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Summary

In the present paper we use the output of multiple expert elicitation surveys on the future cost of key low-carbon technologies and use it as input of three Integrated Assessment models, GCAM, MARKAL_US and WITCH. By means of a large set of simulations we aim to assess the implications of these subjective distributions of technological costs over key model outputs. We are able to detect what sources of technology uncertainty are more influential, how this differs across models, and whether and how results are affected by the time horizon, the metric considered or the stringency of the climate policy. In unconstrained emission scenarios, within the range of future technology performances considered in the present analysis, the cost of nuclear energy is shown to dominate all others in affecting future emissions. Climate-constrained scenarios, stress the relevance, in addition to that of nuclear energy, of biofuels, as they represent the main source of decarbonization of the transportation sector and bioenergy, since the latter can be coupled with Carbon Capture and Storage (CCS) to produce negative emissions.

Keywords: Sensitivity Analysis, Integrated Assessment models, Expert elicitation, Technology Cost

JEL Classification: O30, O33, Q41, Q50, Q55

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Sensitivity to Energy Technology Costs: A Multi-model comparison analysis

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Abstract

In the present paper we use the output of multiple expert elicitation surveys on the future cost of key low-carbon technologies and use it as input of three Integrated Assessment models, GCAM, MARKAL_US and WITCH. By means of a large set of simulations we aim to assess the implications of these subjective distributions of technological costs over key model outputs. We are able to detect what sources of technology uncertainty are more influential, how this differs across models, and whether and how results are affected by the time horizon, the metric considered or the stringency of the climate policy. In unconstrained emission scenarios, within the range of future technology performances considered in the present analysis, the cost of nuclear energy is shown to dominate all others in affecting future emissions. Climate-constrained scenarios, stress the relevance, in addition to that of nuclear energy, of biofuels, as they represent the main source of decarbonization of the transportation sector and bioenergy, since the latter can be coupled with Carbon Capture and Storage (CCS) to produce negative emissions.

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1. Introduction

Future costs of low-carbon technological options are a key factor in determining climate policy costs and feasibility. The recent Fifth Assessment report of the IPCC WG III (IPCC, 2014) stresses the relevance of assumptions concerning the availability and costs of future technologies in shaping the range of policy costs. This has long been recognized within the Integrated Assessment modeling (IAM) community (Edmonds et al., 2012), and the quantitative analysis of the future availability/cost of carbon-free and low-carbon technologies has been at the center of a growing literature. The most commonly adopted approach relies on the use of an IAM and the running of climate-constrained scenarios with and without the availability of key energy technologies, in order to assess the increase in climate mitigation costs/carbon prices under each alternative. A few studies have comprehensively analyzed the impact of advances in future energy technologies on the cost of greenhouse gas mitigation by means of sensitivity analysis and using an individual model (McJeon et al. 2011; Lemoine and McJeon, 2013; Rogelj et al. 2012, Anadón et al. 2014.). In parallel to these pioneering works, a set of modeling comparison analyses has been performed. We recall the Energy Modelling Forum (EMF) 27 (Kriegler, 2014) and the Assessment of Climate Change Mitigation Pathways and Evaluation of the Robustness of Mitigation Cost Estimates (AMPERE) Project (Riahi, 2013). The latter studies are characterized by selected sensitivity analyses to extreme technology realizations and a focus on robust results across models. The findings that emerged from these and other studies, as summarized in the IPCC latest assessment report (IPCC, 2014) are that:

(a) Carbon Dioxide Removal (CDR) technologies, which can be used to generate negative emissions, are the most critical class of technologies, as they allow a modification in the time path of the emissions constraint (the possibility of negative emissions by the end of the century would allow postponing peak emissions later in the century); (b) bioenergy coupled with CCS would have a central role, and the unavailability of either component of this technology would result in an increase in policy costs between 18% and 300%, depending on the stringency of the climate scenario analyzed and whether the limitation of technology availability concerns bioenergy or CCS. Assumptions about the availability of other low-carbon energy technologies also matter (for example, the availability of low-cost renewables, CCS alone, and nuclear power), although their impact on mitigation costs are typically less pronounced.

In this study, by building on this existing knowledge, we use a different approach to evaluate the extent to which uncertainty about future technology costs in key energy technologies translates to different model outcomes. Instead of switching on and off one technology at a time (or in combination) in various models, we explore the space of future technological costs and other parameters, parameterized by using a set of expert elicitation surveys. In particular, we take stock of extensive efforts that have been carried out independently by researchers at UMass Amherst (Baker & Keisler, 2011; Baker, et al., 2009b; Baker, et al., 2009a; Baker, et al., 2008), Harvard (Anadon, et al., 2011; Anadon, et al., 2012; Anadón, et al., 2014a; Chan, et al., 2011), and FEEM (Bosetti, et al., 2012; Catenacci, et al., 2013; Fiorese, et al., 2013). Each of these groups collected the opinions of

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leading experts from the academic world, the private sector, and international institutions on the probabilistic

distribution of future costs of the most promising clean energy technologies, conditionally to different levels of

R&D efforts. The technologies include liquid biofuels, electricity from biomass, carbon capture (CCS), nuclear

power, and solar photovoltaic (PV) power. All surveys were carried out by means of structured protocols aiming

at minimizing potential biases and overconfidence that can characterized experts elicitations(Morgan, 2014).

Although different groups carried out surveys covering the same set of technologies, each group worked

independently, and thus asked questions using different formats, looking at different endpoints and cost metrics.

Therefore, the effort of harmonizing the data across surveys has represented a complex endeavor which is fully

described in Baker et al. (2014a). The resulting estimates span a wide array of uncertainties including those that

might be related to different methodology employed to collect the data from experts.

By using this data we can explore differences in the sensitivity of various models to parameter uncertainty as

expressed by a vast collection of recently elicited subjective expert judgments.

This is important per se, as it permits us to systematically explore the technological cost dimension as defined by

experts (rather than only exploring the extremes of the cost space). In order to do so, we employ a combination

of global sensitivity measurements and estimation methods that allow us to address in depth key questions about

the behavior of the alternative models. In particular, we obtain quantitative insights about whether key-

uncertainty drivers are the same across models and whether this is robust across alternative output of models (as for example cumulative emissions or technology penetration).

Aside the modeling insights, this analysis is also an essential step toward the design of optimal energy R&D portfolios as described in (Baker et al. 2014b), because it improves our understanding of the extent to which technology assumptions drive results as well as of what other parameters affect differences across models.

This paper is structured as follows: the next section provides a general overview of the experimental protocol and the methodology used to assess the sensitivity of the models, and in addition it introduces the integrated assessment models used and the ways in which they have been modified to incorporate the information coming from the expert elicitation surveys. Section 3 presents the main sensitivity results, while Section 4 states our conclusions.

2. Methods

Our objective is to assess the implications of changes in the future costs and performance parameters of a few key energy technologies in relation to important macro-economic and global environmental metrics. We set out using as an input to integrated assessment models the results from the aggregated expert elicitations data described in (Baker et al, 2014a).

In this section we present methodological details on the technology input specifications, the sampling strategy, the models used, the explored climate policy scenarios, and the metrics adopted for the evaluation of the sensitivity across models and technologies.

2.1 Technology input specifications

In the present analysis we focus our attention on the following technologies (and metrics): solar power (levelized cost of electricity), nuclear power (overnight capital cost), biofuels (cost and conversion efficiency), bioelectricity (cost and conversion efficiency) and carbon capture and storage (CCS) (capital cost and energy penalty). By harmonizing and aggregating the data across experts and across surveys by means of the process described in (Baker, 2014a), we obtain eight probability distributions representing the values of these uncertain metrics (summary statistics for the distributions are reported in Table 1). We generate 740 scenarios, representing combinations of technology performances drawn from these eight cost distributions. Each model is then set up to implement the assumptions of the 740 scenarios.

Table 1. Importance Sampling Distributions

Quantities	Distribution	Units	Min	Median	Max	Mean	St. dev
Solar LCOE	LogUniform	$/KWh	0.02	0.09	0.45	0.14	0.12
Nuclear	LogUniform	$/KW	385	1534	5728	2017	1489
Biofuels cost	LogUniform	$/GGE	0.22	1.57	10.56	2.56	2.54
Biofuels efficiency	Uniform	%	19	52	85	52	19
Bio-electricity cost	LogUniform	$/KWh	0.01	0.04	0.23	0.06	0.06
Bio-electricity efficiency	Uniform	%	7	47	85	47	22
CCS cost	Uniform	$/KW	5	2019	3920	2006	1142
CCS energy penalty	Uniform	%	0	22	43	22	12

2.2 Sampling method to define model runs and policy scenarios

Instead of sampling the cost or parameter values space by means of an equally distanced sample, we use

importance sampling (Glynn and Iglehart, 1989). Importance sampling has generally been used as a version of

Monte Carlo-type analysis, when the area of interest in the distributions of cost and performance has a very low

probability. In our case this is relevant because, for example, very low nuclear costs (which are also associated

with low probabilities of occurrence) are expected to have a large impact on societal and environmental

outcomes in the models, in particular in climate constrained scenarios which are at the heart of our analysis. In

other words, if we had sampled randomly, we might not have had enough runs covering the part of the

technology cost distribution of interest. [1]

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[1] Importance sampling allows us to sample from a different distribution, and renormalize back to the actual distribution of interest. We use it here as in the portfolio analysis discussed in Baker et al. 2014b to limit the number of times we ran the three IAMs. Since we have four alternative distributions of technology costs and performance (one for each of the teams that conducted the elicitations—UMass, FEEM and Harvard—plus the combined distribution) and three to five possible R&D portfolios (as we consider three levels of R&D for each of the five technologies, the number of runs needed to capture the impact of technology uncertainty on model outputs in the IAMs would have been exceedingly large. Thus, we defined

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Each of the 740 runs is repeated for three policy scenarios: a baseline scenario where no climate policy is in place, and two climate policy scenarios where global emissions (US emissions for MARKAL-US) are constrained. The two constrained scenarios are in line with two of the four representative concentration pathways (RCPs) developed for the modeling experiments of the climate modeling community and spanning the range of radiative forcing values[2] for the year 2100 from 2.6 to 8.5 W/m2 (International Institute for Applied Systems Analysis 2009, RCP Database). In particular, models run with emissions caps in line with scenarios imposing a radiative forcing of 2.6 and 4.5 W/m2 by 2100. In our experiment when-flexibility on emission reduction is not allowed, that is, the constraint on emissions is not only on the carbon budget but also on the emissions time profile (this allows greater comparability across models). The cap on emissions is however global and can be efficiently allocated across countries, except for MARKAL-US, where the cap is for the US only and is derived by the emission cap obtained for the US from the GCAM model. Each of the runs assumes immediate learning: i.e. full anticipation of the realization of technology costs/parameters in 2030 between 2010 and 2030. For the subsequent years we assume that additional learning will take place, but for each run this additional learning will be a function of the actual realization of the parameter and the assumed maximum learning rate, β, following the asymptotic rule below:

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an "importance distribution" that defined the IAM runs. There is only one importance distribution, rather than 4 (for each team) * 35 (for each possible R&D portfolio).

