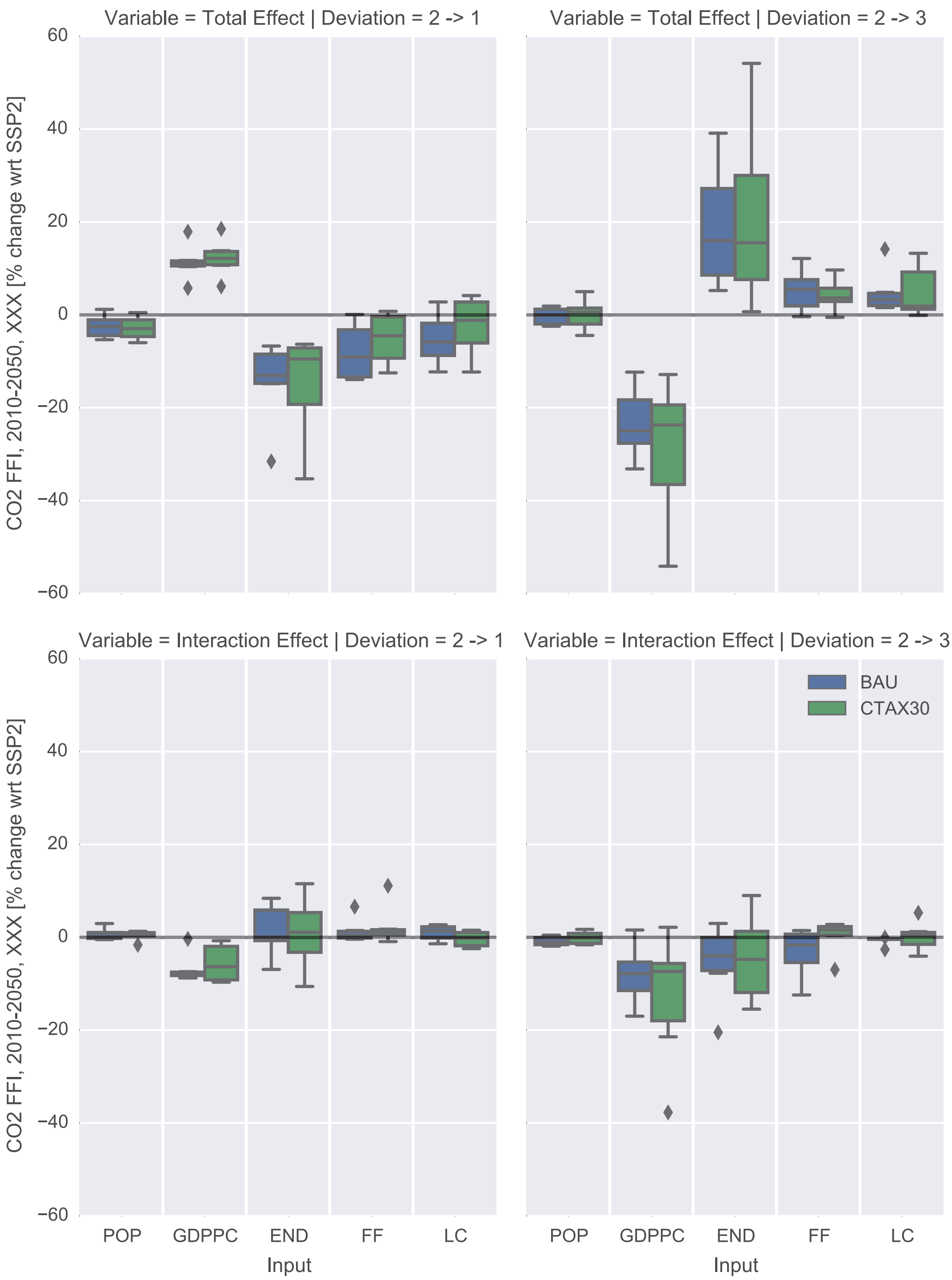
Supplementary Figure 3 | CO2 emissions from Fossil Fuel and Industry difference between BAU SSP2 and either SSP1 or SSP3 scenarios, as implemented in this exercise.



Supplementary Figure 4 | Time series of representative variables for the 5 considered scenario inputs, plotted across scenarios sharing similar assumptions for that input in the BAU case.



Supplementary Figure 5 | Boxplot across models of total and interaction effects on CO2FFI till 2050 vs 2090, BAU case.



Supplementary Figure 6 | Boxplot across models of total and interaction effects on CO2FFI till 2050, BAU vs CTAX30 case.

Supplementary Tables

Supplementary Table 1 | Details on the implementation by 5 of the 6 modelling teams of the END, FF and LC changes across SSP levels.

Model	Energy Demand	Fossil Fuels	Low-carbon Techs
GEM-E3	Regional energy intensity improvements from WITCH	Reserves from ROSE project. Prices follow.	LbD rates of Non-BIO REN.
IMACLIM	Motorisation rate / residential space / industrial goods consumption increase w/ wealth.	Extraction costs and availability of unconventional oil/gas.	LbD rates and max potential of REN (opposite for NUC).
IMAGE	Preference factor for low carbon fuels, energy intensity for services, reliance on trad. fuels	Learning factors, trade barriers.	Learning factors of REN and H2 (opposite preference for NUC), support for REN capacity.
TIAM-UCL	Growth in the service / industrial sectors via demand curves exponents.	Extraction costs and availability of oil/gas.	Inv./O&M costs of REN, max potential of BIO, support for NUC capacity.
WITCH	Factor productivity of energy in the production function tree. Transport fuel eff. and travel intensity.	Reserves and extraction costs from ROSE project.	LbD rates of REN and battery. Inv./O&M costs of NUC.

Supplementary Table 2 | Names and details of the scenarios needed for the decomposition analysis and implemented by modellers. Each number under an input column refers to the setup taken from the corresponding SSP base scenario for that input.

Scenario #	Scenario Name	POP	GDPPC	END	FF	LC
1	SSP2_BASE	2	2	2	2	2
2	SSP2_POP1	1	2	2	2	2
3	SSP2_GDPPC1	2	1	2	2	2
4	SSP2_END1	2	2	1	2	2
5	SSP2_FF1	2	2	2	1	2
6	SSP2_LC1	2	2	2	2	1
7	SSP2_POP3	3	2	2	2	2
8	SSP2_GDPPC3	2	3	2	2	2
9	SSP2_END3	2	2	3	2	2
10	SSP2_FF3	2	2	2	3	2
11	SSP2_LC3	2	2	2	2	3
12	SSP1_BASE	1	1	1	1	1
13	SSP1_POP2	2	1	1	1	1
14	SSP1_GDPPC2	1	2	1	1	1
15	SSP1_END2	1	1	2	1	1
16	SSP1_FF2	1	1	1	2	1
17	SSP1_LC2	1	1	1	1	2
18	SSP3_BASE	3	3	3	3	3
19	SSP3_POP2	2	3	3	3	3
20	SSP3_GDPPC2	3	2	3	3	3
21	SSP3_END2	3	3	2	3	3
22	SSP3_FF2	3	3	3	2	3
23	SSP3_LC2	3	3	3	3	2

Modelling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models

James Price* and Ilkka Keppo

UCL Energy Institute, Central House, 14 Upper Woburn Place, London, WC1H ONN

*james.price@ucl.ac.uk

Introduction

Avoiding dangerous global climate change, a goal that has been defined by international political agreement as limiting global mean surface temperature to a rise of no more than 2°C above pre-industrial levels, is probably the greatest challenge currently facing humanity. Achieving this goal will require large scale changes to the global energy system that serve to mitigate greenhouse gas emissions, and indeed are environmentally sustainable in the wider sense, while at the same time radically enhancing energy equity and maintaining continuity of supply.

Long time horizon energy-environment-economy models (hereafter E3 models) are one set of tools that can provide valuable insight into possible transition pathways which satisfy at least a stylised version of this formidable trilemma and as such provide key support to decision makers. However, a critical challenge when working with E3 models is appropriately exploring the large uncertainties inherent in the modelling procedure. Without careful elucidation, analysts and policy makers alike can be misled by the precision of the model output and lured into a false sense of security at the certainty of the implied energy system transition(s). We note that E3 models themselves adopt a broad range of under-lying methodologies and here we specifically focus our discussion on those that optimise some system parameter, usually seeking to minimise total system cost although other objectives may be equally valid, in a linear programming framework.

In general, E3 models function in a deterministic way, producing a single cost optimal pathway that meets the set energy service demands subject to any additional constraints that have been imposed on it (e.g. a cumulative greenhouse gas emission budget). Of course, it is very unlikely that today's, or indeed future, decision makers will follow such a well-defined cost optimal pathway, particularly on a global scale. In addition to such structural uncertainties, i.e. the model's formulation does not capture the full complexity of the real energy-environment-economy system, there are also significant input parameter uncertainties, e.g. the evolution of the capital cost of solar PV throughout the model's time horizon.

Parameter uncertainty is usually assessed using Monte-Carlo methods, within which we include more targeted scenario or sensitivity analysis as well as more general sampling techniques, which function by repeatedly perturbing input parameters in some way, solving the model and generating new realisations of the model's output (see e.g. Pye et al. (2015)). Once a sufficient number of realisations have been obtained it is then possible to establish probability distributions for key output parameters.

Exploring the impact of uncertainty associated with structural assumptions or simplifications on the other hand requires altering the underlying formulation of the model while keeping its input parameters fixed. Here we use the technique of modelling to generate alternatives (MGA; E. Downey Brill et al. (1982); DeCarolis (2011); Trutnevyte and Strachan (2013)) to relax one key assumption of an E3 model, that of cost optimality, and map the diversity of different energy systems that lie within its near cost minimum solution space. The aim being to assess the stability of the results implied by the model's least cost solution and to search for consistent insights that emerge under at least a portion of the full structural uncertainty budget. Viewed from a different but related perspective, MGA can also be used by the analyst to provide information on possible pathways which may meet additional criteria that decision makers value while at the same time being near least cost, e.g. what would a pathway look like with higher shares of renewables than the cost optimal solution.

In this study we apply MGA, the specific methodology of which will be detailed in a later section, to the TIMES Integrated Assessment Model in University College London (TIAM-UCL), a global E3 model built within the International Energy Agency's Energy Technology System Analysis Program (IEA-ETSAP) TIMES framework[1].

The Model

TIAM-UCL is a technology rich, bottom-up, cost optimising global energy system model instantiated within the generic and flexible TIMES model generator General Algebraic Modelling System (GAMS) code. The model aggregates the Earth's countries into 16 regions, each with their own energy system which is represented by technologies (processes) and commodities covering resource extraction/supply of all primary energy sources (e.g. coal, gas, oil, nuclear, biomass and renewables) through conversion and eventually culminating in end-use demand. On the supply side, fossil and biomass resources can be traded between regions while energy service demands are exogenously prescribed at the regional level based on drivers such as GDP, GDP per capita and population. The model runs from its base year of 2005 to 2100, first in 5 year intervals and then after 2050 in 10 year intervals. Within these periods the model "sees" the same energy service demands on a yearly basis so, for example, the 2020 interval has the same demands between 2018 and 2022.

