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STRATEGIC INVESTMENT DECISIONS IN THE ENERGY SUPPLY AND DEMAND SECTORS UNDER UNCERTAIN TECHNICAL CHANGE AND SUSTAINABILITY CONCERNS

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Abstract

THE problem of transforming the energy sector towards more sustainable alternatives in a cost-effective way is complex and multi-faceted. Five sets of questions related to energy innovation, both on the supply and the demand side, needed or helpful for a successful climate-constrained strategy, are explored in this thesis. Answers tackle the problem from different angles and are elaborated through a variety of quantitative tools, resulting in both generalizable novel approaches and specific policy-relevant insights.

The thesis demonstrates the feasibility and usefulness of different combinations of techniques, including integrated assessment modelling with endogenous technical change, global sensitivity analysis, decomposition scenario techniques, experts' elicitations, approximate dynamic programming and energy data analytics. As decisions are informed by increasingly complicated models and always larger datasets, priority is given to keeping a clear understanding of the robustness of findings, especially as our empirical or probabilistic knowledge of uncertain inputs change.

Climate policy makers, clean energy investors and power operators will find relevant insights on optimal clean energy R&D investment portfolios, best R&D risk-hedging strategies, and smart-meter potential for emission reductions. The contribution of this Ph.D. thesis lies at the intersection of these topics, exploring sensitivities of emissions and abatement costs to uncertain technological and economic factors, proposing optimal clean energy R&D investment portfolios under different climate policy contexts and degrees of uncertainty, and exploring new venues of energy conservation possibilities from behavioral interventions. The combination of novel and robust methodologies will hopefully be of inspiration for the design of improved strategies to prepare the ground for future stringent climate stabilization.

Contents

CHAPTER 1

Overview

1.1 Policy and research context

In September 2013, the Intergovernmental Panel on Climate Change (IPCC) released the first part of its Fifth Assessment Report (AR5), which is considered the result of the largest and most rigorous process of peer review conducted in any scientific field in history. Three main points emerge from this work (Stocker, Qin, and Platner, 2013):

1. the recent observed changes in the climate system are unequivocal and unprecedented over decades to millennia (e.g. atmosphere and ocean has warmed, coverage of snow and ice has diminished, sea level has risen, and the concentrations of greenhouse gases (GHGs) have increased);
2. the likelihood for human influence to be the dominant cause of these and other climatic changes is now estimated to be greater than 95% (a figure 5% bigger than the one obtained 6 years ago in the previous assessment);
3. limiting climate change to avoid irreversible consequences with sufficient probability (e.g. limiting temperature increase to 2°C with respect to the levels before the Industrial Revolution) will require substantial and sustained reductions of greenhouse gas emissions.

As the scientific community develops clearer prospects on the global risks that current rates of climate change may pose to human welfare, policy-makers are faced with the responsibility to either hedge against these risks today, or adopt a wait-and-see approach. While governments started to acknowledge anthropogenic climate change and the need for action 20 years ago with the first Earth Summit conference, a certain inertia followed from the expectations of strong economic repercussions along with emissions mitigation, especially at the deep levels required for limiting warming to safe thresholds. According to the climate scientists, global atmospheric temperature increase should not exceed two degrees Celsius with respect to pre-industrial levels in order to avoid irreversible climate damages. This would require a comprehensive international agreement as the one envisioned in the UN Climate Change Conference held in Durban in 2011.

An important step forward in international climate policy negotiations occurred in December 2015 in Paris, at the 21st 21^{st} Conference of the parties (COP) of the United Nations Framework Convention on Climate Change (UNFCCC). Representatives of 180 countries stated their commitments to reduce their carbon emissions (Intended Nationally Determined Contributions, or INDCs). As a result of the conference, the so-called Paris Agreement was finally produced and adopted, with the ultimate objective of preventing dangerous anthropogenic interference of the climate system. In quantitative terms, the goal is to limit global warming to less than two degrees Celsius, with an even more stringent proposal than the one elaborated in Durban. As of October 2016, 191 Parties signed the Agreement, and 74 Parties ratified it. With the ratification stage, countries signal their intent to be legally bound to the terms of the international treaty.

How to turn these century-long future ambitious goals in decisions for today? Climate scientists and economists help informing these decisions by resorting to so called Integrated Assessment Models (IAMs). IAMs have been proved to be a useful tool in exploring the possibility space of future sustainable energy systems, and identifying the most-effective options, as extensively reported in the mitigation chapters on assessing transformation pathways of the AR5 (L. Clarke et al., 2014). These models employ numerical optimization or simulation methods to provide economic assessments of climate change policies, and propose ideal pathways to decarbonize our economies. These pathways usually envisage a deep and potentially very costly transformation of the energy system, which is the main source of anthropogenic GHG emissions, one of the main driver of recent global warming according to IPCC.