[2] When reporting radiative forcing values, it is assumed that they include the forcing of greenhouse gases and other forcing agents, but do not include direct impacts of land use (albedo) or the forcing of mineral dust.

$$x_{(i,t)} = x_{(i,2005)} + \frac{x_{i,t'} - x_{i,2005}}{1-\beta} + (1-\beta^{\frac{t-2005}{t'-t}})$$

where $x_{i,t}$ is the cost (or efficiency level) for technology i at time t, t' is the period for which information on

cost/efficiency was elicited (namely 2030) and β is the maximum additional technological change beyond t',

which we assume to be 20% (i.e., 80% of cost reduction occurs before 2030 and is in accordance with the

realization from the elicited distribution. The remainder of 20% cost reduction occurs after 2030). In addition,

we assume that the evolution of cost and performance parameters after 2030 is capped by a floor (ceiling) value

for cost (efficiency) which is the minimum (maximum) provided with the sampling statistics.

2.3 Description of models and implementation

We assess the implications of the judgments of experts on the future cost of key energy technologies by using

three integrated assessment models: GCAM, MARKAL-US and WITCH.

The difference between the three models can be clustered in two groups:

1)   Structural differences: i.e. WITCH and MARKAL_US are solve through intertemporal optimization

with perfect foresight; GCAM is a recursive dynamic simulation model. WITCH aggregates technologies via a

constant elasticity of substitution functions, whereas in GCAM the aggregation is linear but the cost of

technologies has a logistic distribution; system integration and flexibility is modelled in different ways in the

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three models considered. GCAM and MARKAL-US are more detailed in their descriptions of technologies, while WITCH describes in greater detail the macro-economy component; MARKAL-US describes the US, while GCAM and WITCH have a global coverage.

2)   Parametrical: future costs and performance of technologies varies across models, as parameters controlling for technology adoption. Some of these key parameters were varied in a uniform way as an input to each simulations, but other parameters exist and influence the dynamics of the models in different way (an example could be the cost of capital or the cost of nuclear waste management).

We did our best to harmonize the second source of variation (see the Appendix) in order to emphasize as much as possible the implication of the first source of variation (as an example the assumptions on nuclear waste management cost in WITCH were moderated in order to be comparable with those in GCAM).

However, the distinction between sources of difference in the first and second group is not as clear cut as one might like and differences across models' results presented later will certainly include part of both.

These differences are key to the main purpose of this paper, namely that of assessing the robustness of findings with respect to different model specifications. The research groups involved in this work performed a thorough comparison of the models. In the Appendix we provide the synthesizing result of this comparison effort. Because of the existing structural differences, implementation of the sampling strategy had to be model specific. Details

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on how costs and efficiency parameters were implemented are also provided at the end of each model

description in the Appendix.

2.4 Comparison methodology and sensitivity methods

Each of the 740 model runs carried out for the various technology cost combinations constitute an uncertainty

analysis (Helton, 1993). Thus, from the corresponding model input-output datasets it is possible to obtain an

examination of the statistical properties of the output distribution. The analyst then obtains an indication about

how much variability in the output of each model is induced by uncertainty in the same model inputs.

To augment these insights, we make use of the *post-processing* or *given data* logic (Lewandowski, Cooke, &

Duintjer Tebbens, 2007; Elmar Plischke, Borgonovo, & Smith, 2013). This type of approach to sensitivity

analysis uses the results of Monte Carlo simulations to extract additional information that can help the analyst to

obtain additional insights about the input-output mapping. In particular, we inspect the following two insights

(Anderson, Borgonovo, Galeotti, & Roson, 2014):

1) Key-uncertainty drivers

2) Sign of change

In sensitivity analysis jargon, these two types of insights are referred to as "sensitivity settings" (Andrea Saltelli,

2002). In our case, the methods used to investigate the two families of questions above need to be probabilistic

because we not only are testing for deterministic changes of parameters' values but we have subjective

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probabilistic information about these parameters. As regards the key-uncertainty drivers setting, we use global

sensitivity methods (Emanuele Borgonovo, 2006; A Saltelli et al., 2008). The setup is as follows. The

relationship that binds the model inputs ($\mathbf{x}$) to the model output (y) is regarded as a generic mapping of the form

$$y = g(\mathbf{x}), \ \ g : \Omega_{\mathbf{X}} \to \mathrm{R} \tag{1}$$

with $\Omega_{\mathbf{X}} \subseteq \mathrm{R}^k$ and k denoting the number of model inputs. To illustrate, in our case, we have k=8, $\Omega_{\mathbf{X}}$ is

Cartesian product of the eight ranges displayed in Table 1, g is the input-output mapping in WITCH, GCAM and

MARKAL_US.

Evaluation of key-uncertainty drivers

As for the key-uncertainty drivers setting, we adopt the three global sensitivity measures synthetically illustrated

in Table 2 [for a more detailed overviews the reader is referred to (Anderson et al., 2014; A Saltelli, Ratto,

Tarantola, & Campolongo, 2005)].

Table 2: Sensitivity measures used in this work for the identification of key-drivers

Sensitivity Measure	Equation
Variance-Based	$\eta_i = \dfrac{V[\mathrm{E}(Y\lvert x_i)]}{V[Y]} = \dfrac{V[Y] - \mathrm{E}[V[Y\lvert x_i]]}{V[Y]}$
Density-Based	$\delta_i = \dfrac{1}{2}\mathrm{E}[\int_{\Omega_Y} \lvert f_Y(y) - f_{Y\lvert X_i}(y)\rvert\, dy]$
CDF-based	$\beta_i^{KU} = \mathrm{E}\left\{\sup_y \left\lvert F_Y(y) - F_{(Y\lvert \mathbf{X}_i = x_i)}(y)\right\rvert + \sup_y \left\lvert F_{(Y\lvert \mathbf{X}_i = x_i)}(y) - F_Y(y)\right\rvert\right\},$

These sensitivity measures are statistics of the form (E Borgonovo, Hazen, & Plischke, 2014):

$$\xi_i = \mathrm{E}[s\left\{F_Y(y), F_{Y|X_i}(y)\right\}]$$

(2)

where $s\{F_Y(y), F_{Y|X_i=x_i}(y)\}$ is some form of separation measurement between the unconditional ($F_Y(y)$) and

conditional model output distribution $F_{Y|X_i=x_i}(y)$ [we refer to (Glick, 1975) on the concept of separation

measurement].

Variance-based sensitivity measures (second row in Table 2) quantify the separation as expected variance

reduction. In particular, the sensitivity measure η_i is Pearson's correlation ratio (Lewandowski et al., 2007;

Pearson, 1905). Thus, according to η_i the most important model input is the one that, when fixed, reduces the

model output variance the most. Density-based importance measures (third row in Table 2), identify the most

important model input as the one that shifts the model output density the most (E. Borgonovo, 2007). The CDF-

based sensitivity measure in the last row of Table 2 quantifies the influence of model input X_i through the

Kuiper distance on cumulative distribution functions [see (Tygert, 2010) for properties of the Kuiper metrics and

(Baucells & Borgonovo, 2013) for properties of the sensitivity measure in the fourth row of Table 2]. It should

be noted that all these sensitivity measures are normalized between zero and unity.

The rationale for using a combination of sensitivity measures is as follows. Each sensitivity measure considers a different property of the model output distribution. Thus, if a model input is deemed irrelevant by all the measures, then we can have greater confidence that its influence is low. Second, each sensitivity measure has limitations. For instance, in using variance based sensitivity measures one is exposed to the risk of deeming a model input uninfluential when, indeed, Y is dependent on it (see the example in (Elmar Plischke et al., 2013)). Conversely, density and CDF-based sensitivity measures are null if and only if Y is independent of X_i, avoiding such risk.

Evaluation of sign of change

As for sign of change, we rely on the first order effects of the functional ANOVA expansion of the model output. The rationale is explained in (Anderson et al., 2014), to which we refer for further details and mathematical aspects. We limit ourselves here to the following observations on the underlying intuition. Assuming that the multivariate mapping as in eq. (1) is integrable, we can expand it in the form

$$g(\mathbf{x}) = g_0 + \sum_{i=1}^{n} g_i(x_i) + \sum_{i<j}^{n} g_{i,j}(x_i, x_j) + ... + g_{1,2,...,n}(x_1, x_2, ..., x_n) \qquad (3)$$

where the terms in eq. (3) have the following meaning. g_0 is the mean value of y. $g_i(x_i)$ is individual effect of x_i, namely, the expected behavior of g as a function of x_i alone. In formulae,

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$$g_i(x_i) = \mathrm{E}[g(\mathbf{x}) \mid X_i = x_i] - g_0 = \int ... \int g(\mathbf{x}) \prod_{s=1,s\neq i}^{n} dF_s - g_0 \qquad (4)$$

that is, $g_i(x_i)$ is the conditional expectation of g given x$_i$, from which the mean value of g is subtracted. Note

that in eq. (4) g is integrated over all variables but x_i. The second order terms $g_{i,j}(x_i, x_j)$ account for the

residual effects of the interactions of the corresponding model inputs, and so on. These terms are obtained

through conditional expectations followed by proper orthogonalization, see (Rabitz & Aliş, 1999).

By determining sign of change, we mean a generalization of the comparative statics question of (Samuelson,

1947): *it is hoped to formulate qualitative restrictions on slopes, curvatures, …*(Samuelson, 1947). That is, we

are interested in studying whether, on average, the variation in a model input leads to an increase or decrease in

the model output. The literature has ascertained that, under uncertainty, this answer can be gained by considering

the first order effects of the functional ANOVA expansion. In fact, it is proven in (Beccacece & Borgonovo,

2011) that these effects retain the monotonicity of the original input-output mapping. To clarify, if *g* is

increasing in x_i, then $g_i(x_i)$ is increasing, see (Anderson et al., 2014) for further details.

Finally, a note on the estimation. All sensitivity measures and functional ANOVA effects are obtained by using a

post-processing logic (Lewandowski et al., 2007). A set of methods has been examined by the authors. For

variance-based, we used the COSI method of (E Plischke, 2012) the given-data estimator of (Elmar Plischke et

al., 2013), the cut-HDMR estimator of (Ziehn & Tomlin, 2009), as well as a recent smoothing spline estimation

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subroutine[3]. For first order effect interpolation, we also used the smoothing spline ANOVA metamodel of

(Ratto, Pagano, & Young, 2007). For density- and CDF-based sensitivity measures, we used the given-data

estimators of (Elmar Plischke et al., 2013) and (Baucells & Borgonovo, 2013).

In the next Section, a selected subset of the numerical results obtained is presented and discussed.

3. Discussion of Results

3.1 Baseline Scenario

In a baseline scenario, the model output on which it is most interesting to assess the effects of technology

performance are fossil fuel emissions. Effects on GDP would also be relevant, as the future cost of energy

technologies does affect the pace of growth, but we abstain from this type of analysis as it is not possible to

perform it with all three models: GDP does not change in response to technology performance parameters

changes in the GCAM model. As MARKAL_US has a US focus, we will compare results from MARKAL_US

with those emerging from the WITCH model for the US region.

Figure 1 reports the global (left hand side panel) and US (right hand side panel) emissions spanned by the runs

performed with the GCAM and WITCH, MARKAL_US and WITCH (reporting the US region only) models,

respectively. In addition, for the sake of comparison, we also report the RCP 2.6 and 4.5 global fossil fuel

emissions that we impose on the models for the climate-constrained runs described later.

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[3] By W. Becker, personal communication to the authors, and available at http://ipsc.jrc.ec.europa.eu/?id=756.