In standard formulation, the aim of the model is to ensure supply at least matches demand (i.e. supply $\geq$ demand) across the energy systems of all regions and for all time-steps simultaneously while minimising total system cost (the objective function) and subject to all specified user constraints. This linear program is solved by the commercial optimiser CPLEX. In the MGA methodology described in the next section, which involves maximising a new objective function, the supply/demand matching is altered such that supply = demand throughout the entire energy system. Also, owing to the computational expense of the technique, the model is run from 2005-2050.

The MGA Method

MGA is a general, catchall term for any method that seeks to sample the near cost optimal solution space of a model and has a number of steps that are, typically, common to all implementations of the technique:

1. The model is solved in standard formulation and a least cost energy system transition pathway obtained.

2. The total system cost of this pathway, scaled up by a small amount or slack (usually $> 1\%$), is entered into the model as a new constraint. Here we use a cost slack of 1%, i.e. the new constraint is $total\_system\_cost \leq optimal\_system\_cost * 1.01$, chosen both to demonstrate the technique and to ensure that solutions produced are very close to the cost minimum. We note that the deviation of real world decision makers away from cost minimisation may well be significantly larger (Trutnevyte, 2015).

[1] `http://www.iea-etsap.org/web/Times.asp`

3. A new objective function is formulated with the specific aim of exploring the near optimal region defined by the constraint in step 2. This reformulation of the model is also subject to all constraints from the standard formulation in step 1.

The scope of possible formulations for the new objective function is large and could include, for instance, maximising the amount of primary energy from wind or minimising the utilisation of certain end-use technologies, with both energy systems being only marginally more expensive than the optimal run. Here we use an objective function formulation that searches for a set of transition pathways that are very nearly least cost but also maximally different from one another in terms of the fuel mix of their cumulative primary energy consumption:

$$\text{maximise } D^{jk}_{min}$$

$$D^{jk} = \sum_i |PE^j_i - PE^k_i| \tag{1}$$

$$\text{s.t. } tot\_sys\_cost \leq optimal\_sys\_cost * 1.01$$

where i is a set that includes all the primary energy carriers considered, i.e. coal, gas, oil, biomass, nuclear, wind, solar, tidal, hydropower and geothermal, PE is the cumulative consumption (summed globally and temporally between 2010-2050) of that primary energy carrier and D^{jk} is the set of L1 or Manhattan distances between this MGA iteration (j) and all previous iterations including the optimal run (k). That is, the first MGA iteration ($j = 1$) is generated such that its primary energy consumption is maximally different (greatest possible distance) from that used by the optimal run. For the next MGA iteration the set k includes the optimal and the first MGA iteration and the set D^{jk} now contains two distances, the minimum of which must be maximised. The procedure can then be repeated, each time ensuring that the newly generated scenario is maximally different from all previous pathways and we note that this particular iterative approach to MGA has been applied outside the energy and climate field in a number of studies (Loughlin et al., 2001; Zechman and Ranjithan, 2007; Rosenberg, 2015).

In this way the subset of model solutions that exist within the cost space defined by the new constraint added in equation 1 is sampled and a set of radically different pathways obtained. As will be shown, this set of pathways then allows the analyst to begin to understand how stable and robust various features of the energy system transition proposed by the cost minimal solution are by identifying key consistencies across MGA iterations. Such a set can also begin to facilitate an exploration of additional criteria that may be of interest to decision makers.

The Scenario

The purpose of this study is to describe and then demonstrate the implementation of a form of MGA within a whole energy systems model and to that end we use a version of the TIAM-UCL representation of Shared Socio-economic Pathway 2 (hereafter SSP2). SSPs are a new scenario framework that detail a range of plausible future story lines for the evolution of the global socio-economic system and are being used by the climate change community to carry out research on impacts, adaptation and mitigation (for further details see ONeill et al. (2014)). SSP2 describes a so-called “middle of the road” world with intermediate challenges to mitigation and adaptation with respect to SSP1 and SSP3. Quantitatively, this is implemented in TIAM-UCL using projections of country level population and GDP per capita, provided by the OECD and aggregated to the model’s 16 regions, combined with a set of assumptions which are calibrated to the SSP marker models[2] for final energy demand, low carbon technology availability and fossil fuel resource

[2] https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about

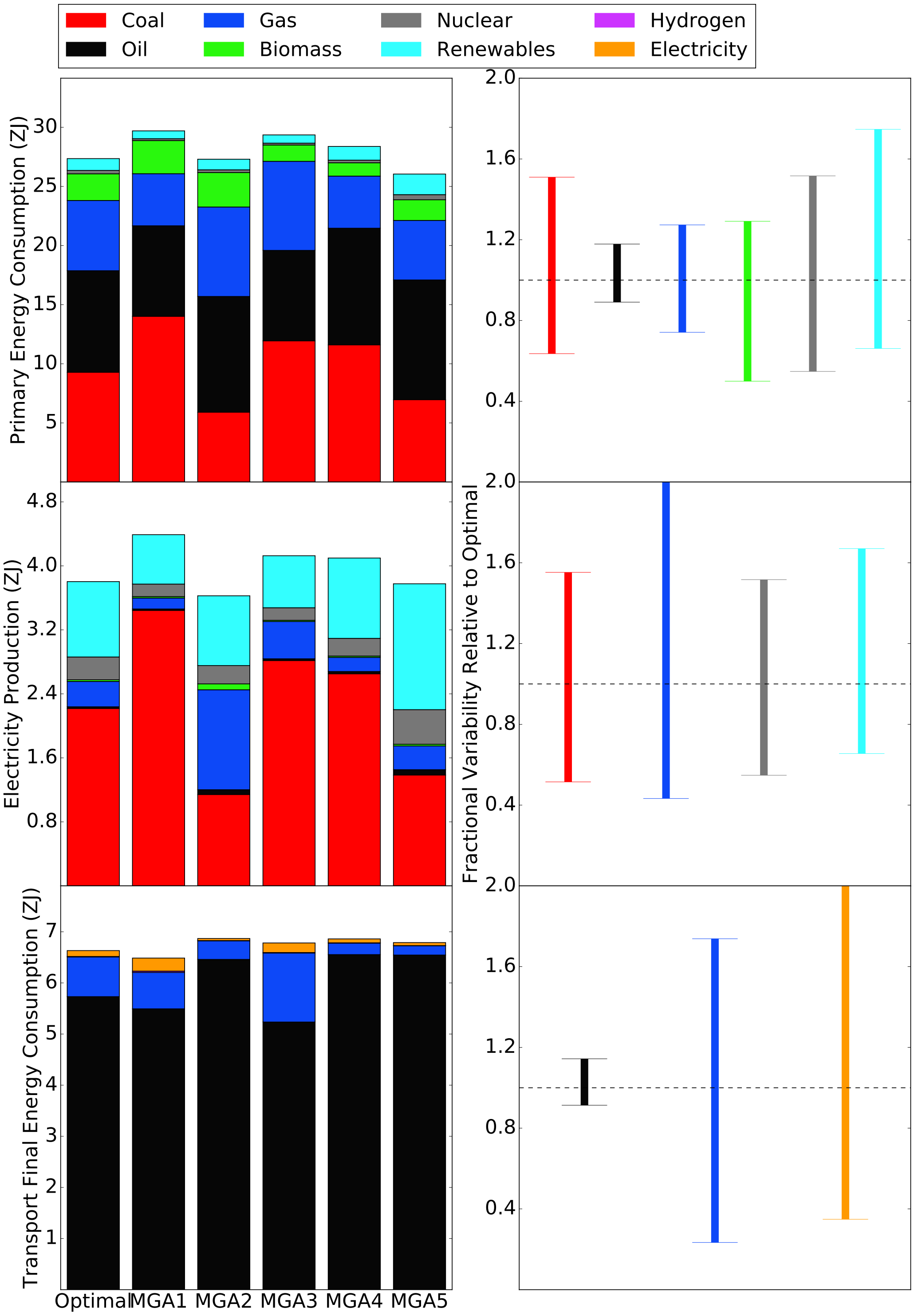


Figure 1: Results from applying MGA to our BAU scenario. The left column shows, from top to bottom, cumulative global primary energy consumption, electricity production and final energy consumption in transport between 2010-2050 (inclusive). The right column assesses the fractional variability of each energy carrier across the MGA runs in the corresponding left panel with respect to the optimal.

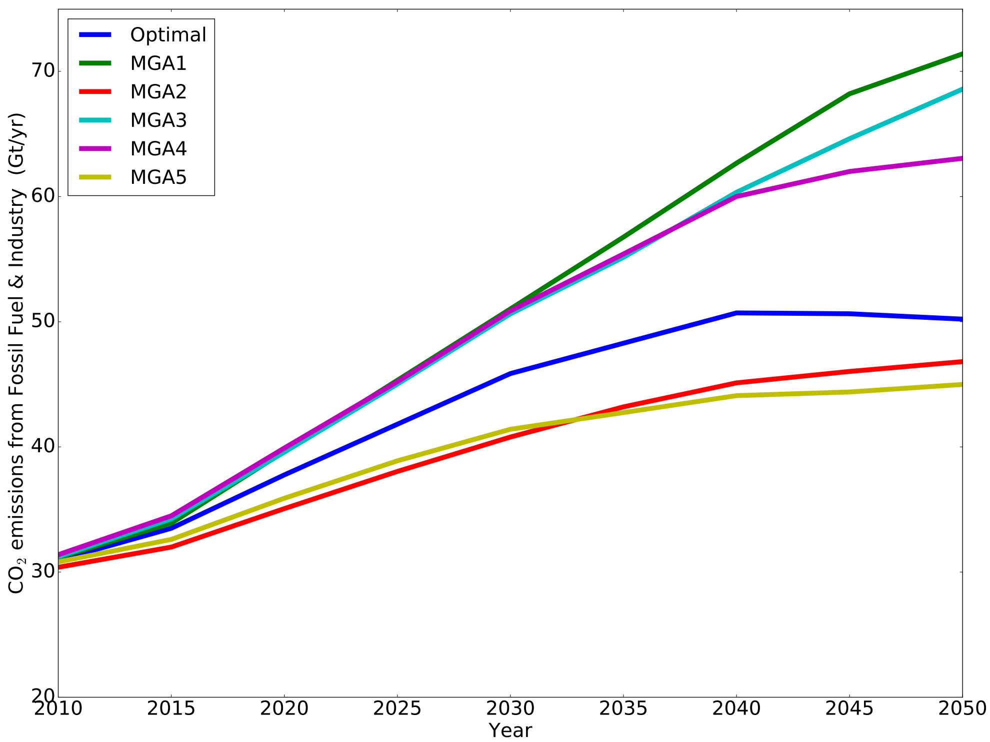


Figure 2: CO_2 emissions from fossil fuel and industry for our BAU scenario, including the optimal pathway and all MGA iterations.

potentials. We consider both a business as usual (BAU) case and a global CO_2 reduction pathway scenario applied to SSP2, i.e. 50% cut relative to 2005 levels by 2050 with emissions peaking in 2015 and linearly declining. However, it is worth pointing out that the detailed specifics of the underlying scenarios used here are not of key importance, apart from it being in keeping with those used by other cutting edge E3 models, as they are employed as a means to showcase our implementation of MGA and its ability to examine optimal solution stability.