Two key strategies emerge from the research of this and previous studies, if we want to contain the cost of decarbonization: improving energy efficiency, and reducing the costs of low-carbon technologies. Both of these strategies involve some form of innovation, either in producing or consuming energy. Including innovation in the quantitative assessment of climate policy options has been challenging, especially considering uncertainty in future technological change and socio-economic contexts, complexity of interactions between economic-energy sectors and between regions, unoptimal behavioral aspects of energy demand, current fragmented national policy commitments and future stringent environmental constraints.

The contribution of this Ph.D. thesis lies at the intersection of these topics, exploring sensitivities of emissions and abatement costs to uncertain technological and economic factors, proposing optimal clean energy R&D investment portfolios under different climate policy contexts and degrees of uncertainty, and exploring new venues of energy conservation possibilities from behavioral interventions.

1.2 Objectives

The chapters composing this thesis address five sets of questions related to energy innovation, both on the supply and the demand side, needed or helpful for a successful climate-constrained strategy.

First, we explore how different assumptions on energy intensity improvements and low-carbon technologies, along with other socio-economic factors, affect long-term projected CO_2 emissions from energy combustion with and without climate regulation. Baseline emissions, i.e. in the absence of climate policies, are one of the most important determinant of mitigation policy cost assessment. Different uncertainties around the drivers of future baseline emissions, and potentially complex interactions among them, make unclear which driver might be the most significant. Going beyond the current sensitivity analysis literature, we use a novel scenario decomposition scheme with an ensemble of six state-of-the-art complex IAMs, and apply it to the recently developed framework of future alternative narratives called Shared Socio-economic Pathways (SSPs).

As reducing energy demand turns out to be one of the factors contributing the most to avoiding unconstrained carbon atmospheric pollution, we focus on the potential benefits of new technologies, like smart meters, in reducing residential power consumption. Information feedback on the amount of electricity consumed, provided with adequate frequency, may overcome the lack of knowledge and/or salience required for optimal behavior. What is the potential energy conservation effect of information feedback on power consumption in the residential sector? This question is still debated in the literature. Earlier optimistic estimates are as high as 20%, while most recent studies with more representative samples provide a more realistic large-scale conservation effect of 3-5%. We focus on a pilot project involving the delivery of an in-home display for real-time power consumption feedback to thousands of households in Italy. We analyze the resulting high-resolution consumption dataset drawing from both statistics and machine learning literature. We try to identify the impact of such an in-home device, both in terms of quantity of reduced energy, persistence of this effect, and shifting in preferences of daily consumption patterns.

When dealing with highly constrained carbon emissions, the capacity to provide gradual or breakthrough innovation in low-carbon alternatives to traditional fossil fuels energy production is essential. In the hypothesis of a post-2020 global commitment to the objective of limiting the average global surface temperature increase of 2°C above the pre-industrial average by the end of this century with sufficient probability, what are the clean energy R&D investment needs to comply cost-effectively with such a target? Specifically, we focus on two channels of innovation, a gradual one directed to improve energy efficiency, and a breakthrough one meant to support the decarbonization of the non-electric sector. Furthermore, we investigate the potential lack of R&D efforts in the current short-term climate policy scenario, being dominated by fragmented and modest emission reduction pledges. The risk is a technological lock-in in carbon-intensive technologies, with cleaner alternatives not mature enough when a deep transition of the energy system will be unavoidable. What if national pledges are replaced by a concerted international R&D programme? We contribute to the literature by optimizing clean energy R&D investments under realistic climate policy scenarios, and exploring alternative R&D-based policy instruments potentially better suited at preparing the ground for future stringent climate stabilization.

When using economy-energy-climate models, due to their computational complexity, it is common to treat uncertainty only in discrete terms, analyzing a finite numbers of alternatives. Nonetheless, the design of optimal energy R&D portfolios also rely on our understanding of the extent to which technology assumptions drive model results when changing in a continuous space. How this uncertainty propagates in different IAMs in shaping emissions and abatement efforts under different climate scenarios? We systematically explore a set of relevant low-carbon technological cost dimensions as recently elicited by leading experts. The main goal is to identify the most/least important input parameters in determining crucial model outcomes, like cumulative emissions or climate policy costs, both individually and interactively. We also analyze the sign and magnitude of the relation between outcomes and varying cost inputs, with computationally parsimonious techniques borrowed from the sensitivity analysis literature.