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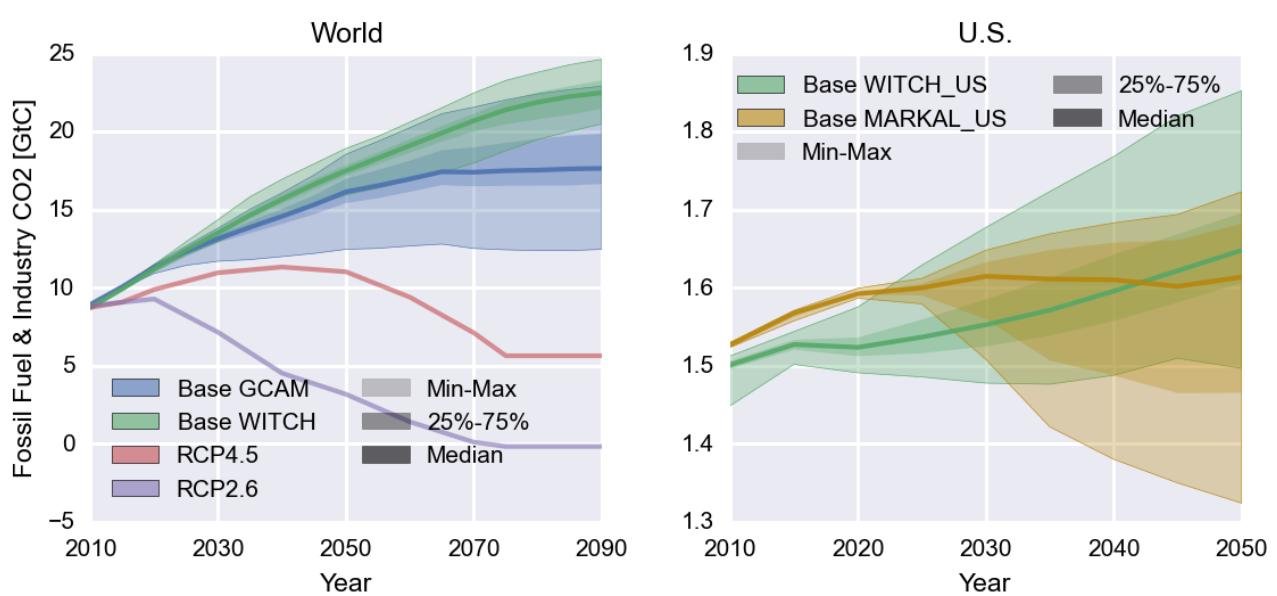
Figure 1: Global (left panel) and US (right panel) carbon dioxide emissions from Fossil Fuel combustion and Industrial processes (FFI). Different colors correspond to different policies, where the light color encompasses the minimum-maximum range, and the darker one encompasses the 25%-75% quantiles range. This color convention is adopted throughout the paper in all the time-series figures.

When looking at global numbers, it is interesting to note how the GCAM model spans a much wider range of variations in baseline emissions, both at the extreme and for the 25th-75th percentiles (darker shaded area). In GCAM, for some extreme realizations of cost and efficiency parameters, emissions remain almost at their 2015 levels throughout the century. For some other combinations they double by 2100. Conversely, the WITCH model is much less sensitive to cost and efficiency variations considered in this exercise and, in average, emissions grow more by the end of the century, even under the most optimistic realization of parameters. This difference in the response to energy costs realization, as will be unpacked even more in later discussions, mainly hinges on the structural set up differences between the WITCH model, that overall entails slower and more costly technological adoption and evolution, and the GCAM model. Looking at the right hand panel of Figure 1

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we can immediately notice the difference between WITCH and MARKAL_US: though the magnitude of the variation is roughly the same, the timing is different. Indeed, both models are solved through intertemporal optimization, but in the WITCH model the anticipation effect allows for larger short term adjustments than are allowed for in the MARKAL_US model.

Figure 2 portrays the extent changes in baseline emissions, both in sign and magnitude, are attributable, in a first order approximation, to the individual variations of each input. This type of analysis casts light on the sign of change setting discussed in the methods section. The lines in Figure 2 are the first order effects of the functional ANOVA expansion of g(x) obtained through numerical interpolation. These lines represent the expected variation of output *y* (in this case cumulative emissions) as a function of each individual model input. The top panels in Figure 2 show that the capital cost of nuclear energy is the factor that, when varying in the assigned range, influences the output of both GCAM and WITCH the most. In particular, WITCH reacts almost linearly to changes in the capital cost of nuclear energy, while the reaction in GCAM is non-linear, with a higher rate of change in the low-nuclear energy cost region. As before, the smaller extent of the reaction in WITCH can be explained by the model structure itself which is based on constant elasticity of substitution nested functions to mimic the energy sector (a detailed description of each of the three models is provided in the Appendix). Such a structure is inherently less flexible and implies slower pace of technological shifts than that of models, as for example the GCAM model, that assume other functional relations among technologies, as for example linear

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aggregation across technologies (see Kriegler et al., 2014 for a comparative analysis and classification of alternative model types). In addition, WITCH includes a constraint on the flexibility of the energy sector technological mix that penalizes excessive penetration of low flexibility technologies (i.e. renewables as well as base load technologies as for example nuclear) versus high flexibility ones (i.e. gas power plants) (Sullivan et al., 2013). A further potential difference between the WITCH and GCAM models is in the way nuclear waste management cost are treated (in WITCH nuclear waste management costs increase with the world cumulated capacity of nuclear capital installed to mimic some sort of saturation effect). However, as the objective of the analysis is to look deeply into model structures and how they might affect models' reactions to input parameter variations, assumptions about nuclear waste management costs were harmonization across the two models.

Notwithstanding these differences, the direction of change is clear; an increase in nuclear energy costs increases baseline emissions both in WITCH and GCAM[4].

In addition, in the GCAM model, bioelectricity efficiency and non-energy costs (and biofuels, to a lesser extent) do play a role in shaping emissions, in particular for high cost (low efficiency) realizations.

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[4] The slightly oscillatory behavior is mainly due to the smoothing method adopted and the finite sample size.
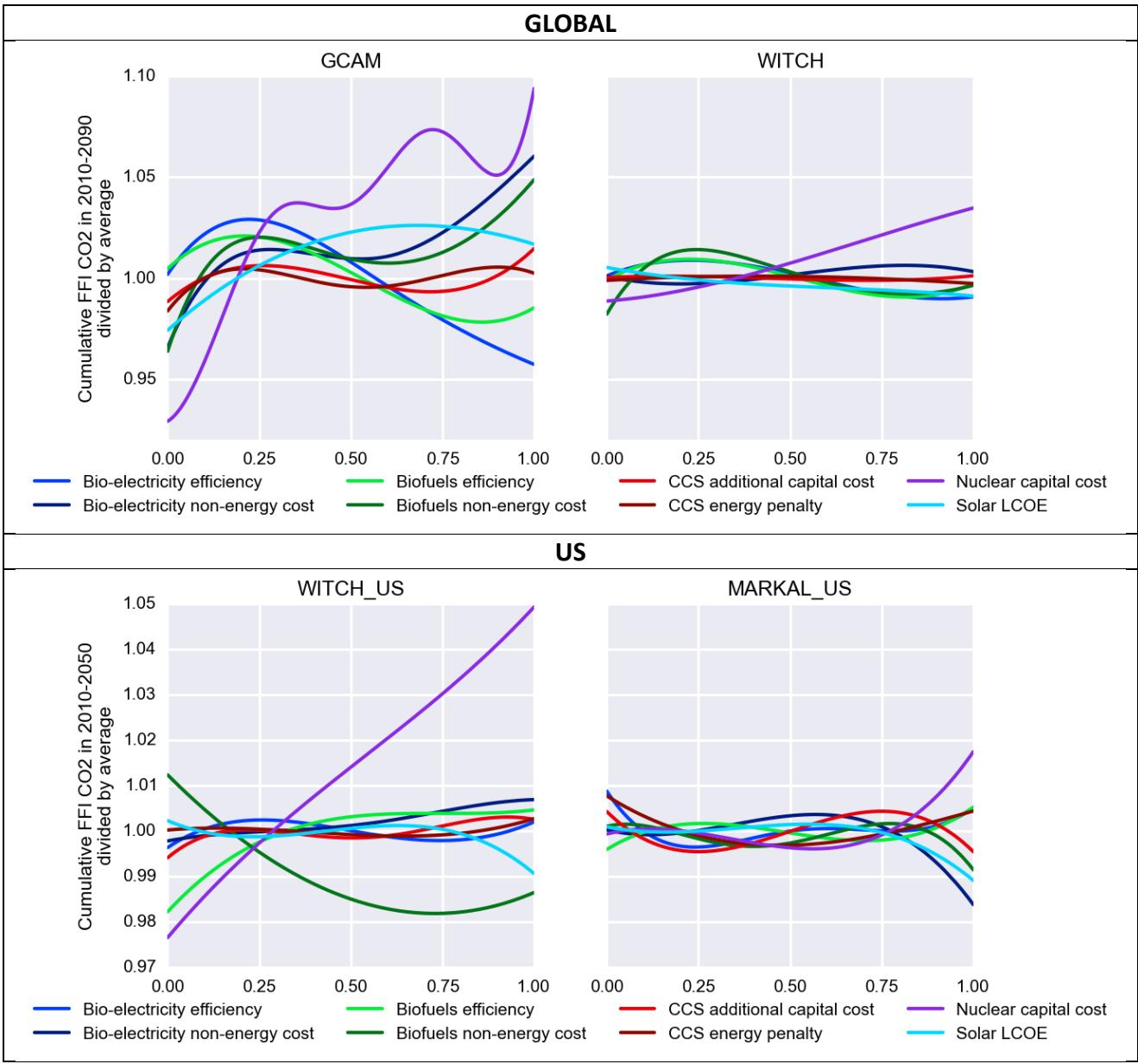
Figure 2: First order effects of the functional ANOVA expansion for the 8 model inputs on global (upper panels) and US (lower panels) cumulative FFI CO2 emissions over the century, according to a functional ANOVA expansion. The realizations of each input are ordered on the x-axis from their min (=0) to their max (=1).

The lower panel of Figure 2 reports a similar analysis but with a US focus. Within this single region as well, the

cost of nuclear energy is again the main player for WITCH. For MARKAL_US, an effect is registered for

nuclear energy at the extremes of its variation ranges. However, MARKAL_US, while producing an emission

variation range comparable to that of the WITCH model for the US (see Figure 1, right hand side panel),

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displays a very low sensitivity to individual changes in technology costs and efficiency values. The almost

horizontal shape of the first order effects and the very overlapped curves practically indicate that the model

inputs play the effects of numerical noise, when considered individually. Indeed, the MARKAL_US baseline

includes a number of assumptions and policies, in the form of additional constraints, that contribute to a less

clear sensitivity to technology costs and efficiency levels when considered as individual determinants of the

model output. Conversely, these constraints increase the interaction effects, as confirmed shortly when

considering the sensitivity measures in Table 2. Let us describe in detail what these constraints are. First of all,

the inclusion of state level renewable portfolio standards (RPS) and wind generation tax credits in

MARKAL_US lead to a higher level of renewable generation already by 2020, and independently on the

technological performance realization. Additionally, the assumed ability to apply for a second 20-year life

extension for nuclear power plants and the assumption that fossil steam plants do not have fixed retirement

schedules (instead the retirements are determined endogenously) also limits the potential market for new

technologies. Furthermore, the inclusion of the renewable fuel standard (RFS), as legislated by the Energy

Independence and Security act of 2007, requires 36 billion U.S. gallons of biofuels by 2022. Hence, while

biomass-based fuels gain market share versus petroleum-based fuels in MARKAL_US, biomass-based power

generation is relatively disadvantaged by other fuels in the electric generation market in MARKAL_US.