Results

BAU

First we begin by analysing the results from our BAU scenario which are shown in Fig. 1. The top left panel of this figure displays cumulative global primary energy consumption between 2010-2050, i.e. the metric whose difference is maximised between each MGA run and all those previous to it including the least cost solution, for the cost optimal run and five MGA iterations while the top right panel shows the fractional variability of each energy carrier across the MGA runs with respect to the optimal. Note the variability panel is not a standard box plot but simply reports a maximum and minimum variation over the MGA iterations normalised by the results of the optimal run. From this plot, it is immediately apparent that sizeable variability is seen for important, i.e. significant shares of total primary energy, fuels such as coal and gas. The former varies by $\sim \pm$ 50% across the runs while the latter $\sim \pm$ 30% and so we see that just a minor deviation away from the structural assumption of cost optimality leads to large uncertainty in primary energy carrier consumption under this scenario. That said, by comparison one consistent insight does begin to emerge in terms of oil consumption, which shows variability of $<$ +20% and $\sim$ -10%.

The middle and bottom panels of Fig. 1 take a more sectoral view of the outcome of applying MGA to this scenario and allow us to assess how the variability at the primary

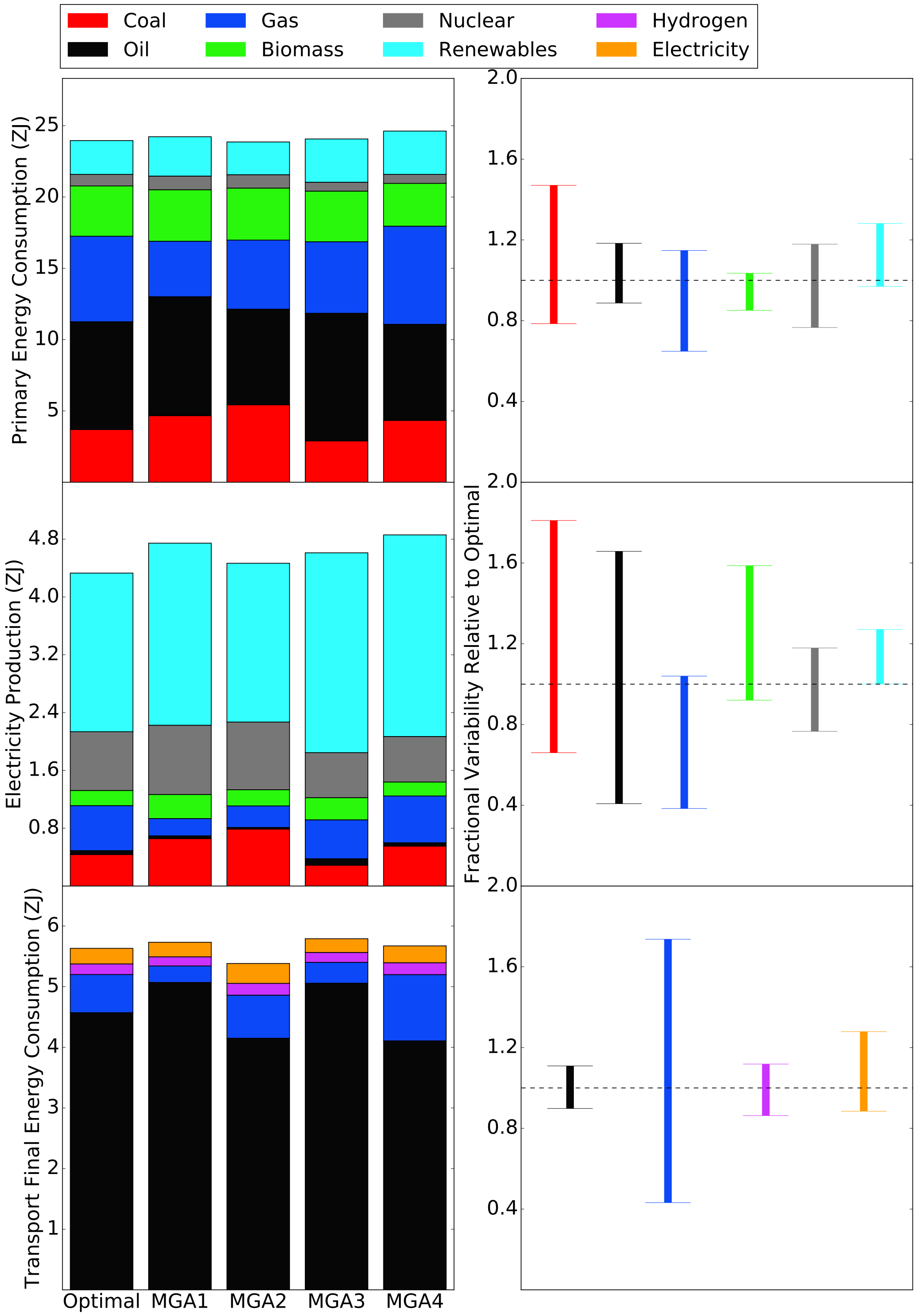


Figure 3: Results from applying MGA to our 50% CO_2 reduction by 2050 scenario. The layout of the figure is identical to Fig. 1.

energy level propagates through the energy system. The middle left panel shows cumulative global electricity production again between 2010-2050. Here we see the variability of coal and, in particular, gas discussed above mapping through to the power sector. Indeed, all fuel sources considered show a significant, i.e. $\sim \pm$ 50%, spread. However, as shown in the bottom pair of panels in Fig. 1, a consistent result is identified for the cumulative final energy consumption of oil in the transport sector. This indicates that this sector continues to rely heavily on oil even when total system cost is allowed to increase by 1%.

Fig. 2 shows an alternative view of how the variability of energy carrier consumption discussed above impacts the energy system. Here we see how an increase in coal use in MGA1, MGA3 and MGA4 relative to the optimal drives the system along a much higher CO_2 emissions trajectory. In fact, CO_2 emissions from fossil fuel and industry in MGA1 are almost 50% larger than those in the optimal run in 2050. On the other hand, MGA2 and 5 have significantly less emissions throughout the model's time horizon in part because they rely less on coal and more so on gas and renewables in the power sector, respectively.

To summarise, in this section we have demonstrated that applying a relatively small cost slack of just 1% to our BAU scenario and seeking to map the diversity of solutions within that cost space leads to significant variability around the optimal solution's results throughout the energy system. Put another way, these results highlight how unstable certain parts of the optimal solution are to fairly minor alterations in this portion of the model's structure.

50% CO_2 reduction

Next we move on to examining how a small deviation from the structural assumption of cost optimality impacts our mitigation scenario. Fig. 3 displays the results for the optimal run and a set of MGA iterations in the same format as Fig. 1. It is immediately apparent that all panels in the former figure show less variability than in the latter case. In primary energy terms, particularly consistent results stand out for oil, biomass and renewables with only coal use showing a sizeable range, i.e. $\sim$ +50% to $\sim$ -20%. Renewables and nuclear appear to be stable features of the power sector and, while not shown here, a similar plot for 2050 alone indicates that the near complete decarbonisation of the electricity system by that year is a robust finding across the MGA iterations. In the transport sector, the spread in oil use is again small ($\sim \pm$ 10%) indicating consistency in the narrative that electricity generation would be expected to decarbonise before transport when the energy system is responding to mitigation targets.

To show how the transition of the energy system proceeds in this scenario as a function of time, in Fig. 4 we plot the same three left hand panels as in Fig. 3 but this time at 5 yearly steps between 2010-2050 rather than cumulative totals over that period. This chart demonstrates the growth of renewables in the power sector and the steady decline of oil use toward mid century in transport. It also serves as a feasibility check for the pathways found by the MGA method used here by showing that no large or erratic jumps are observed and differences between MGA iterations and the optimal typically grow as one moves closer to 2050 and the model's flexibility increases.

In summary, the results presented in this section demonstrate how the MGA technique used here can assess the impact of structural uncertainty on key model output and establish that, while in some cases the spread of results is large, consistent insights do emerge. It is of particular importance to communicate such information to policy makers whose task it is to make robust decisions under uncertainty.

Conclusions

This work has described and demonstrated an MGA approach that generates a number of near cost optimal energy transition pathways which, within the context of the metric used here, are maximally diverse. We have shown that this technique can be used to elucidate

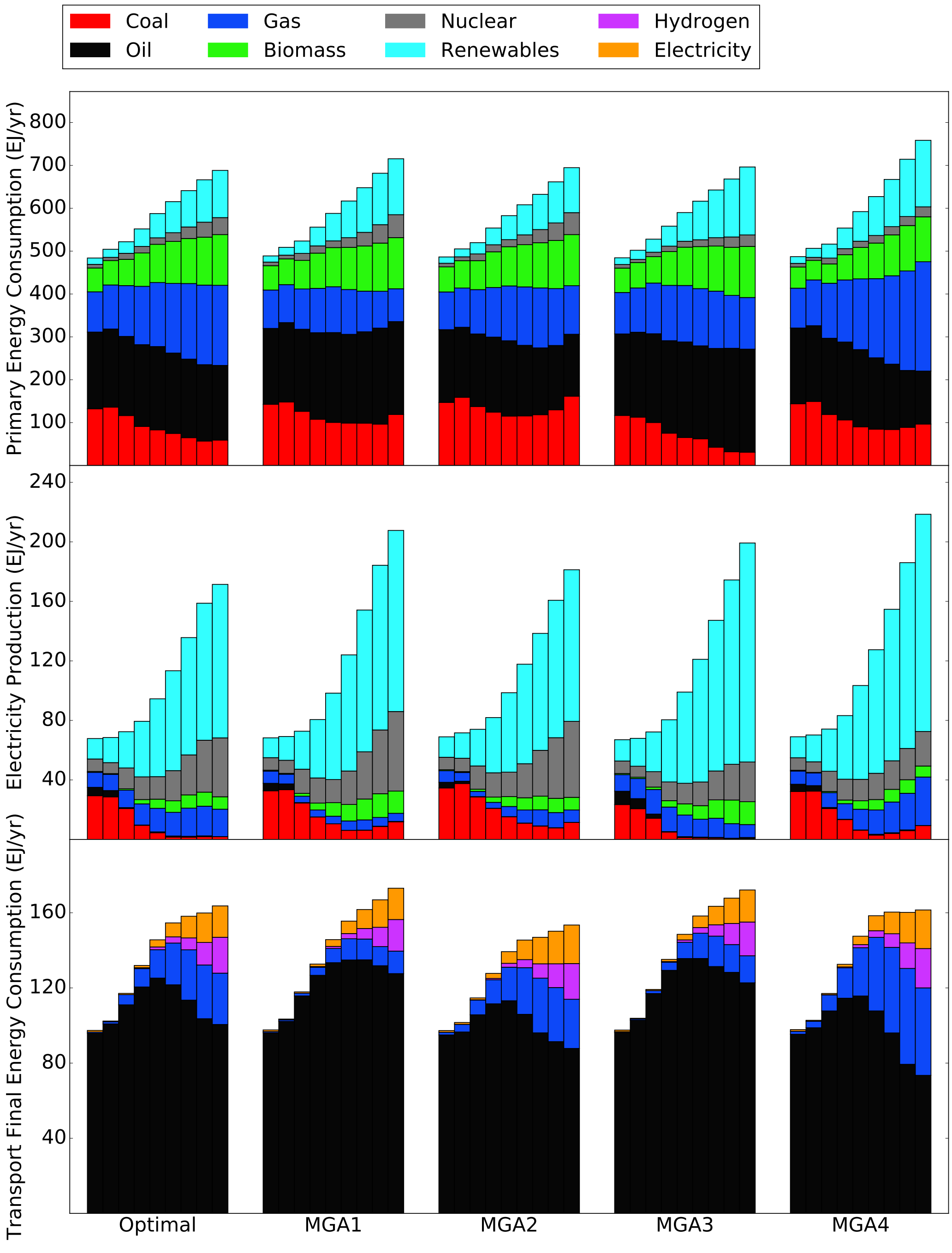


Figure 4: Plot showing how different components of the global energy system evolve between 2010-2050 in our mitigation scenario. The panels are the same as the left hand column of Fig. 1 but at 5 yearly steps rather than cumulative over the modelled period.

how structural assumptions in an energy system model may result in sizeable uncertainties across the system but also employed to tease out robust and consistent insights. At the same time, MGA can also be used to explore whether pathways in the near cost optimal space could address additional, unoptimised criteria. We believe both facets of MGA are important when working at the science-policy interface.