The ultimate challenge is to introduce uncertainty endogenously in a coupled IAM and R&D portfolio problem. Efforts in innovation of clean energy technologies are risky, and deciding how to allocate the scarce funds available ideally mean to account for these risks also in the decision-making process. Given experts' probabilistic judgments on the uncertain effectiveness of R&D in reducing future technological costs, we identify optimal clean energy R&D investments, with welfare calculated through a complex IAM. We explore the robustness of the result to different limited budgets, risk-aversion preferences, and crowding out assumptions.

Despite the policy relevance of the topics covered, the research also have important methodological implications. Deep uncertainty related to the effectiveness of R&D investments on technical change, the complexity of a comprehensive integrated modelling of the energy sector and the economy, and the large dimensions of available datasets to be mined for evaluating innovative demand-side power conservation measures, provide room for innovating the quantitative treatment of such issues.

Answering to these questions could be beneficial both for integrated assessment modellists and decision-makers. These latter, including climate policy makers, clean energy investors and power operators, will find relevant insights on optimal R&D portfolios, best R&D risk-hedging strategies, and smart-meter potential for emission reductions. The combination of novel and robust methodologies with complex models, as well as the attention to transparency of assumptions, will hopefully be of inspiration for the design of improved strategies to solve the climate change mitigation puzzle.

1.3 Methods

Each set of questions presented in the previous section will be addressed with a combination of mathematical tools. Some tools, like climate-energy-economy models or experts' elicitation, are common to several chapters. Some others, like Approximate Dynamic Programming or K-Means clustering, are specific to the needs of the question they try to answer.

1.3.1 Integrated Assessment Models

With the exception of one strictly empirical question, proper pursuit of the objectives of this thesis involves a quantitative model for the climate-energy-economy nexus. IAMs represent a good compromise between complexity and completeness. The goal of IAMs is to inform climate policy decisions and identify ideal pathways to decarbonize our economies. IPCC, among other international institutions, heavily rely on IAMs to explore the possibility space of future sustainable energy systems, and identify the most-effective options, both in terms of mitigation and adaptation to climate change. IAMs employ either optimization or simulation methods to model with different detail a certain number of sectors of the economy and the environment. Specific modelling focus is commonly directed to energy production, energy consumption, land use, and atmospheric pollution from greenhouse gases (GHGs). They usually have a century-long time resolution, and a global spatial coverage, with different regional disaggregations.

Among the available IAMs, preferential attention was given to the World Induced Technical Change Hybrid Model (WITCH) developed within FEEM's Sustainable Development research programme (Bosetti, Carraro, Galeotti, et al., 2006; Bosetti, Tavoni, et al., 2009; Emmerling et al., 2016). Its fairly rich technological and economical description, and its distinctive features of modelling strategic interactions across regions and endogenous clean energy innovation, make it a good candidate for answering several of the above questions.

WITCH divides the worldwide economy into 13 regions, whose main macroeconomic variables are represented through a top-down inter-temporal optimal growth structure, while the energy sector is detailed in a bottom-up fashion. The different regions behave as forward-looking agents optimizing their welfare in a non-cooperative game-theoretic set-up, where actions interrelate through several externalities: GHG emissions, dependence on exhaustible natural resources, trade of oil and carbon permits, and technological R&D spillovers.

In the sensitivity analyses that follow, an ensemble of IAMs, encompassing different modeling paradigms, is used. These other models are described in the individual chapters, and were operated by other authors who provided the corresponding data for the joint analysis. The difference between the models are both structural and parametrical. While an harmonization process tried to minimize the second source of variation for the sake of comparability in the sensitivity exercises, the remaining differences are key to assess the robustness of the findings with respect to different model specifications.

IAMs and Endogenous innovation

Endogenous innovation is not a common trait in the IAMs community. In Carraro, Gerlagh, and Zwaan (2003) and Grubb, Carraro, and Schellnhuber (2006) we find interesting overviews of how different innovation modelling approaches developed through history in the context of global energy-economy models applied to climate change. A first generations of these models (roughly from the late 1980s to the mid 1990s) exploited a series of exogenous assumptions for technical change. In the early 1990s, top-down modeling of energy demand started to be combined with bottom-up modeling of energy supply, still relying on essentially exogenous assumptions about both. In all these modeling studies, the costs of deep emission reductions were almost entirely dependent on the assumptions about AEEI and low-carbon technology costs. Yet, theoretical and empirical studies were already demonstrating that technology would itself be modified by climate policy. From around the mid 1990s, the top-down modeling community began to incorporate both explicit knowledge functions using accumulated R&D, and learning-by-doing equations. Also the bottom-up community began endogenizing technical change through learning-curves-explicit functions of how scale might be associated with cost reductions into their analyses.