Figure 3 reports the ranking of the different parameters for their uncertainty importance. It can immediately be

seen that for both GCAM and, to a lesser extent, WITCH nuclear capital costs are, as expected, the key-drivers.

The three uncertainty importance indicators tend to agree on their ranking, especially for the first three positions,

which are the most relevant for the analysis.
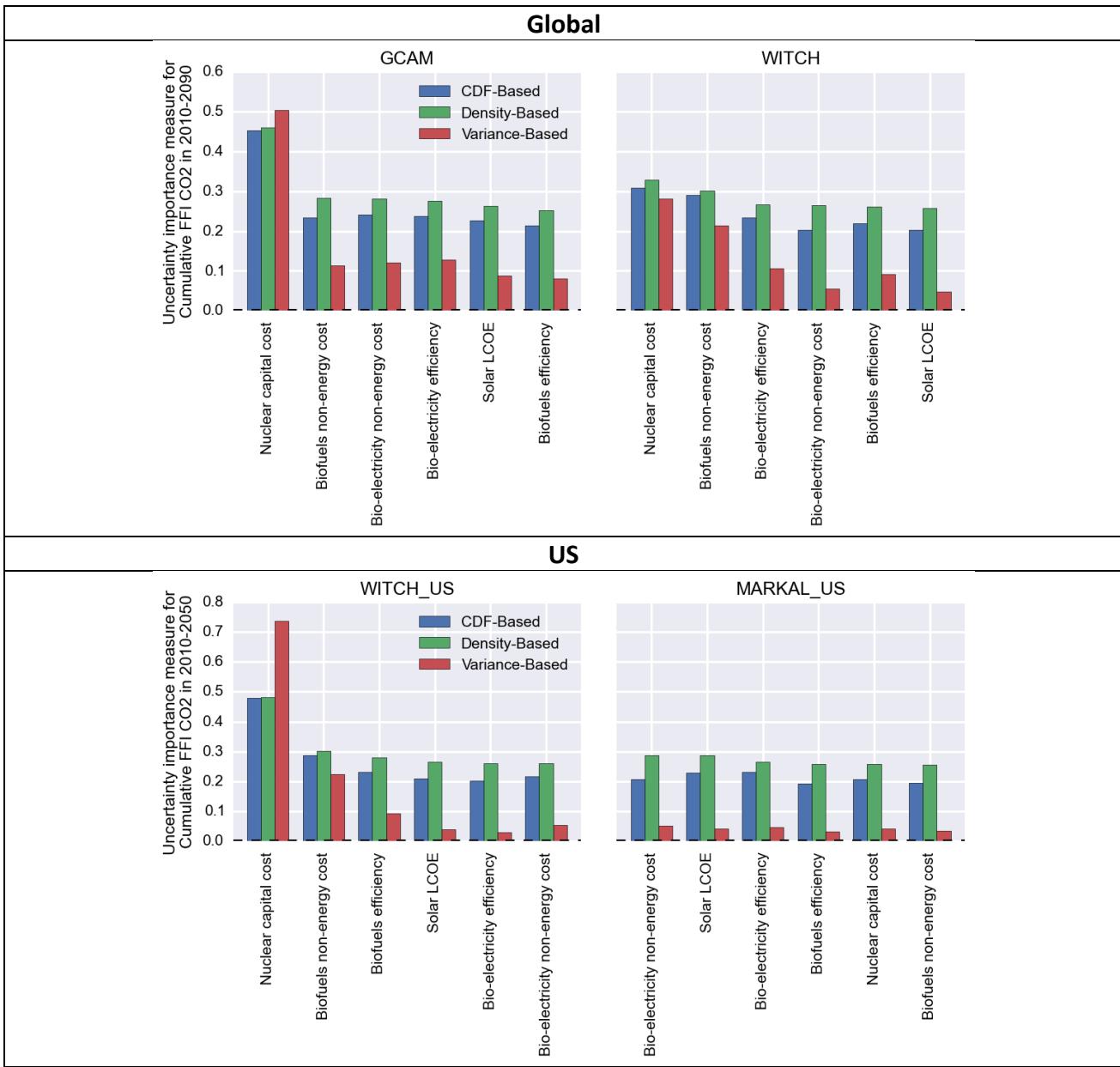
Figure 3: Ranking of uncertainty drivers for global (upper panels) and US (lower panels) cumulative FFI CO2 emissions over the century (over the half century for the US metric). Inputs on the x-axis are ordered from most important to least important, according to a density-based measure. In other colors also CDF- and Variance-based indicators are reported.

In the lower inset of Figure 3 a similar set of indicators with a focus on the US is displayed for WITCH and

MARKAL_US. The latter shows an almost uniform sensitivity to the model inputs, as well as an almost null

value for the first order variance-based sensitivity indices. However, distance-based sensitivity measures display

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a non-null value. This combination indicates that individual effects are negligible in MARKAL_US, and that the relevance of model inputs is mainly due to their interactions. As noted before, this is likely to be caused by the inclusion of a number of concurrent policies and constraints in the baseline.

3.2 Climate Constrained Scenarios

Let us now move on to the analysis that includes a constraint on global emissions in line with a 4.5 and a 2.6 RCP scenario. The first and most straightforward output to study is the cost of CO_2 abatement policy as a share of baseline GDP. Policy costs are measured in slightly different ways in different models (for MARKAL_US only the price of carbon is available and will be discussed below). In WITCH policy costs are measured as the difference in global consumption in the policy case versus the baseline. In GCAM, as GDP is exogenous and independent of the climate policy, the policy cost is measured in the reduction of social surplus, i.e. the area under the marginal abatement cost curve. In both cases costs are discounted at 5% and reported as share of GDP. Although these two metrics are not entirely comparable, as a matter of fact they are typically used for relative effort comparisons across models (see for example Clarke, 2009). In particular here, as we are interested in the relative effect of each technology performance rather than on the estimates of climate policy costs per se, it seems appropriate to compare these two metrics. The two models produce fairly comparable cost estimates for the 4.5 RCP scenarios, while they vary widely for the 2.6RCP scenario (see Figure 4).

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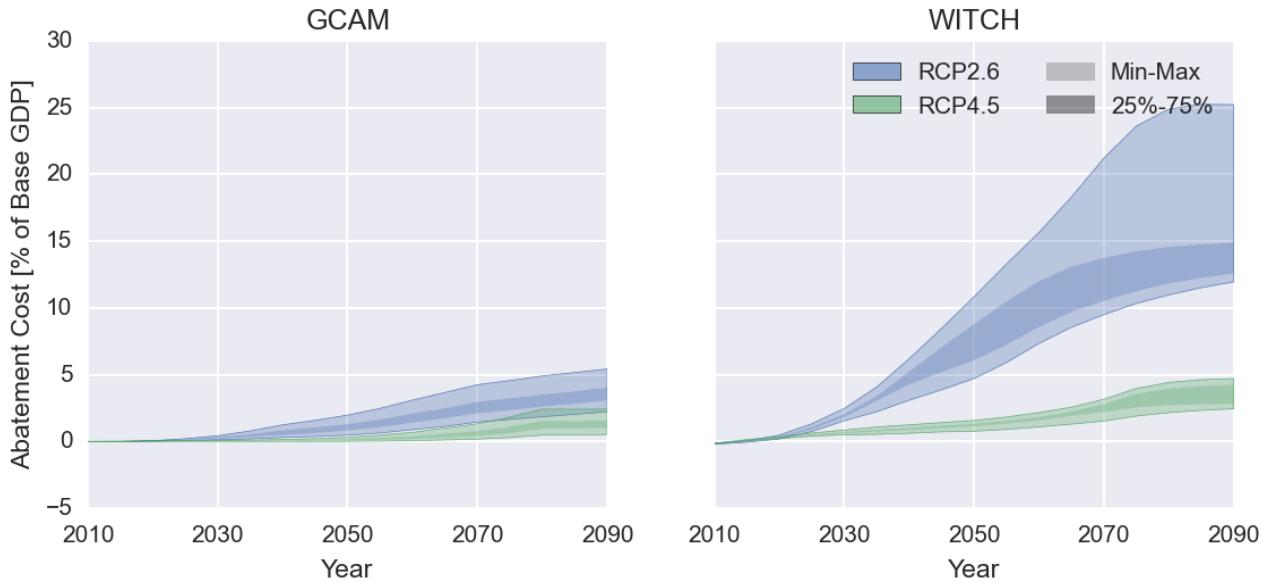
Figure 4: Abatement costs of the two implemented climate policies as percentage of Base GDP. For GCAM, absolute costs are expressed as the area under the MAC curve. In WITCH they correspond to consumption losses.

Notably, WITCH reports much higher costs and a much larger variation in cost realizations associated with the

range of technology performance. Figure 5 shows that the models appear to respond monotonically to changes in

the technological cost and efficiency space. Visually, we can also appreciate that the first order effect analysis

shows a dominance of the nuclear cost realization for GCAM, while biofuels stand out in WITCH.
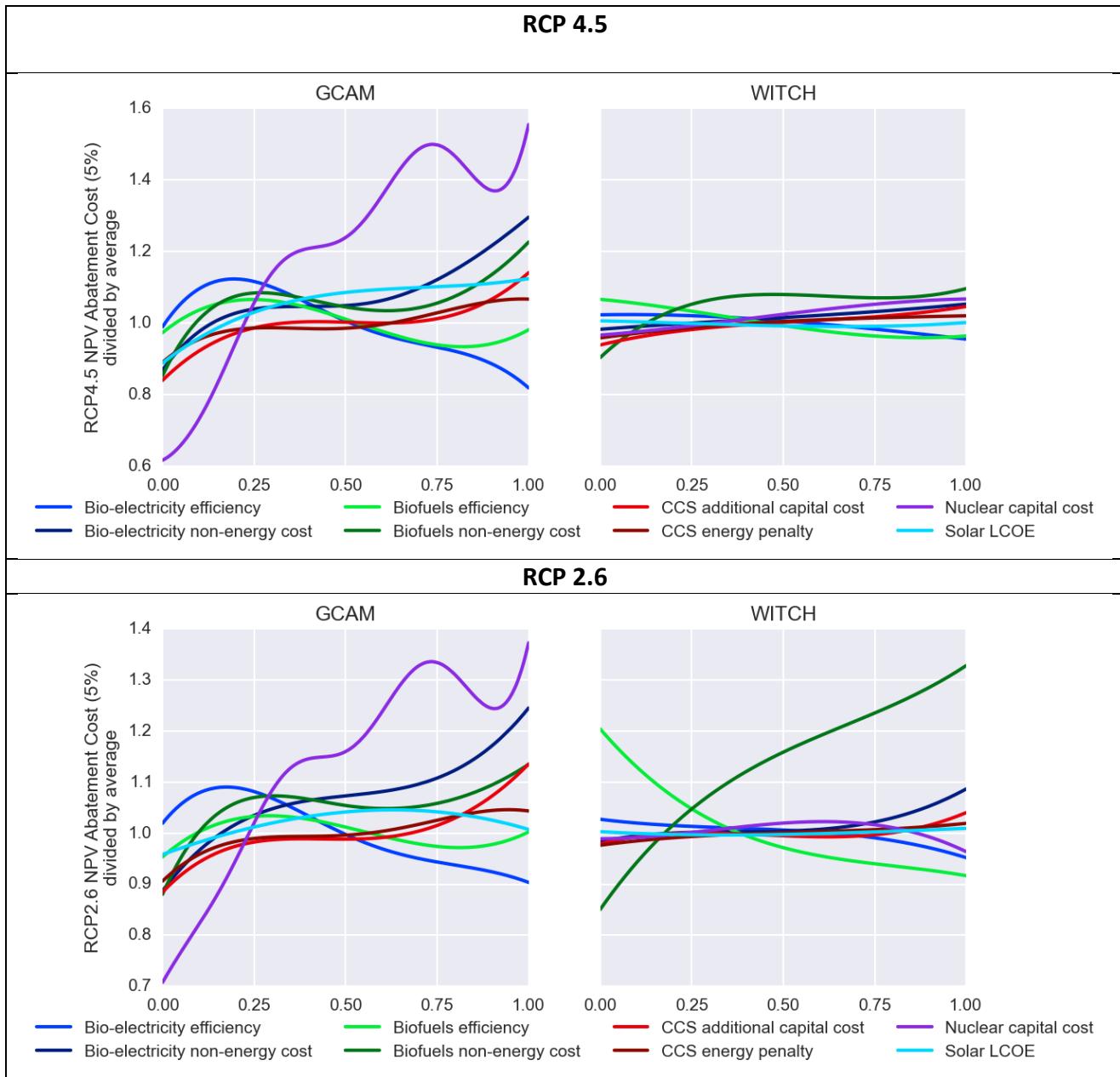
Figure 5: First order effects of the functional ANOVA expansion of discounted abatement costs for the RCP 4.5 (upper two panels) and RCP 2.6 (lower two panels) policies, using a discount rate of 5%.