That said, while such near optimal methods are useful for characterising model flexibility, they assess but a portion of the model's full uncertainty budget and it remains a topic of further research to include both parametric and structural uncertainty simultaneously.

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Decision Frameworks and the investment in R&D

Erin Baker[a,1], Olaitan Olaleye[a], Lara Aleluia Reis[b]

[a] *Department of Mechanical and Industrial Engineering, College of Engineering, University of Massachusetts, Amherst, MA, 01003*.

[b] *Centro Euro-Mediterraneo per i Cambiamenti Climatici, Fondazione Eni Enrico Mattei (FEEM)*

Abstract:

In this paper we provide an overview of decision frameworks aimed at crafting an energy technology Research & Development portfolio, based on the results of three large expert elicitation studies and a large scale energy-economic model. We introduce importance sampling as a technique for integrating elicitation data and large IAMs into decision making under uncertainty models. We show that it is important to include both parts of this equation – the prospects for technological advancement and the interactions of the technologies in and with the economy. We find that investment in energy technology R&D is important even in the absence of climate policy. We illustrate the value of considering dynamic two-stage sequential decision models under uncertainty for identifying alternatives with option value. Finally, we consider two frameworks that incorporate ambiguity aversion. We suggest that these results may be best used to guide future research aimed at improving the set of elicitation data.

Keywords:

Decision making under uncertainty

Climate change

Stabilization Pathways

[1] Department of Mechanical and Industrial Engineering, College of Engineering, University of Massachusetts, Amherst, MA, 01003. Email: edbaker@ecs.umass.edu

Energy technology

Ambiguity Aversion

JEL Classification:

Q42

1. Introduction

The ultimate goal of collecting information on the impacts of R&D and of running simulations on Integrated Assessment Models (IAMs) is to inform decision making. In this paper we discuss how R&D data and IAM outputs can be used in different decision frameworks, and the impact that the different frameworks have on the ultimate results. We do this with an objective of providing insights into the optimal government funded energy technology R&D portfolio.

The Elicitation and Modeling Project (TEaM)[2] has provided a set of probability distributions over the outcomes of energy technology R&D investment, based on three sets of expert elicitations performed over 5 years by three different research teams [Anadon et al. [(2011), (2012), (2014)], Baker et al.[(2008), (2008), (2009), (2009), (2010), (2011)], Bosetti et al. [(2011), (2011), (2012)]]. The R&D outcomes are measured in terms of the future performance of energy technologies, including their costs and efficiencies. Though it is informative to consider the impact of R&D investments on these technological outcomes, it is also important to consider how specific technological outcomes are likely to impact economy-wide outcomes. The implications of R&D on the cost of a specific technology might be very large, but if there are less expensive alternatives to that technology, this impact might be smaller than one would expect prior to a general or partial equilibrium analysis. In order to evaluate the impact of technology improvements on societal outcomes, the TEaM project has used three IAMs – GCAM, Markal, and WITCH – to translate technological characteristics into metrics of interest, such as the cost to achieve a particular carbon emissions path, or the diffusion of different technologies into the economy. In this paper we focus on results from GCAM, but a similar analysis can be done using the results from the other IAMs.

[2] http://www.feem.it/getpage.aspx?id=4278&sez=research&padre=18&sub=70&idsub=86&pj=ongoing

Baker et al. (2014) presented the results of the effort to collect, standardize, and aggregate the results from the expert elicitation surveys, highlighting the diversity of results that stem from differences across experts and studies. In the present paper we analyze the impact of this diversity, as well as the impact of the decision framework, on optimal decisions about R&D investment allocations.

While an understanding of the distribution of data about technology inputs is very important, it is not easy to anticipate *a priori* how data distributions translate into economic results and finally into optimal decisions. In some cases, a wide range of probability distributions may nevertheless lead to a single robust decision (Baker & Solak, 2011); while in other cases probability distributions that look very similar may lead to divergent decisions. It is important to note that the optimal decision under uncertainty is not necessarily some average of the optimal decisions under certainty, nor is it necessarily near the optimal decision under a central case ((Baker, 2009); (Dow & Werlang, 1992)). For example, Santen and Diaz Anadon (2014) show that the investment path in solar R&D is qualitatively different under uncertainty, with a high initial investment followed by a very low investment in the deterministic case, and a medium initial investment followed by high investments in the stochastic case.

Some past work has shown optimal technology R&D portfolios to be surprisingly robust to assumptions about climate damages, about the opportunity cost of R&D, and about the underlying policy environment (i.e. a Stern-type stringent policy vs a Nordhaus-type mild policy) (Baker & Solak, 2014). Other work has shown that the type of policy (e.g., whether CO2 emissions are limited at all, through a cap and trade program, or through a clean energy standard for electricity) affects the optimal R&D investment portfolio (Anadon, et al., 2014).

Different questions require different decision support frameworks. In a world in which a stabilization goal has been chosen through political negotiation, then clearly the best framework is one that takes this goal as given. However, in a world in which decisions about environmental goals are ongoing, and are likely to depend on the outcome of uncertainties, a framework that allows for flexible adjustment of the strategy once learning about technological outcomes and/or climate damages has taken place is more appropriate. Additionally, some people argue that in a world with multiple conflicting probability distributions, decision frameworks should account for ambiguity-aversion. In this paper we consider how the optimal R&D portfolio differs across elicitation teams, and when (1) the stabilization pathway is a second stage choice compared to when it is given; and (2) the impact on a one-stage model of using a simple ambiguity-averse framework.

We consider how to use both the set of expert elicitation data collected in the TEaM project and energy-economic models to best support decision making. A first, important question is what the purpose is of explicitly including uncertainty in energy-economic models, specifically into IAMs. One reason for explicitly including uncertainty into models is to avoid nasty surprises; in the jargon of economics, we are concerned about risk aversion. Decision makers may be willing to give up some value with certainty in order to reduce the chance of a very negative outcome. A second reason is that some alternatives may have what is called "option value": they may provide us with flexibility to react to uncertain outcomes in the future, thus increasing their overall value. These kinds of alternatives cannot be identified without explicitly considering uncertainty. A third reason is what Sam Savage has termed the "Flaw of Averages" (Savage, 2009), or what economists know as Jensen's Inequality: the expected value of a non-linear function is not generally equal to the function of the expected value. All three of these reasons have one thing in common – non-linearities. In a non-linear system it is crucial to explicitly include uncertainty, or else risk significantly mischaracterizing the situation. Energy technology R&D in the face of climate change is a highly non-linear problem. Finally, some of the literature has argued that when the underlying probability distribution is deeply uncertain, ambiguity aversion should also be taken account of.

In the rest of this paper we discuss different frameworks for combining probabilistic data on energy technology R&D with IAMs in order to support decision making and present numerical results based on different elicitations and decision frameworks. In Section 2 we discuss a number of different frameworks and discuss the optimization models that we focus on. In section 3 we describe our detailed numerical example, comparing decision frameworks across different elicitation teams. Along with presenting assumptions, data, and solution methods, we discuss the methods for integrating the elicitation data into IAMs. In Section 4, we present the results of our numerical example; and provide a discussion and conclusions in Section 5.

Section 2: Frameworks for Uncertainty Analysis.

2.1. Decision frameworks

In this subsection we discuss a set of frameworks, including sensitivity analysis, Monte Carlo type analysis, single-stage decision making under uncertainty (DMUU), sequential DMUU, and full stochastic-dynamic programming. We conclude this subsection by discussing some frameworks to account for ambiguity aversion.

Sensitivity Analysis: When there is uncertainty over the values of inputs, the first level of analysis is sensitivity analysis. This is the most common approach taken by Integrated Assessment modelers. Sensitivity analysis can reveal which parameters are most important to carefully characterize, and can sometimes provide an estimate for how outputs of interest change with the uncertain input parameters. An example of sensitivity analysis is provided in this issue, in (Bosetti, et al., 2014). In this paper they consider how a range of technological parameters impact emissions paths and costs of stabilization. They find that the results vary somewhat by model, but that changes in the cost of nuclear seem to be important in a wide range of cases.

The benefits of sensitivity analysis are that it is relatively easy to undertake this analysis, and it nicely provides comparative statics, that is it shows how one output changes when an input changes. This allows modelers to get an idea of which parameters are most important to model carefully; and it can give some policy insights into how outputs change with inputs. The limitation of sensitivity analysis is that it will often not address the impact of non-linearities if they are present, as indicated above. That is because, as expressed in Jensen's inequality, the best alternative under uncertainty may not be equal to some kind of average of the best alternatives under certainty. Moreover, sensitivity analysis is generally done in the absence of probabilities, thus the analyst is unable to determine whether "interesting" effects have much, or even any, likelihood of arising.

Monte Carlo-type Analysis: When a probability distribution over one or various uncertain inputs is available, a Monte Carlo-type analysis can be performed. In this type of analysis, the analyst is able to estimate the distribution of the outputs by using draws from the distribution of the inputs. (We call it "Monte Carlo-type" analysis to include more sophisticated sampling techniques such as Latin Hyper Cube). In the case of TEaM, we can use Monte Carlo to estimate the probability distribution over outcomes of interest, given a particular R&D portfolio. This approach is numerically tractable when only a few uncertain inputs are used, although it gets computationally intensive with a growing number of uncertain inputs if one wants to ensure that the variance of outputs truly reflects that of inputs. Monte

Carlo-type analysis can provide a layer of insights above sensitivity analysis. It is particularly useful for descriptive models, in which we are most interested in gaining an understanding of the state of world. It is slightly less useful for decision models, in which we are most interested in understanding near term optimal decisions. In fact, the key limitation to Monte Carlo is that, generally, each run of the model is run under the assumption of the certainty of the sampled input values. It is possible, but not often done, to restrict early decisions in a model to be identical across all samples. However, this early scenario tends to be arbitrary, rather than any response to the actual uncertainty. Monte Carlo cannot tell us what the impact of uncertainty on the optimal decisions is, just what range of uncertainty over the outcomes is.