Starting from these approaches, WITCH brings further sophistications. In its basic formulation, it includes international R&D spillovers, crowding out effects between different R&D investments, two-factor learning curves, and backstop technologies, making the implications between climate policies and R&D efforts more subtle. While already used for the purpose of analyzing this relationship (Bosetti, Carraro, Massetti, et al., 2008), in the following chapters new policy elements are considered. For example, when finding the clean-energy strategy for 2 degrees, specific regional policy realism and new alternative short-term R&D-based policies are introduced.

IAMs and uncertain technical change

A further element of complication is given by the deep uncertainty of technical change, which has started to be included in the models, despite the many challenges it entails (L. E. Clarke and Weyant, 2002). While outside the climate change literature the theory of investment under uncertainty and the real option literature has been extensively applied to study R&D investments, only few works explored the intrinsic uncertainty of innovation in the context of climate change.

Baker and Shittu, 2008 provide a broad picture of the literature linking uncertainty with endogenous technical change, and highlight how the joint modelling of the two has important quantitative and qualitative impacts on optimal climate change technology policy. The three primary questions emerging from their study are: how much should be invested in climate R&D, how R&D should be allocated among possible research projects, and how the presence of endogenous technical change impacts optimal emissions. Including uncertainty seems to have several impacts on optimal R&D investments: it can lead to much higher investments, it can reinforce the substitability between R&D and near term abatement, and it can affect the degree of diversification.

In this context, it is common to treat uncertainty withing a simple analytical framework, with inputs derived from the output of IAMs. Following this approach, G. J. Blanford, 2009 try to capture the essential elements underlying the relationship between R&D investment and research outcomes. The valuations of potential research outcomes are determined by the markets in which they will diffuse. This is achieved by running an energy-economy model (MERGE, a model for evaluating regional and global effects of GHG reduction policies) in a variety of technology scenarios, representing outcomes of alternative R&D programs. Building on top of this a simple decision model linking R&D investment to a probability distribution over alternative outcomes, it is possible to calculate optimal portfolios.

WITCH was already used in similar ways by Bosetti and Tavoni, 2009. The authors develop a simple analytical model, with two time periods and two technologies, which mimicks a social planner who minimizes costs by choosing optimal abatement and innovation efforts consistently with a given environmental target. Uncertainty is introduced by modeling the R&D outcome on the abatement cost of a carbon-free breakthrough technology (backstop) as uncertain. A stochastic version of WITCH is devised to account for such uncertainty.

In this thesis, for the optimal R&D portfolio under uncertainty we consider a wider space of possibilities for the effectiveness of R&D. Solving the resulting stochastic program is made possible thanks to the Approximate Dynamic Programming approach mentioned below.

1.3.2 Experts' elicitation

Experts' elicitation has been used in several research fields to come up with educated probabilistic descriptions of very uncertain parameters, with little historical or experimental data, like new technologies cost reduction rates.

For the optimal R&D portfolio questions, distributions of costs were estimated from the data collected by the ICARUS project (Bosetti, Catenacci, et al., 2011). Leading experts from the academic world, the private sector, and international institutions took part in a survey designed to collect information on the role of RD&D investments in 8 carbon-free technologies, with respect to lowering future costs of these technologies and assessing the potential for their deployment. While the survey questioned the experts only on a limited amount of RD&D budgets for each technology, the results are used to fit a continuum of R&D budget scenarios, which allows to look for optimal budget allocations.

The work on sensitivity to technology costs leverages on the combined efforts of the ICARUS survey with the elicitations carried out independently by researchers at UMass Amherst and Harvard. Although surveys varied considerably across groups, they were all carried out by means of structured protocols, in order to minimize potential biases and overconfidence issues.

1.3.3 Approximate Dynamic Programming

Handling multiple technologies and continuous distributions in an optimal portfolio problem under uncertainty leads to an analytically intractable problem, whose size increase exponentially with the number of random variables considered. If we have also to wait tens of minutes, or even hours, for the solution of one instance of a complex model like WITCH for each welfare evaluation needed, the "curse of dimensionality" becomes soon intractable.

In a different context of climate change economics research, Cai, Judd, and Lontzek, 2013 show an interesting approach, called Approximate Dynamic Programming, to account for uncertainty in IAMs. The authors jointly model the uncertain elements of catastrophic climate change damages and annual economic productivity within a dynamic stochastic general equilibrium version of a widely accepted IAM. The problem is solved within the framework of dynamic programming, where the value function given by the solution of the original model is approximated with a finitely parameterized collection of functions.