The dominant technology, though different across the two models, tends to be robust across mitigation targets (upper and lower insets in Figure 5). This is an important insight that comes from a multi-model comparison. It suggests that what could be considered as a robust response for a single model becomes less clearcut when

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including several models in the analysis. Obviously, the climate policy cost metric is sensitive to the choice of the discount rate. We also perform the ANOVA analysis for policy cost metrics computed with different discount rates. Although we are not reporting them, results are extremely robust for this additional layer of sensitivity analysis: the first two positions of the ranking do not vary for a wide range of discount rates (as low as 0%, i.e. costs are aggregated undiscounted). This is also true if we consider a different metric altogether, that is if we consider carbon prices. This is shown in Figure 6 for the 2.6 RCP scenario, where we can also include the results for the MARKAL_US model.
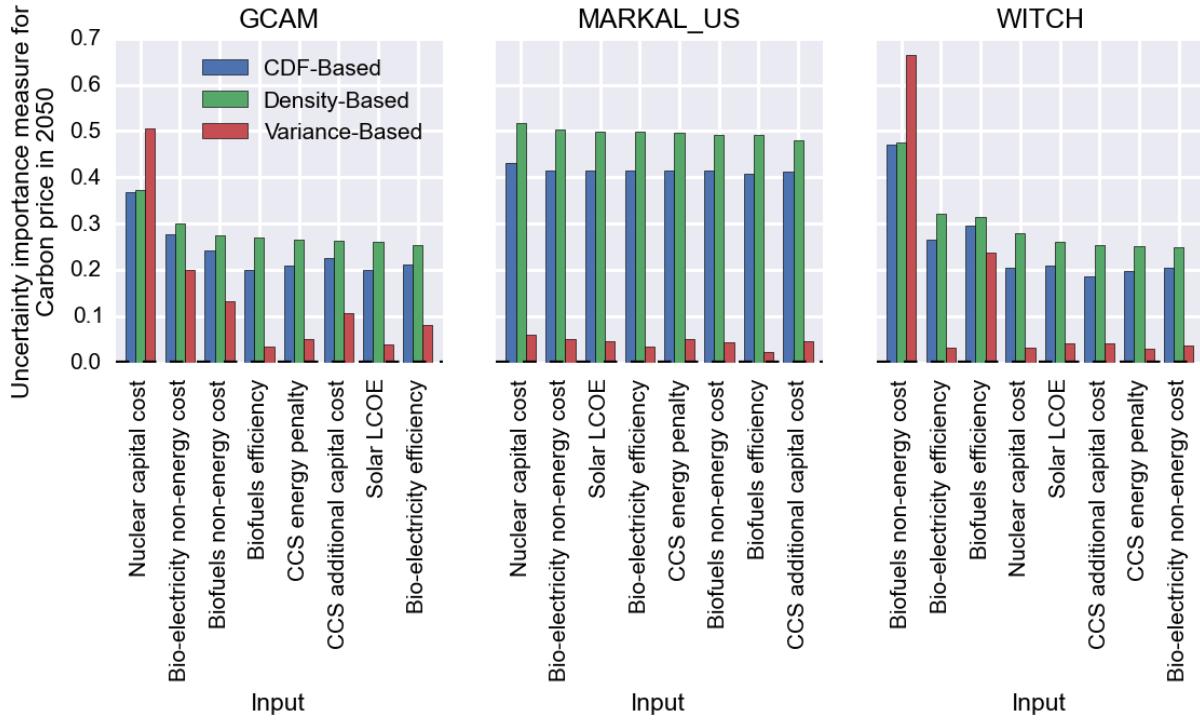
Figure 6: Ranking of uncertainty drivers of Carbon Prices for the RCP 2.6 policy

To appreciate how the uncertainty in technology costs propagates in the shadow price of carbon before 2050, the full time series of carbon prices for the different models and for both the climate constrained scenarios considered are reported in Figure 7. Despite the structural differences across the models, several similarities can be identified: under the less stringent (RCP4.5) climate scenarios model tend to agree on the median level of the carbon price; uncertainty increases over time; the min-max bands for the two scenarios do not overlap; and the near-term growth rates in the stringent (RCP2.6) scenario are similar.
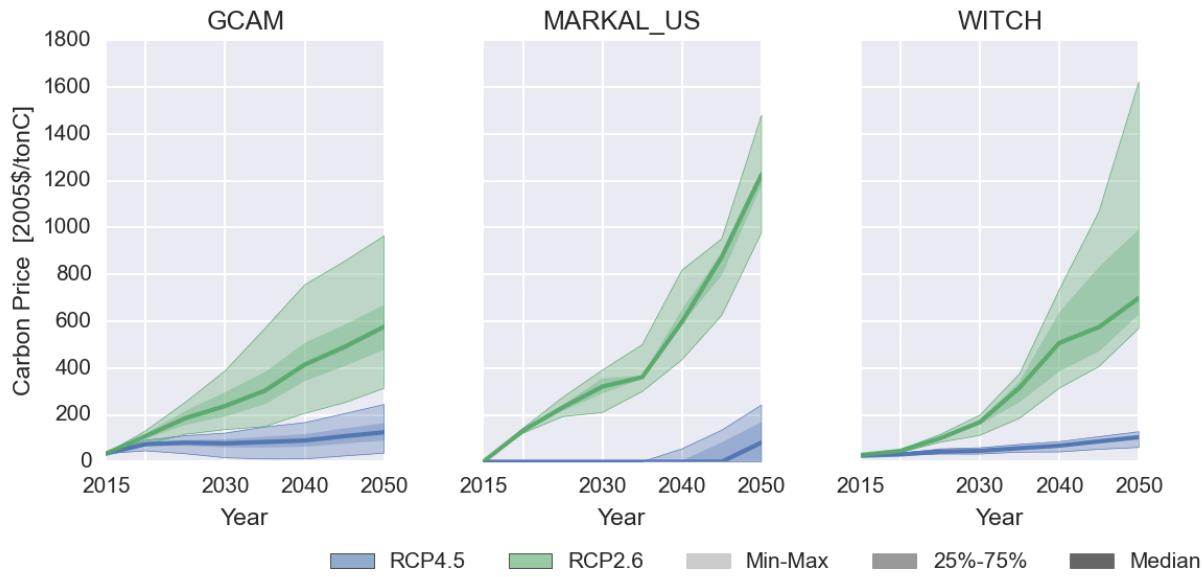
Figure 7: Price of carbon up to 2050 for each of the models in the climate constrained scenarios.

Another common result across models is that both policy costs and carbon prices are more sensitive to technological performance realization, and are so earlier in time, under scenario 2.6 RCP than 4.5 RCP. While in the latter case just a few advanced technologies are sufficient to reach the target, the feasibility and costs of the former scenario rely greatly on the availability of a wider portfolio of cheap and efficient technologies.

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Notwithstanding these similarities, models' structural difference account for the huge variation in the extent and timing of the sensitivity as discussed previously.

Finally, in Figure 8 we show the results of different technology penetrations under the different technology performance realizations. This shows, from a different angle, that GCAM results are more sensitive to technology performance than those of WITCH. At the lowest cost and highest efficiency, GCAM results indicate that renewable and nuclear energies can take up to 60% and 75% of the world's electricity supply in 2090, respectively. In comparison, WITCH results show smaller variance. For instance, at the lowest solar costs considered, the renewables' share of electricity does not exceed 20%, while nuclear energy does not take more than 60% of the power production mix. These differences bring forward the fundamental structural differences in the model architecture. Given sufficiently low prices, GCAM's flexible structure allows solar, nuclear, or CCS energy to saturate the electricity market. For instance, at $385/kW capital cost of nuclear energy, GCAM allows most electricity markets to be dominated by nuclear energy within a few decades. Conversely, at the very unlikely extreme of $5727/kW there are virtually no new nuclear plants being built in the future. Such built-in flexibility of the architecture results in a lower cost of abatement, as well as a large sensitivity to either extremes of the technology costs.

On the other hand, WITCH results indicate a more limited role of each technology. For instance, the market penetration of renewables in WITCH is less sensitive to the cost, because of strictly binding constraint on grid-

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integration of intermittent renewables (the constraint on the flexibility of the power generation fleet mentioned early). Similarly, nuclear power generation is constrained in WITCH for a variety of reasons, as the built in flexibility constraint. As we have already mentioned, the greater presence of renewables requires more flexibility in the mix, which is not conveniently provided by nuclear power plants. Hence, instances when both solar and nuclear technologies realization are low cost are not necessarily particularly favorable.

CCS technologies are key to the decarbonization implied by the climate policy scenarios under consideration.

Under the RCP 2.6 in particular, with both GCAM and WITCH the minimum level of carbon stored is a considerable 2-3 GtC by the end of the century (notice how this differ from many multi model analysis set up where CCS is considered fully unavailable in the worst case scenario). In WITCH storage of carbon is performed basically independently of its cost and variation is really modest (as said all low carbon technologies are basically required in the mix to comply with these climate targets). In GCAM the deployment of CCS is much more sensitive to the vector of cost realization as more substitution with other technologies is possible.

4. Conclusions

This paper investigates the impact that technology assumptions have on a set of alternative environmental and economic metrics across models by means of a well-defined framework taken from the sensitivity analysis literature. This effort is extremely important for improving the usability of models to support policy making. First, because this type of exercise helps unpack the model structure and address the "black box" critique by means of showing the drivers in operation. In addition, given that different metrics might be of interest to policy makers, depending on the focus of the policy under consideration, we explore sensitivity of different types of output of Integrated Assessment models, rather than concentrating on the sole objective function (or policy cost

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metric). This exercise is also extremely important from the viewpoint of modelers, who can better understand what is driving the results of their complex models and, as a consequence, focus their modelling and calibration efforts where it is more crucial in terms of model responses.

In unconstrained emission scenarios, low-carbon technologies have to compete with fossil fuels without accounting for the social cost of emissions. As such, within the range of future technology performances considered in the present analysis, the cost of nuclear energy is shown to dominate all others in affecting future emissions. Although different models imply different variations in baseline emissions, the predominance of nuclear energy cost as the main source of variation across models is a robust result. The variability across models in the magnitude of this effect reflects, in turn, the existence of structural model differences that affect the speed and ease of technology replacements.