Single Stage Decision under Uncertainty: Like Monte Carlo, this framework explicitly incorporates uncertainty. Unlike Monte Carlo, this method includes an optimization component that allows the analyst to determine the impact that uncertainty has on near term optimal decisions, therefore accounting for the effects of non-linearity. However, this framework does not include learning or recourse, therefore will miss alternatives with “option value”. It can provide insights into non-linear problems and problems with risk aversion.

Two-stage Decision under Uncertainty: One step up from the previous is to add a second stage, in which a second set of decisions may be made after some or all the uncertainty is resolved. Adding this second stage has proved to be very powerful, allowing for a number of insights not otherwise available. The most prominent example of this was the work on investment under uncertainty, and the idea of “real options” (Dixit & Pindyck, 1994). That book, and many others since then, showed that the optimal near term action is not only significantly quantitatively different, but often qualitatively different as well. Some near term alternatives have “option value,” that is, they allow for more flexibility in the future to change course once the uncertain outcomes have been revealed.

Multi-Stage Decision Making under uncertainty: In the real world, of course, information is revealed over time, and many decision points exist. In order to reflect this, some models use a framework of multi-stage sequential DMUU. This framework can be implemented using sophisticated techniques such as stochastic programming or dynamic programming, with approximate dynamic programming (ADP) gaining popularity recently. For example, Santen & Anadon (2014) applied ADP techniques to solve R&D and power capacity expansion decisions in a realistic electricity systems model. Regardless of the solution technique, it is very computationally intensive. Therefore, most models implement considerable simplifications in order to implement this framework. Whether the addition of extra stages beyond 2 or 3 adds considerable insight is an open question [(Baker E. , 2006), (Webster, Santen, & Parpas, 2012)].

Frameworks to Account for Ambiguity Aversion: There is an increasing literature that suggests that policy makers should take ambiguity aversion into account when choosing climate change policies [(Lemoine & Traeger, 2012), (Kunreuther, Heal, Allen, Edenhofer, Field, & Yohe, 2013), (Gilboa, Postlewaite, & Schmeidler, 2009), (Heal & Millner, 2014)]. The idea is as follows: there is deep uncertainty around climate change (and climate change technologies) in the sense that scientists do not agree on a single prior probability distribution. It has been shown that behaviorally many people are in fact ambiguity-averse (See Ellsberg (1961) for classic case); that is they will choose an alternative with lower expected value if that alternative is presented as having “certain” probabilities rather than “ambiguous” probabilities, or as having an aggregated probability distribution rather than a compound probability distribution. While the Savage (Savage L. J., 1951) Subjective Expected Utility (SEU) framework, based on a set of very reasonable axioms, does not allow for ambiguity aversion, there exist alternate sets of axioms that do allow for ambiguity-aversion in decision making. There is not, however, widespread agreement on which framework to use in order to account for ambiguity aversion. In this paper we apply two simple frameworks found in the literature. The first is MiniMax Expected Utility (Gilboa & Schmeidler, 1989). This framework allows for using existing probabilities (as opposed to some frameworks which ignore all probabilities in favor of using very worst-case scenarios). This framework finds the expected utility for all possible priors, and then chooses the alternative that gives the highest expected utility under the worst case prior. This approach reflects an extreme ambiguity aversion since it does not rank or weight the possible priors. It has been shown that a more moderate framework such as "smooth ambiguity" often will give the MiniMax solution as ambiguity aversion moves to its maximum (Millner, Dietz, & Heal, 2010). The second approach we consider is a MiniMax Regret Expected Utility framework. It is similar to a traditional MiniMax Regret framework, but uses the priors to calculate expected utilities. This framework minimizes the regret of the expected utility for all possible priors, under the worst case prior.

In **Errore. L'origine riferimento non è stata trovata.** we present influence diagrams for the one-stage and two-stage decision frameworks that we consider in this paper.

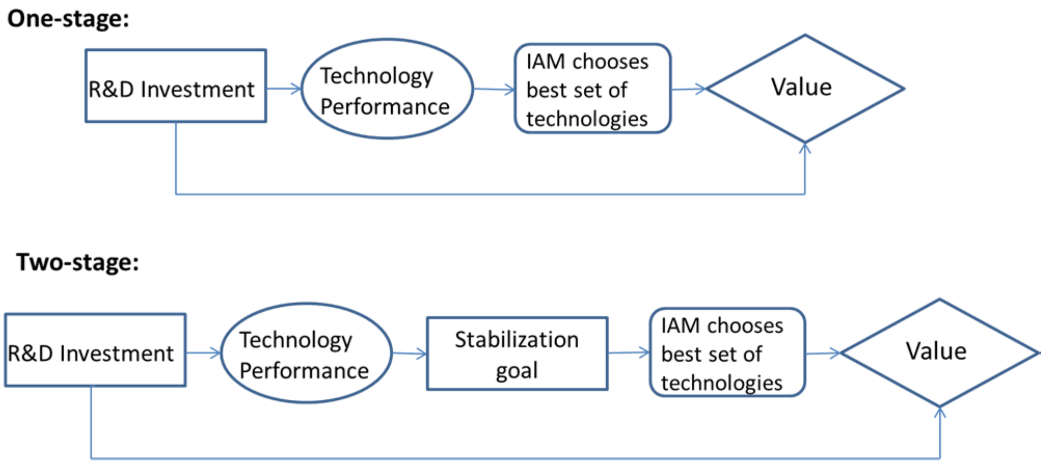

Figure 1: Influence Diagrams representing the two decision frameworks. Square nodes represent decisions; oval nodes represent uncertainties; rounded squares represent functions; diamond nodes represent values.

The top Influence diagram is a one-stage problem. The key decision (represented by a square node) is how much to invest in which technologies. The key uncertainty (represented by an oval node) is the performance of the technologies starting in 2030. The arrow going into the oval indicates that the probability distribution over technology performance is conditional on the R&D investment decision. We model the next step as a function: each IAM, when given a set of technology performance parameters and a Representative Concentration Pathway (RCP)[3] , minimizes the cost of the RCP by choosing deployment investments in different energy technologies. The overall objective (represented by the diamond value node) is to minimize the cost of abatement plus the climate damages plus the cost of R&D investment. Climate damages have some relevance in this framework even though damages are primarily related to the RCP; different technological outcomes can lead to slightly different emissions paths under the RCPs and therefore to different damages. In the unconstrained cases, technology is the only thing that drives any differences in the damages.

The lower Influence diagram represents a two-stage problem of sequential DMUU. In this problem the RCP – either 2.6 W/m^2, 4.5 W/m^2, or unconstrained – is chosen after the decision maker learns about the technology performance parameters. Climate damages play a more important role in this model, as information about the level of climate damages is in many cases the primary reason for choosing one RCP over another one. Everything else in this problem is the same as the one stage problem.

The decision maker is a social planner, considering both the cost of the public R&D and the global costs and benefits of stabilization pathways.

[3] We consider two RCPs, 2.6 and 4.5 W/m^2, roughly equivalent to a 450ppm and 550ppm stabilization goal in the GCAM model. See Van Vuuren et al. [(2011) , (2013)] for more details on RCPs.

2.2. Optimization models

To implement these frameworks we use a multi-model framework consisting of an IAM and simple optimization models. The IAM provides the estimated abatement costs and temperatures from climate change; and the optimization models determine the optimal R&D portfolio. In this section we describe the specific optimization models that we use to examine the importance of the different decision frameworks.

2.2.1 One-stage

For this framework, we take the RCP as given. The objective is to minimize the expected total abatement cost to achieve the given RCP plus climate damages plus the R&D cost.

$$\min_{I}\left\{E_I\left[\widetilde{TAC}_s+\tilde{D}_s\right]+\kappa F_I\right\} \tag{1}$$

Where $\widetilde{TAC}_s$ is the total abatement cost (the Net Present Value over the entire time horizon) to achieve the given RCP s, where $s\in\{2.6,\ 4.5,\ unconstr\}$. The $\widetilde{TAC}_s$ is a random variable whose outcome depends on the technological outcomes. The probability distribution over the technological outcomes depends on the portfolio, $I=\left[I_1,\ldots,I_5\right]$where I_j is the level of investment in technology j. F_I is the R&D funding amount for portfolio I:

$$F_I=\sum_{j=1}^{5}I_j \tag{2}$$

The opportunity cost of R&D funding is represented by a multiplier, κ. We include $\tilde{D}_s$, the estimated damages given RCP s, to be consistent with the second framework. They play some role, but a small one, since damages are dominated by the RCP, s. We will refer to this as a traditional SEU framework, in contrast to the MiniMax and MiniMax Regret frameworks below which account for ambiguity aversion.[4]

2.2.1.1 One-stage MiniMax Models

The MiniMax EU model is presented here:

$$\min_I \left\{ \max_\tau \left[E_{I(\tau)} \left[\tilde{TAC}_s + \tilde{D}_s \right] + \kappa F_I \right] \right\} \tag{3}$$

Where τ represents the elicitation team, $\tau \in \{\text{FEEM, Harvard, UMass}\}$; the τ in parentheses means that the expectation is being taken using the probability distribution from team τ. In this model, for each portfolio I we find the team that produces the highest expected cost; we then choose the portfolio that minimizes this cost.

The MiniMax Regret EU model is as follows:

$$\min_I \left\{ \max_\tau \left\langle \left[E_{I(\tau)} \left[\tilde{TAC}_s + \tilde{D}_s \right] + \kappa F_I \right] - \min_{I_\tau} \left[E_{I_\tau(\tau)} \left[\tilde{TAC}_s + \tilde{D}_s \right] + \kappa F_{I_\tau} \right] \right\rangle \right\} \tag{4}$$

Where I_τ represents a portfolio for team τ. The second "min" expression finds the optimal portfolio for a given team τ. The expression inside the triangle brackets gives the regret, the difference in cost

[4] We are minimizing costs rather than maximizing utility. We are not accounting for risk aversion.

between the portfolio under consideration and the optimal portfolio. We maximize this value across the teams to find the team distribution that gives us the most regret. Finally, we choose the portfolio that minimizes this regret.

2.2.2 Two-stage

In this framework, the RCP is a decision rather than an assumption. The objective is to minimize the expected total abatement cost plus climate damage cost plus R&D cost. This framework is solved only under traditional SEU.

$$\min_{I}\left\{E_{I}\left[\min_{s} TAC_{s}+D_{s}\right]+\kappa F_{I}\right\} \quad (5)$$

All variables are as defined in the section above. Note that the difference between this framework and the one-stage is that the RCP, s, is being chosen, and it is being chosen after we learn about the outcome of technological change. Thus, this is a two stage decision model, with sequential DMUU, albeit a very simple one.

2.3 Damages and Abatement Cost

The climate damage, represented by D_S, is calculated as follows:

$$D_{S}=\sum_{t}\delta^{t}\pi T_{t,S}^{2}G_{t} \quad (6)$$

Where $T_{t,s,}$ is the global mean temperature at time t, under RCP s; δ is the discount factor; π is a multiplier that converts the square of temperature to a fraction of GDP lost (based on the formulation in DICE (Nordhaus 2008); and G_t is the GDP (in trillions of dollars) at time t. This results in damages in the unit of trillions of dollars. The damages will show some variation under different technology scenarios, since different scenarios lead to slightly different abatement choices through time. However, these differences are small under an RCP.

Similarly, the TAC is defined as

$$TAC_s = \sum_t \delta^t AC_{s,t} \tag{7}$$

Where $AC_{s,t}$ is the annual abatement cost (in trillions of dollars) at time t, under an RCP. Note that the IAMs only report values for every 5 years. We assume that the temperature and the AC are linear between the reported years.

Section 3 Numerical Example

In this section we describe the numerical example we use to illustrate the roles of the different decision frameworks.

3.1 Technologies

We consider 5 technology categories: Solar PV, Electricity from Biomass, Liquid Biofuels, Nuclear Fission, and Carbon Capture and Storage (CCS). We use data on 8 parameters: Levelized Cost of Electricity ($/kWh) for solar PV; non-energy cost for electricity from biomass ($/KWh) and for liquid biofuels ($/gallons of gasoline equivalent); conversion efficiency for electricity from biomass and for biofuels (both in %); overnight capital cost for nuclear ($/kW); additional capital cost for CCS ($/kW); and Energy Penalty for CCS (%).

3.2 Generation of Payoffs using Energy Economic Models

Frameworks for DMUU (as opposed to sensitivity analysis and Monte Carlo) can be quite computationally intensive, and therefore are sometimes quite difficult to use with technologically-detailed IAMs. There have been a number of implementations of 2-stage and multi-stage DMUU frameworks using versions of models in the DICE family, a relatively simple IAM (See for example (Webster, Santen, & Parpas, 2012), (Lemoine & Traeger, 2012), (Crost & Traeger, 2010), (Yongyang, Judd, & Lontzek, 2012), (Traeger, 2013)). Even using the simple DICE model, however, most of the multi-stage frameworks have made simplifications of the original model. Moreover, DICE has a simplified technological set up, so while it might be very useful in investigating problems that look into climate system uncertainties, it provides fewer insights when studying problems concerned with technological change uncertainty and R&D decision making.

A couple of medium-sized IAMs have made some headway at incorporating stochastic programming, including WITCH ((Bosetti & Tavoni, 2009), (Johannes & Tavoni, 2013)), and MERGE (Durand-Lasserve, Pierru, & Smeers, 2010).

One approach that can be found in the literature is to take a multi-model approach. In this method, a technologically-detailed IAM is used to estimate the impact of technological change. Then, outputs of this model are used as input into a simpler decision framework that can explicitly incorporate sequential decision making. Examples of this approach can be found in Blanford (2009), combining MERGE with a simple decision model; Baker and Solak (2011) combining GCAM with a simple decision model; Baker and Solak (2014) combining GCAM with a stochastic programming version of DICE; and Anadon et al (2014), combining MARKAL with an analysis model to determine an optimal portfolio. In this paper we provide an example of this kind of analysis. We use modeling outputs from GCAM (Kim, Edmonds, Lurz, Smith, & Wise, 2006) to compute the payoffs that are used in simple one-stage and two-stage decision models. The GCAM model follows a protocol that encompasses one unconstrained baseline and two different RCPs, 2.6 and 4.5 W/m^2. A detailed description of the generation of the outputs we use here is in (Barron & McJeon, 2014); model characteristics and some basic results of a scenario-based model comparison are provided in (Bosetti, et al., 2014).

Importance Sampling: For this project we have piloted a new use for an old technique, importance sampling. Importance sampling has generally been used as a version of Monte Carlo -type analysis, when the area of interest in the input distribution has very low probability. That is, sometimes the function of concern is only non-zero over a portion of the distribution with very low probability. If one samples the distribution randomly, it is possible that there are no points in the sample from the area of interest. Importance sampling allows one to sample more frequently on the most valuable part of the distribution, and renormalize back to the actual distribution of interest, correcting for the use of an importance distribution (Owen & Zhou, 2000).

We use it here for a different reason. We wanted to be able to minimize the number of times we ran the large IAMs. As we have four alternative sets of distributions (one for each of the three elicitation teams plus the Combined distribution) and 3^5 possible portfolios (three levels of R&D for each of the five technologies), the number of runs for the IAMs would have been exceedingly high. Thus, we defined a single "importance sample" for each technology parameter that defined the IAM runs. Given this sampling of the technology performance space, alternative portfolios can be mimicked by simply correcting for the different R&D distributions. Chan and Anadon (2014) have also implemented the use of importance sampling for the Harvard elicitations in a one-stage decision framework for a portfolio of R&D investments in 6 technology areas and 25 specific technologies using MARKAL to translate technology into societal/economic outcomes.

We first sample from an importance distribution q_j for each technology j. We choose this distribution so that it covers the range of the elicited distributions of all teams. The elicited distributions are called the *nominal distributions,* $p_{j\tau k}$, where there is a nominal distribution for each funding level *k,* team τ, and technology *j.* We then reweight the sampling distribution using the likelihood ratio

$$\frac{p_{j\tau k}(x)}{q_j(x)} \quad (8)$$

Specifically, we generated a 1000-point sampling distribution for each technology parameter. We assume that all technology parameters are independent of each other. This produces an 8-dimensional 1000-point sampling distribution (to account for the 8 technology parameters). Then, for each funding level for each technology and each team, we reweight the sampling distribution using the elicited probability distributions $p_{j\tau k}$ described in ((Baker, Bosetti, Anadon, Henrion, & Reis, 2014)). Finally, we multiply the probabilities across the 8 parameters (and re-normalize) to get the probability of each 8-dimensional point. Thus, each IAM only had to run 1000 points, yet we can analyze a very large number of underlying probability distributions, for different teams and for different portfolios. These probability distributions are used to calculate the expected Total Abatement Cost (TAC) and the expected damages. Such a reweighted sample will have the same expected value as the nominal distribution.

Methods for choosing the importance sample. For the numerical example provided below we used importance samples that over-weighted the low cost regions of each technology. The idea is that the high-cost regions for most of the technologies will not be of much interest: when a particular technology has a high cost it will generally not be competitive and therefore, small differences in the actual cost will have very little effect on the economy. **Errore. L'origine riferimento non è stata trovata.** illustrates a nominal distribution for Solar LCOE along with the covering distribution. A disadvantage of this method in this case is that, because it samples heavily from the far left of the distributions, and because we are working with a large number of different underlying nominal distributions that have different supports (that is the low and high values differ considerably) many of the individual points in the importance sample have a probability of zero in many of the elicited distributions. This is compounded when we calculate the probability of the joint event – the eight individual cost and efficiency outcomes. In some cases well over half of the 1000 points in the importance sample have probability zero. Thus, in a situation like this, it may be better to choose an importance sample that more closely mimics the underlying distributions at hand.

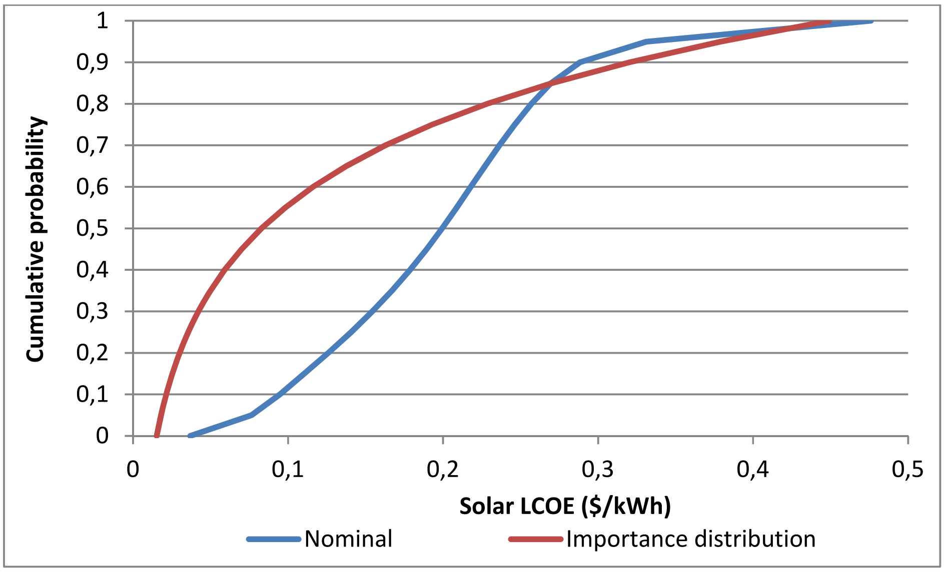

Figure 2: An illustration of how the importance distribution oversamples low costs. The Nominal distribution shown is for Harvard Low Funding Solar LCOE.

3.2 Solution Methodology and Model Calibration

3.2.1 Solution Method for One-Stage and Two-Stage decisions

All frameworks are solved using a simple dynamic program, implemented in Excel and Matlab. For framework two, the two-stage decision, the RCP is chosen in Excel, based on the minimum of the sum of damages and abatement cost, and then this is used in the Matlab model. The MiniMax and MiniMax Regret frameworks are solved in Matlab by cycling over each of the teams' probability distributions for each technology.

3.2.2 Calibration

Here we describe some key assumptions and calibration parameters that determine model outputs.

Discount rate: We take δ=5% for our central discount rate when calculating the TAC and Damages, the discount rate used in GCAM.

Model Outputs: The IAM produces a number of outputs for each of the 1000 points in the importance sample, including annual abatement $AC_{s,t}$ costs and temperature $T_{t,s}$. GDP is exogenous for GCAM. The damages, D_s, and total abatement cost TAC_s are calculated from the outputs as discussed above. The GCAM model timespan runs until the year 2095.

R&D Funding Amounts: The funding amounts vary considerably by team. One key difference between the teams is whether the amount includes development, demonstration, and deployment. The Harvard values include these expenditures; the UMass values do not. FEEM values are based on EU investments; they include research, development, and dissemination. A second difference is that the UMass team developed funding amounts in a bottom up way, discussing the number of labs needed to give a breakthrough a reasonable change; the other teams developed them in a top down way, by looking at current total government spending.

In this paper we use the same R&D funding amounts for each team: the simple average of the funding amounts across the three teams (Baker, Bosetti, Anadon, Henrion, & Reis, 2014). One exception to this is the bioenergy technologies – biofuels and bio-electricity. As Harvard elicited Bio-Fuels and Bio-Electricity together, we combine both technologies into one category called Bio-Combined in the Harvard case. For the MiniMax and MiniMax Regret frameworks, we constrain the Bio-Fuels and Bio-

Electricity funding levels (that is, Low, Mid, or High) to always be the same, so that we can compare all three teams across the same portfolios.

The team funding amounts were presented as annual amounts in (Baker, Bosetti, Anadon, Henrion, & Reis, 2014). Here we convert them to Net Present Values using a discount rate of 3% and a time span of 20 years. Each technology has only three alternative funding amounts, a Low, Mid, and High funding amount.

The technology funding amounts represent actual dollars spent. Theory suggests that the cost to the economy may be considerably greater, particularly if the funding is being diverted from other R&D projects. Thus, we consider an opportunity cost multiplier: a value $\kappa \geq 1$ is multiplied by the funding amounts. Our central assumption for the opportunity cost is κ=4 ((Nordhaus, 2002), (Popp, 2006). We also ran experiments using $\kappa = 2$ and $\kappa = 8$.