Climate-constrained scenarios, and in particular scenarios aiming at a stringent target such as RCP 2.6, stress the relevance, in addition to that of nuclear energy, of biofuels, as they represent the main source of decarbonization of the transportation sector, and bioenergy, since the latter can be coupled with CCS to produce negative emissions. The ranking of the different parameters for their uncertainty importance changes across models, while it is robust for each individual model to changes in the cost metrics and in the stringency of the climate scenario.

Some key policy implications may be drawn out of these results. Since climate policy costs are found to be mostly sensitive to the possibility of very cheap or very costly nuclear options, the importance of exploring

advanced nuclear possibilities, as well as of better understanding the social acceptability of such technology, cannot be neglected by energy R&D investors and policy makers alike. This will be crucial not only for the climate policy maker who intends to minimize policy costs, but also for the one who wants to reduce the uncertainty surrounding those costs. The same considerations hold for fuels and electricity produced from biomass. In this case, the appetite for research in these technologies, while hindered by potential concerns of economic competition with food production, may be supported by the key role of this technologies in reaching stringent climate targets, related in particular to the possibility of achieving negative emissions.

Looking at available statistics for the United States, a certain attention to nuclear development is already reflected in recent R&D spending, with around 1 billion USD yearly allocated to nuclear over a total R&D budget of 5 and 6.5 billions in 2010 and 2011 respectively (IEA RD&D Database). Moving to biofuels, these figures show a marked drop between 2010 and 2011, decreasing from 0.8 to 0.3 billion USD spent in related R&D. This may denote a need to strengthen the R&D efforts in this direction, potentially combined with a synergistic development in technologies like CCS, in order to avoid ruling out technologies that may make a big difference in future. Developing the models to include other technologies, like advanced energy storage solutions, and introducing important synergies, like the one between storage and solar generation, may increase the role of technologies which were assessed to have minor roles in this analysis, like solar.

A further important policy insight that we gain from the MARKAL_US model is that the existence of a complex system of energy policies, which might aim at different objectives and might be designed as independent, but which end up interacting and overlapping, might make the energy system reacting in unexpected ways to the potential improvement of the performance of a single technology.

Regarding the methodology, several lessons may be learned from the analysis performed in the present paper, which allow for potential improvements in similar future exercises. In particular, a finer resolution in the sampling would enable a deeper understanding of the mechanisms involved in a models such as MARKAL_US. Results show that a key role is played by the way and extent models mimic technological adoption and penetration, transition costs and inertia, thus calling for a new set of expert elicitations covering better these topics. Furthermore, the sampling design could account for an analysis of interactions, thus allowing the investigation of potential synergies across pairs of inputs. Nonetheless, the results obtained so far may already inform an initial screening of relevant parameters to be considered in similar sensitivity analyses.

Acknowledgments

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Appendix: IA Models Description

GCAM 2.1 Model

Table A1: Summary of GCAM features.

Model Concept	Solution Method
Integrated assessment model of Energy-Land-Climate. Detailed market equilibrium model for energy and agricultural goods. Embedded simple climate model.	The model is solved for a set of market clearing prices for each period using a combination of Bisection and Newton-Raphson methods.
Welfare Concept	**Parametric Specification**
Net present value of consumer and producer surplus.	Discount rate = 5%
Markets and Trade	**Model anticipation**
Emission permits, primary energy, and agricultural products traded on a single worldwide market. Regional markets for secondary energy.	Static Foresight
Model Regions: 14 Africa Australia and New Zealand Canada China Eastern Europe Former Soviet Union India Japan Korea Latin America Middle East Southeast Asia USA Western Europe	
Base year	**Time horizon and step**
2005	2005-2095, 5 years
Climate	**Climate Change**
Greenhouse gases: CO2, CH4, N2O, HFCs, PFCs, SF6, CO, NOx ,VOC, SO2, BC, OC. Aerosols Considered: yes	Model for the Assessment of Greenhouse Gas Induced Climate Change (MAGICC 5.3) CO2 concentration (ppm) Radiative forcing (W/m2) Temperature change (°**C**)
Mitigation options	**Climate Impacts**
Abatement cost functions for non-CO2 GHGs Land use Decarbonization options in the energy system (renewables, nuclear, biomass, ccs)	Not modeled
Land use	**Resources considered**
Emissions from land use change are considered	Coal, Oil, Gas, Uranium, Biomass, Carbon Storage

Overview

The Global Change Assessment Model (GCAM) is a global integrated assessment model of energy, economy, land-use, and climate. GCAM is originated from the Edmonds and Reilly model (Edmonds & Reilly 1983, Edmonds & Reilly, 1983).

In this paper, we use the standard release of GCAM 2.1 with elicited technologies specifically modified to reflect the common assumptions on the future technology performances. GCAM is an open-source model[5] primarily developed and maintained at the Joint Global Change Research Institute. The full documentation of the model is available at GCAM wiki page (available at http://wiki.umd.edu/gcam/).), and the following description is a summary of the wiki documentation.

GCAM is a long-term global model with particular emphasis on the representation of human dimensions of the Earth system. GCAM integrates representations of the global economy, energy systems, agriculture and land use, with representation of terrestrial and ocean carbon cycles, a suite of coupled gas-cycle and climate models.

The climate and physical atmosphere in GCAM is represented by the Model for the Assessment of Greenhouse-Gas Induced Climate Change (MAGICC) version 5.3 (Wigley and Raper, 2002). The emission trajectories of greenhouse gases are modeled in GCAM's energy and land-use components.

The global economy of GCAM is represented in 14 geopolitical regions, explicitly linked through international trade in energy commodities, agricultural and forest products, and other goods such as emissions permits. The scale of economic activity is driven by population size, age and gender, and labor productivity that determine economic output in each region. The energy and land-use market equilibrium is established in each period by solving for a set of market-clearing prices for all energy and agricultural good markets. This equilibrium is dynamic-recursively solved for every 5 years over 2005-2100. Table A1 above provides an overview of the other key features of GCAM.
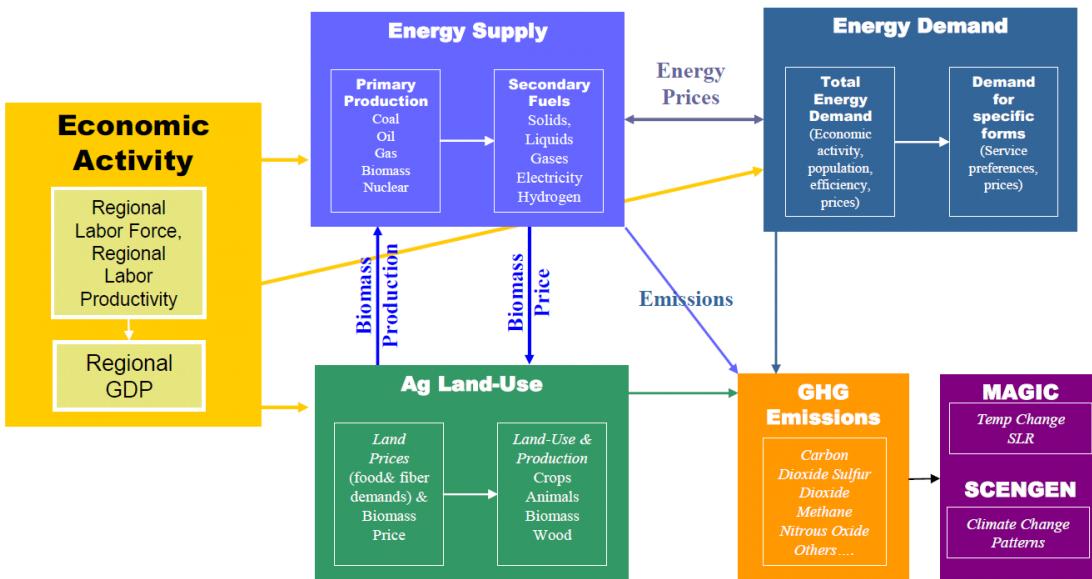
Fig. A1 Overview of the GCAM model.

GCAM combines representations of the global economy, energy systems, agriculture and land use, with representation of terrestrial and ocean carbon cycles, a suite of coupled gas-cycle and climate models.
Source: Wise et al. 2009.

Modeling energy system

In GCAM, the energy system represents processes of energy resource extraction, transformation, and delivery, ultimately producing services demanded by end users. Resources are classified as either depletable or renewable; in either case, the extraction costs of a given resource are assumed to increase as economically

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[5] GCAM Source Code and Data (available at http://www.globalchange.umd.edu/models/gcam/).

attractive resources are employed, but are also subject to technological progress which can lower extraction costs for a given resource grade. In each time period, the market prices of energy goods and services, including fossil fuel resources, are determined within the market equilibrium.

Fossil fuel energy is produced from a graded, regionally disaggregated depletable resource base. Renewable energy forms are also disaggregated by region, and resource grade; however, by their nature the resource is not consumed by use. Primary energy forms can be transformed into final energy products, including electricity, processed gas products, refined liquids, and so on.

Energy transformation sectors convert resources initially into fuels consumed by other energy transformation sectors, and ultimately into goods and services consumed by end users. Multiple technologies compete for market share; shares are allocated among competing technologies using a logit choice formulation (Clarke & Edmonds, 1993). The cost of a technology in any period depends on two key exogenous input parameters—the non-energy cost and the efficiency of energy transformation—as well as the prices of the fuels it consumes. The non-energy cost represents all fixed and variable costs incurred over the lifetime of the equipment (except for fuel costs), expressed per unit of output. For example, a gas-fired electricity plant incurs a range of costs associated with construction (a capital cost) and annual operations and maintenance. The efficiency of a technology determines the amount of fuel required to produce each unit of output. The prices of fuels are calculated endogenously in each time period based on supplies, demands, and resource depletion. The depletion of economically available energy resources are explicitly tracked throughout the modeling period.

Modeling CO2 emissions

GCAM tracks 16 different greenhouse gases, aerosols and short-lived species. Fossil fuel CO_2 emissions are modeled according to the following method:
1. The total emission in the base year is calibrated to the Carbon Dioxide Information Analysis Center (CDIAC) database (Boden et al, 2009) The fossil fuel consumption in the base year is calibrated to the International Energy Agency (IEA) Energy Balances Database 2007.
2. The average emission coefficients are derived from the ratio of the total emission and the total fuel consumption for each fuel (Coal, Oil, and Gas).
3. These emission coefficients are applied to each sector in the base year.
4. For future periods, GCAM solves for market shares of each fuel in each sector, and the emissions are calculated by the product of emission coefficients and the fuel consumption in each sector.

Modeling key TEAM Technologies

Capital costs, fuel costs, and other non-energy costs are amortized to yield the levelized cost of electricity (LCOE) for each technology. Multiple technologies compete for market share; shares are allocated among competing technologies using a logit choice formulation (Clarke & Edmonds, 1993).