Probabilities: Each elicitation team derived probability distributions over each of the 8 technology parameters, based on the elicitation data. In order to get the Combined probability distributions, each of the 8 parameters the probability distributions of the three teams were aggregated using a simple linear average (Baker, Bosetti, Anadon, Henrion, & Reis, 2014) The four nominal distributions used in the importance sampling include the Combined probability distributions and each of the three teams' distributions.

Damage parameter π: This parameter converts the square of the temperature into a fraction of GDP lost. The baseline value in DICE99 (Nordhaus W. D., 2008) is .0035[5]; we use this for our Low Damage value. A value of 0.017 is chosen for the High Damage value because it leads to a case where the optimal

[5] The form of the damage function is slightly different in DICE99, but the baseline damages are very similar.

RCP varies between 2.6 W/m^2 and 4.5 W/m^2. We use this value to compare the one-stage and two-stage frameworks.

3.3 Experimental Design

For this example, our experimental design combines sensitivity analysis over some aspects (the elicitation teams, the climate damages, and the framework) with one-stage and two-stage DMUU.

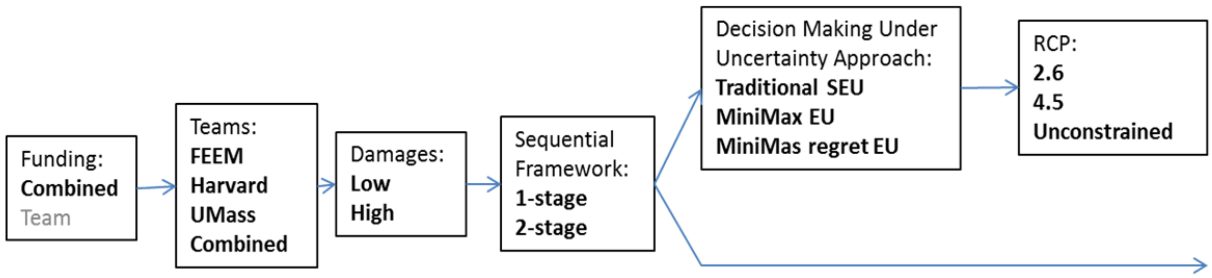

Figure 3: Framework Description

Errore. L'origine riferimento non è stata trovata. provides a chart illustrating the many choices that can be made in running these models. In this paper we will focus on results using only the "Combined" funding amounts (discussed in Section 3.2.2), rather than the individual funding amounts for each team. For the one-stage Framework we consider three possible approaches to DMUU and three RCPs. For the two-stage framework the RCP is a decision that is made after the outcome of technological change is known and we only use a traditional SEU framework.

4 Results

4.1 Framework I: One stage decision making under uncertainty

Errore. L'origine riferimento non è stata trovata. summarizes the results of the one stage problem, under the assumption of an opportunity cost multiplier equal to 4 (the results were nearly identical for opportunity cost multipliers of 2 and 8). The figure shows the optimal portfolio that is obtained using the probabilities from each team, from the Combined probabilities, and from the MiniMax and MiniMax Regret implementations, for each RCP assumption and damage level. We show 2.6 W/m^2 only once since the optimal portfolio is always the same between the high and low damages. Note that FEEM did not elicit CCS; the results shown use the combined CCS probabilities in conjunction with the FEEM data, thus we have shaded these results differently.

We find that, given our data, the most common level of funding in the optimal portfolios is “Low”. To emphasize this, we have striped any funding level that is different from the “Low” funding level. At this time we do not have a zero funding level, so we cannot confirm whether the preponderance of “Low” funding levels is because (1) the investments do not provide a good return on investment and the optimal would be something closer to zero; or (2) the Low investments are highly productive and so the marginal returns from higher investments are not warranted.

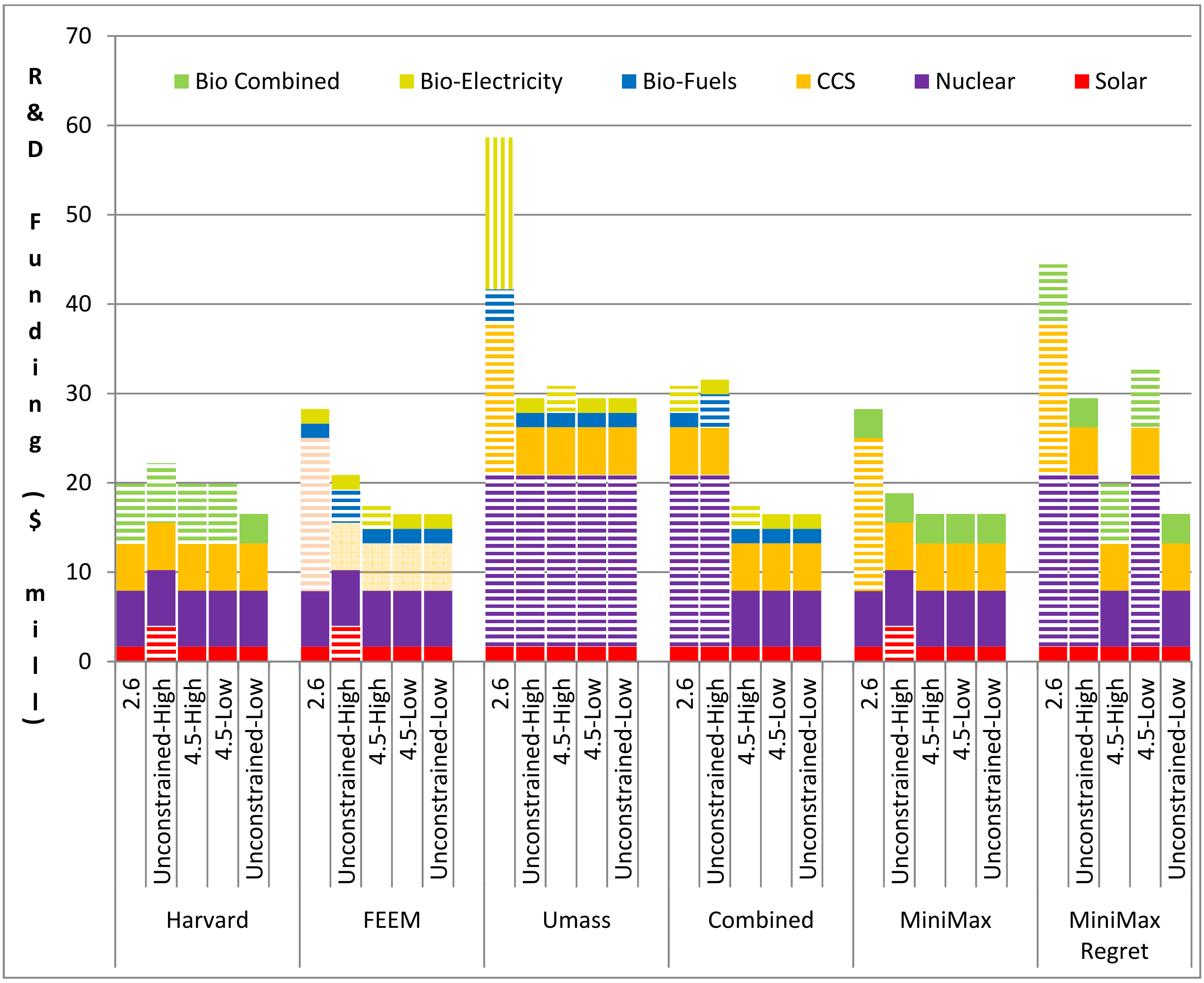

Figure 4: One Stage Decision Framework Results. The Figure compares the results of each of the teams' distributions with the Combined, the MiniMax, and the MiniMax regret strategies. Horizontal and vertical stripes indicate Medium and High investment respectively. The CCS blocks are pale for FEEM since they did not elicit CCS values; these results are based on Combined values.

First we focus on the traditional SEU results and consider how they compare across elicitation teams and the Combined elicitation results. First, as one would expect, the more stringent 2.6 W/m^2 stabilization generally has (weakly) more investment in each technology than the 4.5 W/m^2 RCP. The one exception, and therefore the most interesting, is that when using the FEEM elicitation data we find that a Mid-level investment in bio-electricity is optimal under 4.5 W/m^2 when damages are high; but only a Low investment is in the 2.6 W/m^2 portfolio, which features CCS instead. Note that FEEM did not elicit CCS, this result is based on the probabilities in the "Combined" distribution.

The second interesting result is that the Unconstrained stabilization scenario with high damages actually has some of the highest technology investment. This is because the R&D model is trying to minimize the cost of abatement plus cost of damages plus R&D investment. The cost of the R&D investment is made up for by the reduction in damages in the high damage case. Note that the reduction in damages is due entirely to the improvement in technology: there is no abatement in GCAM in the unconstrained case. This implies that, in the absence of clear climate policies, investing in technology is still worthwhile and has some benefits. We have seen in many studies that technology is not enough – climate change will not be solved by technological breakthroughs alone. But this result says that even if we don't see any significant climate policy on the horizon, it still makes sense to forge ahead with investment in energy technology R&D

Third, if we compare the optimal portfolios to the elicitation results, we see that the optimal portfolio doesn't entirely follow the elicitation results. That is, just because a technology has a higher expectation of technological improvement, it may not justify a higher investment. Based on the elicitations for each study, in the FEEM elicitation bio-electricity has the lowest improvement. Yet, in the 4.5 W/m^2-high scenario, bio-electricity is the only technology that is invested in at a Mid (rather than Low) level under the FEEM distributions. In the Harvard study, CCS has the highest return, but is invested in at a Low level in all portfolios. Finally, we see, given this data, a great deal of disagreement when using the technology inputs from the different teams performing the expert elicitations. Given this disagreement, one possible direction is to look at other optimization approaches such as the MiniMax models, which we turn to now.

We see that, given the set-up of this model, using the MiniMax EU framework tends to lead to smaller investments, taking a more pessimistic view of the R&D returns. This may be because the uncertainty in this case is only about technology, not about climate damages. In this framework, the RCP and the level of damages are taken as given; therefore in an extreme ambiguity-averse framework, these factors receive less negative weight.

The MiniMax Regret, on the other hand, tends to be more optimistic, with larger overall investments than the MiniMax, the Combined case, and most of the individual teams. This is because in this framework the objective is to minimize the regret of not being in the best state, so it tends to be the most optimistic prior that chooses the portfolio.

The question is what to do with this information, especially when frameworks designed to take ambiguity aversion into account give such differing results? Given near term uncertainty over the prospects for advancement in climate technologies, how should a decision maker interpret these results? Since there is no single framework or set of axioms that leads to one ambiguity-aversion framework, it is difficult to recommend that policy-makers choose one or the other. One potential way to use these results is to focus on the cases where there is the most difference between the solutions of the different DMUU approaches, and investigate these particular cases. For example, the key difference between the optimal portfolios among the three aggregated approaches (Combined, and the two MiniMax) in the 2.6 W/m^2 case is the investments in nuclear and CCS, and to some degree the investments into the bioenergy technologies. This indicates that we may want to look very closely at these elicitation data sets. When going back to the original elicitations, we see that there is the most disagreement among the teams in the Nuclear technology; and that the CCS technology results rely strongly on the elicitation of one team. The bioenergy technologies required significant assumptions for two of the teams in order to differentiate between efficiency and non-energy costs. This suggests that an analyst supporting a decision maker should (1) go back and consider weighting the current set of elicitations based on a judgment of quality; and/or (2) put resources toward additional, careful elicitations in these topics.

For the first approach, the analyst can first perform a sensitivity analysis to determine how skewed the weights need to be from equal in order to change the optimal portfolio. They could then look back at the studies and judge them for quality. For example, the nuclear elicitation that is most different from the others also has a very small number of experts. It would be reasonable to consider weighting the elicitations based on the number of experts in each study. For the second approach, a first step would be to review the full set of elicitations and other data that is available. For CCS, for example, there have been a number of studies that could be added into this aggregation [(Rao, Rubin, Keith, & Granger, 2006), (National Research Council, 2007), (Chung, Patiño-Echeverri, & Johnson, 2011), (Jenni, Baker, & Nemet, 2013)]. If additional studies don't exist, then a full-scale elicitation may well be justified. Previous work indicates that the value of better information in the form of careful, well-funded elicitations is far above the cost of such elicitations (Baker & Peng, 2012).

4.2 Framework II: Two-stage decision making under uncertainty

In the two-stage framework, there is an "option" – to choose an RCP based on the outcome of technical change. When damages are low, then it is optimal to choose 4.5 W/m^2 about 80-100% of the time (depending on the R&D portfolio), and unconstrained the rest of the time. In this case of low damages, the two-stage results are not very interesting: in three out of four cases we find that the optimal portfolio is the same for the 2-stage problem, the unconstrained-low 1-stage, and 4.5 W/m^2-low 1-stages; for Harvard, the 2-stage portfolio matches their 4.5 -low. The high damage case is more interesting and the results are shown in **Errore. L'origine riferimento non è stata trovata.**, where we compare the results for the 1-stage problem under 2.6 and 4.5-high alongside the 2-stage results. When damages are high the investment in technology has a large impact on how often the 2.6 W/m^2 RCP is chosen over the 4.5 W/m^2. In the Combined case, when investment is low in all technologies, 2.6 W/m^2 is optimal only 5% of the time. But, when investment is high in all technologies, 2.6 W/m^2 is optimal 43% of the time. Thus, in this case, technology not only reduces the cost of a given RCP, it also causes the optimal RCP to become more stringent, thus reducing damages.

For the Harvard data, the optimal portfolio is the same for these three cases. For the FEEM data, the 2-stage optimal portfolio is the same as the 4.5 W/m^2-high; for UMass data is it the same as 2.6 W/m^2. But, the interesting result is for the Combined case. We see that the results of the two-stage framework is different from both 2.6 W/m^2 and 4.5 W/m^2-high, and not an average or combination of the two. Biofuels is not optimal at the Mid level in either the 2.6 W/m^2 or the 4.5 W/m^2-high; yet it is optimal in the 2-stage. This is an illustration of the kind of results that can only be seen if we explicitly consider a 2-stage problem. The investment in Biofuels, at least when using the combined data, has an option-value not seen in the 1-stage problems, allowing for lower damages by switching to 2.6 W/m^2 more often.

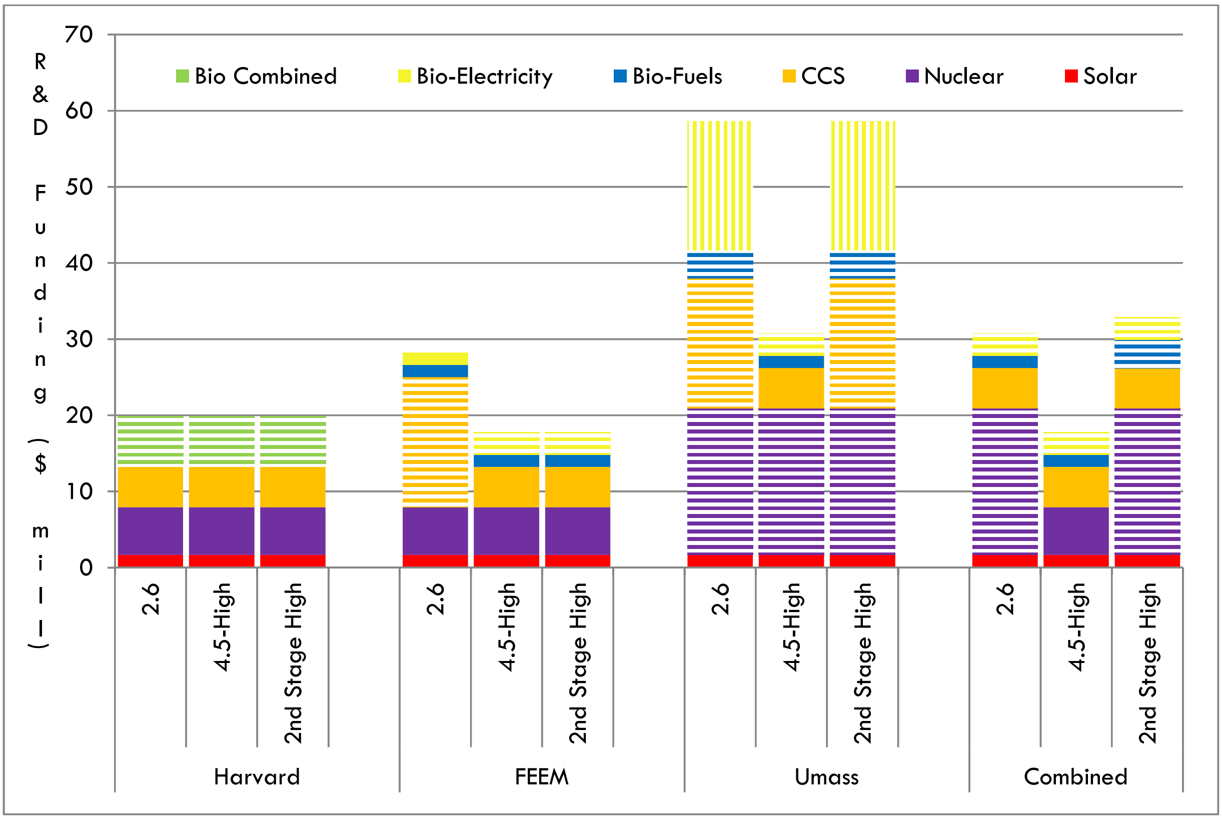

Figure 5: Comparison of One Stage - High and Two Stage - High Decision Framework Results

5 Conclusions

In this paper we provide a brief overview of decision frameworks that can be used to consider the optimal climate-energy technology R&D investment under uncertainty about the prospects for technological change. We then explore the implications of different decision frameworks, especially when there are multiple potential probability distributions for each technology.

Methodologically, we investigate this problem using importance sampling, a technique with great promise for combining large IAMs with expert elicitations. This is a different application of importance sampling, which has typically been used to estimate statistics in cases where the region of interest is of low probability. We use it, instead, to enable a numerically efficient way to use large IAMs for uncertainty analysis. We choose one sampling distribution for each technology, and use that to generate an importance sample. This sample is then run through IAMs to produce outputs of interest such as total abatement cost. The method of importance sampling is then used to reweight the outputs using the nominal distributions resulting from a set of expert elicitations. This allows us to consider the results of multiple elicitation teams as well as multiple funding levels while keeping the number of runs of the large scale models to a reasonable number.

In future work we suggest that the sampling distribution be chosen carefully to avoid a large number of points with zero or near-zero probability. This is particularly important in a case like this where we have probability distributions over 8 parameters that need to be combined through multiplication. Rather than over-sampling at the low end of the distribution a better strategy may be to use a combination of the low and high Combined distribution as the sampling distribution.

From the numerical example using elicitation results from three large scale multi-technology studies, we note a set of findings. First, the results of the portfolio optimization do not directly follow the results of the underlying elicitation data: the optimal investment depends on more than the just the technological outcome. That is, one technology may have the most promising future in terms of the overall improvement that can be achieved with R&D investment, but it may not turn out to be the best investment. The overall benefit of an R&D program depends on how that technology competes with the other technologies available in the economy and how it interacts with climate policy. On the other hand, we see that the optimal portfolio does depend heavily on the underlying probability elicitations (by looking at the differences between elicitation teams). Thus, the conclusion is that both parts of this equation are crucial for crafting R&D policy – understanding the prospects for technological advancement and understanding the complex interactions between technologies in the economy.

An interesting result that we have not seen explicitly in the literature is that energy technology R&D is valuable even in the absence of climate policy. We saw that the optimal portfolio was particularly high in the unconstrained scenario with high climate damages. While technology alone is not the solution to climate change, it is apparently better than nothing. This suggests that policy makers should move ahead with investment in energy technology R&D even if they are uncertain about the future climate policy environment. A similar result was found in Baker & Solak (2014), where the optimal portfolio was quite robust in the face of very different policy environments, from one based on Nordhaus' model (Nordhaus W. D., 1993) to one based on the recommendations of Al Gore[(2006)]. That paper, however, did not consider a "do nothing" policy.

By comparing a one-stage model, which takes the RCP as given regardless of the outcomes of technical change, and comparing it to a simple two-stage model, in which the RCP is chosen knowing which technologies have been successful, we illustrated that some technologies may have an "option value" that cannot be easily identified in one-stage frameworks. Specifically, in our example, we found that when the RCP was fixed at 2.6 W/m^2 or 4.5 W/m^2 the optimal investment in biofuels was Low; but when the stabilization was chosen after the realization of technical change, the optimal investment in biofuels was Mid. This implies that some care should be taken to identify technologies (and other near-term alternatives) that have option value, in allowing for more flexibility in the future to respond as more is learned.

There is a movement in part of the literature to take ambiguity aversion into account when making optimal policy [(Gilboa, Postlewaite, & Schmeidler, 2009), (Millner, Dietz, & Heal, 2010), (Lemoine & Traeger, 2012) (Kunreuther, Heal, Allen, Edenhofer, Field, & Yohe, 2013), (Heal & Millner, 2014)]. This suggestion is quite controversial and contentious [e.g. (Sims, 2001)]. We have presented results on the optimal portfolio using a traditional SEU framework with the results of two very simple MiniMax frameworks. We find that different MiniMax frameworks can produce very different results – some with more and some with less investment than traditional SEU. We suggest that while these results may not give a clear guidance to policy makers, they may instead be more useful to guide future careful study and analysis of how to use available elicitations.

This analysis illustrates that optimization models are not the end of the analysis, providing a clear single best strategy. Rather, they are an important part of the analysis to inform decisions, and can provide insights that are not otherwise easy to see (such as which technologies have option value) or on the other hand provide evidence for existing intuitions that are otherwise difficult to support (such as the value of energy technology R&D even in the absence of climate policy). While there will always be aspects of policy decision making that cannot be captured by models or data, this analysis indicates the importance of using models and data to inform decisions.

Acknowledgements: The research leading to this paper was partially supported by NSF under award number SES-0745161; by the GEMINA project, funded by the Italian Ministry for the Environment, Land and Sea (MATTM); by the Energy Modeling Forum at Stanford University; and by the ADVANCE project, ENV.2012.6.1-2- FP7-ENV-2012. The authors thank Robert Barron for providing the outputs of the GCAM model; and Max Henrion for suggesting the use of Importance Sampling.

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