Renewables integration is limited to 30% of grid capacity, at which point each additional unit of renewable power requires either an equivalent unit of gas0fired backup or battery backup. Fuel costs are determined endogenously by the model. The cost of biomass is endogenously determined by the land-use module. CCS is available for all fuel types starting in the year 2020. The additional capital cost and the additional fuel requirement is amortized and added to the standard powerplants powered by fossil fuel or biomass. CO2 storage can also be treated as a finite geographically distributed resource in GCAM. In this mode GCAM distinguishes five candidate geologic storage reservoirs types: (i) On-shore deep saline formations; (ii) Off-shore deep saline formations; (iii) Depleted oil fields; (iv) Depleted gas fields; (v) Unminable coal deposits. Each type of reservoir is associated with a cost of storage ranging from $0.036/tCO2 to $100/tCO2, depending on the difficulty of access (http://wiki.umd.edu/gcam).

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All non-energy inputs evolve according to the learning equation presented in the paper, where the 2005 value is chosen in consistency with the previous 2005 calibration of the model and are summarized in the table below. Nuclear capital cost and CCS additional capital cost are amortized assuming 15% FCR and 90% capacity factor. Solar LCOE, and bioelectricity and biofuel additional capital cost do not require any conversion as they're already elicited in levelized costs. Efficiencies are converted from HHV to LHV. See (Baron et al. 2014) for a detailed discussion of the conversion process. A fixed fee of 1 mill/kWhr (0.1 cent/kWhr) is charged to nuclear electricity generated for the development and eventual disposal of spent fuel in Yucca Mountain. We apply a fixed cost for waste disposal based on the US disposal fee and utilize a range of assumptions for the potential availability of repository capacity. Uranium supply curve is an upwards sloping curve documented in (http://wiki.umd.edu/gcam). At moderate levels of nuclear deployment, they cost of uranium is around $100/kg (about 0.3 cents/kWh), but as more nuclear power is deployed, it could drive up the cost of uranium to $250/kG or more.

Table A2: Summary of TEAM Technologies characteristics in GCAM

Technology	2005 value	Unit
Bio-electricity efficiency	38.29	%HHV
Bio-electricity non-energy cost	0.0511	2010$/KWh
Biofuels efficiency	44.76	%HHV
Biofuels non-energy cost	0.91	2010$/GGE
CCS additional capital cost	3353.05	2010$/KW
CCS energy penalty	42.8	%
Nuclear capital cost	2859.89	2010$/kW
Solar LCOE	0.592	2010$/KWh

WITCH Model

Table A3: Summary of WITCH features.

Name and Version: *WITCH 2014*	Model developer and main users: *Fondazione Eni Enrico Mattei*
Model objective: WITCH 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. The model considers the positive externalities from leaning-by-doing and learning-by-researching in the technological change.	**Model concept:** Hybrid *Economic optimal growth model, including a bottom-up energy sector and a simple climate model, embedded in a game theoretic setup.*
Solution Method: Regional growth models solved by non-linear optimization and game theoretic setup solved by tatonnement algorithm (cooperative solution: Negishi welfare aggregation, non-cooperative solution: Nash equilibrium)	**Base year:** *2005*
Time Horizon, and time steps: 2005-2150, 5-year period.	**Model anticipation:** Perfect Foresight
Coverage and regions: *Global. 14 regions.* cajaz: Canada, Japan, New Zeland china: China, including Taiwan easia: South East Asia india: India kosau: South Korea, South Africa, Australia laca: Latin America, Mexico and Caribbean indo: Indonesia mena: Middle East and North Africa neweuro: EU new countries + Switzerland + Norway oldeuro: EU old countries (EU-15) sasia: South Asia ssa: Sub Saharan Africa te: Non-EU Eastern European countries, including Russia usa: United States of America	**Policy implementation:** Quantitative climate targets (temperature, radiative forcing, concentration), carbon budgets, emissions profiles as optimization constraints. Carbon taxes. Allocation and trading of emission permits, banking and borrowing. Subsidies, taxes and penalty on energies sources.
Economic sectors (represented separately in terms of value added): ☐ Agriculture ☐ Industry X Energy ☐ Transport ☐ Services X Other **If other, please list or give number. If no separate sectors please give brief explanation of economy:** A single economy sector is represented. Production inputs are capital, labor and energy services, accounting for the Energy sector split into 8 energy technologies sectors (coal, oil, gas, wind&solar, nuclear, electricity and biofuels).	**Exogenous Model Drivers:** ☐ Exogenous GDP X Total Factor Productivity X Labour Productivity X Capital Technical progress ☐ Energy Technical progress ☐ Materials Technical progress ☐ GDP per capita ☐ Other **If other types or endogenous drivers, please describe:** In the energy sector: endogenous Learning-By-Doing and endogenous Learning-By-Researching.
Development:	**Behaviour and behavioural change:**

X GDP per capita ☐ Income distribution in a region ☐ Urbanisation rate ☐ Education level ☐ Labour participation rate ☐ Other **If other, please briefly describe:**	*Production function with constant elasticity of substitution.*
Cost measures: X GDP loss X Welfare loss X Consumption loss ☐ Area under MAC X Energy system costs ☐ Other **If other, please briefly describe:**	**Trade:** X Coal X Oil X Gas ☐ Uranium ☐ Electricity ☐ Bioenergy crops ☐ Food crops ☐ Capital X Emissions permits ☐ Non-energy goods ☐ Other **If other, please briefly describe:**
Resource Use: X Coal X Oil X Gas X Uranium X Biomass ☐ Other **If others, please give brief details or number:**	**Electricity technologies:** X Coal X Gas X Oil X Nuclear X Biomass X Wind X Solar PV X CCS ☐ Others **If others, please give brief details or number:**
Heat and other conversion technologies: ☐ CHP ☐ Heat pumps ☐ Hydrogen ☐ Fuel to gas ☐ Fuel to liquid ☐ Others **If others, or if necessary, please give brief details or number of each technology:**	**Grid and infrastructure:** X Electricity ☐ Gas ☐ Heat ☐ CO2 ☐ H2 ☐ Other **If other, please briefly describe:** *(Optional) Provide summary (3 lines) of main aspects of grids and pipelines modelling?*
Energy Technology Substitution: ☐ Discrete technology choices X Expansion and decline constraints X System integration constraints ☐ Other	**Energy Service sectors** X Transportation ☐ Industry ☐ Residential and commercial

If other, please give brief details or number:	If others, please give brief details or number:
Land-use **Please list land use types:** *Bioenergy related cost and emissions are obtained by an soft linking with the GLOBIOM model.*	**Other Resources** ☐ Water ☐ Metals ☐ Cement ☐ Other **If others or specifics, please give brief details**

Emissions and climate
 	
 Greenhouse Gases coverage:
     X CO2 X CH4 X N2O X HFCs X CFCs X SFs
 (F-gases (HFCs, CFCs and SFs) are aggregated in 2 categories: short-lived and long-lives gases)
 	
 Pollutants and non-GHG forcing agents:
     X NOx X SOx X BC X OC ☐ Ozone ☐ Other
 	
 Modelling of Climate indicators:
 X CO2e concentration (ppm)
 X Radiative Forcing (Wm^2)
 X Temperature change (C^o)
 X Climate damages (%GDP)	

Overview

WITCH (www.witchmodel.org) consists of a dynamic global model that integrates in a unified framework the most important elements of climate change. The economy is modeled through an inter-temporal optimal growth model which captures the long term economic growth dynamics. A compact representation of the energy sector is fully integrated (hard linked) with the rest of the economy so that energy investments and resources are chosen optimally, together with the other macroeconomic variables. Land use mitigation options are available through a soft link with a land use and forestry model (GLOBIOM). A climate model (MAGICC6) is used to compute the future climate. Climate change impacts the economic output through a damage function, depending also on the rate of investments in adaptation. This allows accounting for the complete dynamic of climate change mitigation and adaptation.

WITCH represents the world in a number (currently 13) of representative native regions (or coalitions of regions); for each it generates optimal mitigation and adaptation strategies for the long term (2005 to 2100), as a result of a maximization process in which the welfare of each region (or coalition of regions) is chosen strategically and simultaneously to other regions. This makes it possible to capture regional free-riding behaviors and strategic interaction induced by the presence of global externalities. In this game-theoretic set-up, regional strategic actions interrelate through GHG emissions, dependence on exhaustible natural resources, trade of oil and carbon permits, and technological R&D spillovers. The endogenous representations of R&D diffusion and innovation processes constitute a distinguishing feature of WITCH, allowing todescribe how R&D investments in energy efficiency and carbon free technologies integrate the currently available mitigation options. The model features multiple externalities, both on the climate and the innovation side. The technology externality is modelled via international spillovers of knowledge and experience across countries and time. This formulation of technical change affects both decarbonization as well as energy savings. Figure A2 provides an overview of the key features of WITCH.
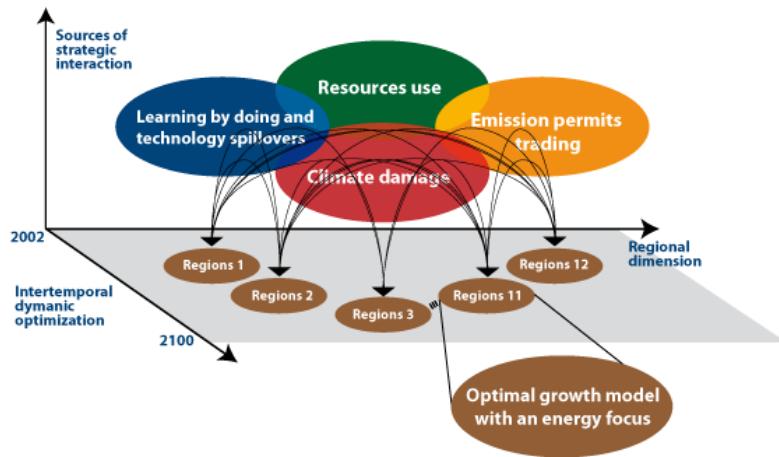
Fig. A2 Overview of the WITCH model.

Each of the model native regions solves a dynamic optimization problem with respect to the key economic, energy and climate variables. Regions interact over climate, technology and resource externalities, modeling the strategic dimension of the climate change policy problem.

Modeling energy system

In WITCH, the energy sector is fully integrated with the rest of the economy. It is distinguished in an electric sector, a transportation sector, and an aggregated non-electric (industry and residential) sectors. The energy sector is described by a production function that aggregates different factors at various levels and with associated elasticities of substitution. All the main energy carriers and technologies are included.

Natural gas is used in the industry and residential sector as well as for generating electricity. Gas power is available with and without carbon capture and storage. WITCH also tracks methane emitted in the non-energy sector. The marginal price of natural gas, along with the other energy carriers, is determined by cumulative global extraction and available resources. Gas is traded among the 13 regions, which can buy or sell it from a common pool (e.g. bilateral trade across each region couple is not accounted for).

Modeling Greenhouse gas emissions

The model generates the greenhouse gases reported in Table A3, either directly or via exogenous assumptions. Mitigation can happen through technology substitution or storage, direct reduction via Marginal Abatement Cost Curves (MAC) or end of pipe via Emission Factors. Emissions are fed to the MAGICC6 climate model, which calculates all the climate outcome.

Modeling key TEAM Technologies

Capital costs for power plants appear directly in the capital update equations, where they translate investments in new capacity additions, which cumulate with previous depreciated capital. While part of them is influenced by learning-by-research endogenous processes in a standard WITCH setup, for this exercise all of them are enforced exogenously. Given this setting, nuclear capital costs can be input in a straightforward way. For the sake of harmonizing the models the most according to the TEAM protocol, the modelling of nuclear was further simplified by assuming constant nuclear waste management unit costs, which normally increase with world cumulated nuclear capacity

Since LCOEs are an output of the model, resulting from the assumptions on capital costs, depreciation rates, interest rates, and load factors, these are first translated in corresponding capital costs, and then input to the model. In the case of solar LCOEs, these will affect both PV and CSP capital cost, considering an extra 20% cost

for the latter. The same approach is used in the case of bio-electricity non-energy costs, affecting the capital cost of both traditional and new IGCC+CCS biomass power plants. Here, the extra capital cost of the more expansive CCS plants is directly given from the CCS capital cost input. CCS capital cost is also included in the capital cost of IGCC+CCS coal plants.

Another type of parameters that appears directly in the structure of the model is the efficiency of power technologies, which translates primary energy consumed into power produced. Thus, the bio-electricity efficiency input can be accounted directly for traditional and new biomass plants. In the case of CCS energy penalty, this input affect in an inversely proportional way the original efficiencies of IGCC+CSS plants, fueled either by coal or biomass.

Finally, biofuels non-energy costs are combined additively with average unit biomass costs to determine average unit price paid for advanced biofuels. Similarly to what was done for nuclear, in this exercise the learning-by-researching and learning-by-doing dynamics, which normally determine advanced biofuels, are replaced by exogenous assumptions consistent with the sampled biofuels costs. The efficiency, as in the case of the CCS energy penalty input, is accounted multiplicatively, so that a 50% efficiency entails a doubling of the unit price.

All these inputs evolve according to the learning equation presented in the paper, where the 2005 value is chosen in consistency with the previous 2005 calibration of the model and are summarized in Table A4 below.

Table A4: Summary of TEAM Technologies characteristics in WITCH

Technology	2005 value	Unit
Bio-electricity efficiency	19.0	%
Bio-electricity non-energy cost	0.2	$/KWh
Biofuels efficiency [6]	31.5	%
Biofuels non-energy cost	10.6	$/GGE
CCS additional capital cost	3781.2	$/KW
CCS energy penalty	42.8	%
Nuclear capital cost	4250.9	$/KW
Solar LCOE	0.335	$/KWh

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[6] WITCH just distinguishes between traditional and advanced biofuels. For this exercise, we took the maximum value of the range for the non-fuel cost of biofuels, and associate it just to the advanced category of biofuels, being the one that is more likely subject to potentially breakthrough learning rates. Using these assumptions, resulting prices are more consistent with the usual advanced biofuel prices of the standard version of the model.

BNL Multi-region MARKAL_US model

Table A5: Summary of MARKAL_US features.

Model Concept	Solution Method
Partial equilibrium model of U.S. energy system. The model was run with elastic demands for the various energy service demands.	Linear optimization based on minimizing total discounted energy system costs.
	Parametric Specification System wide discount rate = 5%
Markets and Trade Emission permits, coal and natural gas are traded nationally. Electricity includes trade with Canada and Mexico. Oil is traded globally	**Model anticipation** Perfect Foresight
Model Regions: 10 California East North Central East South Central Mid-Atlantic Mountain New England Pacific South-Atlantic West North Central West South Central	
Base year 2010	**Time horizon and step** 2010-2050, 5 years
Mitigation options Abatement cost functions for non-CO2 GHGs Decarbonization options in the energy system (renewables, nuclear, biomass, ccs)	**Climate Impacts** Not modeled
Land use Not modeled	**Resources considered** Coal, Oil, Gas, Uranium, Biomass, Carbon Storage
Notes Full MARKAL documentation available at http://www.iea-etsap.org/web/Documentation.asp	

Introduction

The BNL Multi-Region US MARKAL model (US MRM) is a 10 region model of the US energy system designed using the MARKet ALlocation (MARKAL) framework. MARKAL-based models are partial equilibrium models that incorporate a description of the physical energy system (Fishbone and Abilock, 1981, Hamilton et al. 1992). They are thus bottom-up models and are typically solved as cost-minimization problems. MARKAL models are currently used in around 70 countries around the world to analyze a wide array of issues such as environmental policy, energy policy, subsidy and tax regimes, efficacy of R&D programs and associated benefits, assessment of energy efficiency programs, energy market forecasts and many more (ETSAP, 2010).

MARKAL has been developed by the Energy Technology Systems Analysis Program (ETSAP) for over 30 years. ETSAP is an Implementing Agreement of the International Energy Agency (IEA), first established in 1976. It functions as a consortium of member country teams and invited teams that actively cooperate to establish, maintain, and expand a consistent set of analytic tools.

BNL has been involved in ETSAP and the development and application of MARKAL models since the beginning in the 70s and has continually kept a set of models that have been applied to energy technology and policy issues. This document describes the latest incarnation of BNL's main US analytical tool, the BNL Multi-Region US MARKAL model (US MRM).

Reference energy system

MARKAL models represent the components of the physical energy system. At the heart of any MARKAL model is a technology database which holds the definition of a set of energy resource, conversion and end-use technologies. These energy technologies are assigned properties and attributes such as fuel consumed and produced, conversion efficiency, investment and operating costs etc.

The model structure can best be illustrated by a Reference Energy System (RES), which is a flow chart that shows how energy flows through the energy infrastructure as represented in the model. The RES thus show how the components of the energy system are linked together in a flow network where the technologies form the nodes and energy carriers represent the links (arrows). This is illustrated in **Errore. L'origine riferimento non è stata trovata.**, which shows an aggregated energy system representative of most MARKAL models.
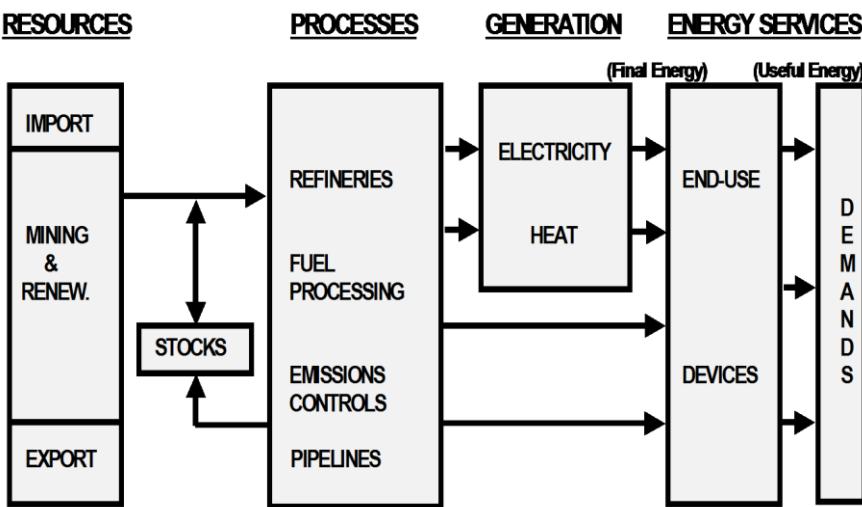
Fig. A3 Overview of the MARKAL_US Energy System

By representing individual technologies, MARKAL provides a bottom-up approach to study the energy system. The whole energy system, from resource extraction to service demand, is included, which allows for full "well-to-wheel" comparison of technology options.

Objective function

MARKAL models are generally solved as a cost minimization problem where future states of the energy system are determined by identifying the most cost-effective pattern of resource use and technology deployment over time (Loulou et al. 2004). The MARKAL objective is thus to minimize the total cost of the system, discounted over the planning horizon. Each year, the total cost includes the following elements:

- *Annualized investments* in technologies;
- Fixed and variable annual *Operation and Maintenance (O&M)* costs of technologies;
- Cost of exogenous energy and material *imports* and domestic resource *production* (e.g., mining);
- Revenue from exogenous energy and material *exports;*
- Fuel and material *delivery* costs;
- *Welfare loss* resulting from reduced end-use demands.
- *Taxes* and *subsidies* associated with energy sources, technologies, and emissions.

MARKAL models are demand driven, which means that, for any feasible solution, exogenously specified energy service demands are met. The model then determines the least cost configuration of capital stock and utilization rates that will meet these demands over the full projection period. This is done while obeying a set of user-

defined constraints, such as natural resource availability, technology and capital availability, environmental limitations.

The model is dynamic, meaning that the capital stock in any period is equal to the capital stock in the preceding period plus/minus any additions or retirements. The model thus keeps track of capital stock, and the solution in one period is directly linked to the solution for other periods.
Optimization is inter-temporal, which means that the optimization is performed for all periods concurrently, implicitly giving decision-makers foresight.

Technology data
Since the US MRM is a bottom-up model that individually represents thousands of energy technologies the data requirements are substantial. Costs and performance characteristics for all technologies are needed as well as information on policy, regulation, resource constraints, environmental constraints, expansion and growth constraints.
The main source of technology data for the US MRM is the EIA. Much of the relevant information is published annually as part of the AEO and the associated NEMS documentation. Other information was gathered from the residential, commercial and manufacturing energy consumption surveys, the annual coal, natural gas and petroleum annual reports, the refinery report and the electricity generator database. A range of other sources, too numerous to include here, have been consulted as well.

Like electricity prices the prices for liquid fuels are determined by the interaction of the technologies that produce them as well as the cost of the input feedstocks. Liquid fuels however, are not subject to time-of-use pricing and capacity markets which makes the price formation process less complex than for electricity. Marginal cost pricing is still used and most fuels will be priced at the crude oil price plus a cost of upgrading the crude oil (refinery margin) to the fuel in question. Alternative fuels such as corn ethanol, biodiesel or other advanced bio- and synthetic fuels are also available and will impact the pricing of marketed fuels.

Modeling key TEAM Technologies

The technologies in MARKAL that correspond to the technology classes as described in table 1, which are sensitized in terms of cost and performance parameters, include for solar power all centralized solar pv, for bioelectricity the biomass integrated gasification combined cycle power plants with and without carbon capture and sequestration (CCS), for nuclear the currently available light water reactors as well as the generation III/ III+ reactors and for biofuels the biomass to liquids fuel plants. Furthermore, the additional capital and energy cost sensitivity for carbon capture is also applied to coal integrated gasification combined cycle and natural gas combined cycle power plants with CCS.
In order to harmonize the input data sample with MARKAL's default input parameters all cost data for each sensitized technology had to be converted to investment cost, a total cost of investment for new capacity. Of particular interest are solar power and bio-electricity as their investment cost calculation requires factoring in the capacity factor and the charge rate for each technology; while for solar power, investment cost is also adjusted for the available investment tax credit, as currently set at 10%. Nuclear power investment cost is calculated as the product of the overnight capital cost with the technology's capital interest factor. All investment costs are the regionally adjusted by a cost multiplier. For the coal and gas power plants with CCS the price premium for the carbon capture is applied on top of the investment cost of the model's corresponding baseline technology without CCS. Efficiency is a direct input for MARKAL technologies, therefore the integration of the data sample in the model only required the proportional adjustment of the carbon emission factors for each technology. Finally the CCS energy penalty was applied as an incremental efficiency penalty for all relevant technologies.

Table A6: Summary of TEAM Technologies characteristics in MARKAL_US

Technology	Start Year	Efficiency	Cost	Units
Biomass to Liquids	2015	69.80%	1.297 (non-energy)	2010$/GGE
Biomass to Liquids with CCS	2015	60.40%	1.516 (non-energy)	2010$/GGE
Biomas IGCC	2025	25.30%	0.0486 (non-energy)	2010$/KWh
Biomas IGCC with CCS	2025	22.70%	0.0559 (non-energy)	2010$/KWh
Solar PV	2015	N/A	0.294 (LCOE)	(2010 US) $/KWh
Gen III Nuclear LWR capital cost	2020	N/A	1650.36 (Capital)	(2010 US) $/KW

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