Approximate dynamic programming is used here to evaluate optimal near-term innovation investment strategies for multiple technologies under continuous distributions of future learning rates and without sacrificing the use of a model like WITCH. The optimal R&D portfolio problem is cast as a usual two-stage stochastic program, under two important assumptions. First, the choice of near-term R&D investments in the first stage (from 2010 to 2030) have negligible repercussions on the economy and energy production mix in this first stage. Second, the uncertainty on technological change in the second stage does not impact the first stage objective function. Given this independency between the two stages, it is possible to replace the evaluation of the second stage value function with the evaluation of a surrogate function representing WITCH model welfare output. In particular, a polynomial can be fit for (potentially thousands) of technology costs realizations, and then used in place of the actual model. This way, the portfolio problem becomes computationally tractable.

1.3.4 Sensitivity analysis

A problem with IAMs is that it is virtually impossible to have a direct or thorough understanding of the relationship between the endogenous and exogenous variables. As Risbey et al. (2005) wrote, climate scientists and decision-makers are exposed to the risk of drawing conclusions without a full appreciation of the model behavior and of the most critical assumptions. As decision-support models become more sophisticated, sensitivity analysis will increase in relevance (Saltelli, 2002). In this thesis, we consider two types of sensitivity analysis.

First, we employ a recently developed scenario decomposition algorithm (E. Borgonovo, 2010) to understand the impact of different socio-economic and technological factors on long-term projected CO2 emissions. Three scenarios (one central and two alternative) are considered, characterized by three different configurations of a set of inputs. A scenario protocol is designed in such a way that when deviating from the central scenario, it is possible to attribute the observed change in output to changes in each of the inputs. Given that inputs do not act in isolation, it is interesting to have information also on the impact of joint input changes. This is done by changing the factor of interest from a reference to an alternative value, as well as changing all of the other factors except the one of interest. The first set of model runs provides the individual effect. The second - with a change in sign - gives us the total effect of that same factor, i.e. an effect that contains both the individual and interaction effects. The interaction effect includes all the interactions of one factor with all the other factors and is equal to the difference between individual and total effects. Thank to this technique, it is possible to obtain interaction effects with a parsimonious number of model evaluations, an important feature given the complexity of the models involved in the study.

Second, given the distributions of projected future cost and efficiency technology parameters, and configuring them as input of an IAM accordingly, it is possible to build an input-output dataset usable for a post-processing or given data logic sensitivity approach (Plischke, Emanuele Borgonovo, and Smith, 2013). In particular, the following two insights are considered:

1. key-uncertainty drivers, which are identified thanks to global sensitivity indicators that measure the separation between the unconditional and conditional model output distribution (e.g. the more important the uncertainty of the input, the more the variance of the output will drop when the input is fixed);

2. sign of change, expressing the output of interest as a function of a single input, obtained through conditional expectations on all the other inputs (e.g. this allows to see whether increasing this single input also increases the output, in a first-order approximation where we average on the values that the other inputs may take).

Both sensitivity analyses, as mentioned before, consider an ensemble of IAMs. This corroborates the findings against the structural uncertainty inherently present in integrated assessment modelling.

1.3.5 Energy data analytics

Given the dataset of high frequency electricity consumption data for a large sample of households, where in-home displays were installed for tracking and notifying energy consumption levels to household members, we want to evaluate the impact of the display. We adopt two different methodologies.

First, a classical OLS regression is used to estimate the average power conservation effect of the in-home display (Houde et al., 2013). The gradual phase-in design of the experiment is exploited to compensate for the absence of external control group data, so that households who haven't received the displays yet act as counter-factual for those who already received it. If we were to look only at conditional averages of consumption between those with and without an in-home display over time, we would risk to attribute to the display the merit of an already decreasing trend in demand.

Second, a small set of representative daily load curves normalized to daily consumption (i.e. load shapes) are identified using K-Means clustering (Kwac, Flora, and Rajagopal, 2014). While originally used in the context of static load profiling, this technique is applied for detecting behavioral changes. In particular, a distribution of preferences for representative load shapes for each household, calculated as frequencies of occurrence, is built before and after the delivery of the display to understand whether any shift in preferences took place.

1.4 Overall structure

The research undertaken in each chapter gravitates around one main question: where to innovate the energy sector for supporting effective climate change mitigation policies? As we aim for a transformation on both the way we consume and produce energy, we can classify innovation options between those related to energy demand and those related to energy supply.

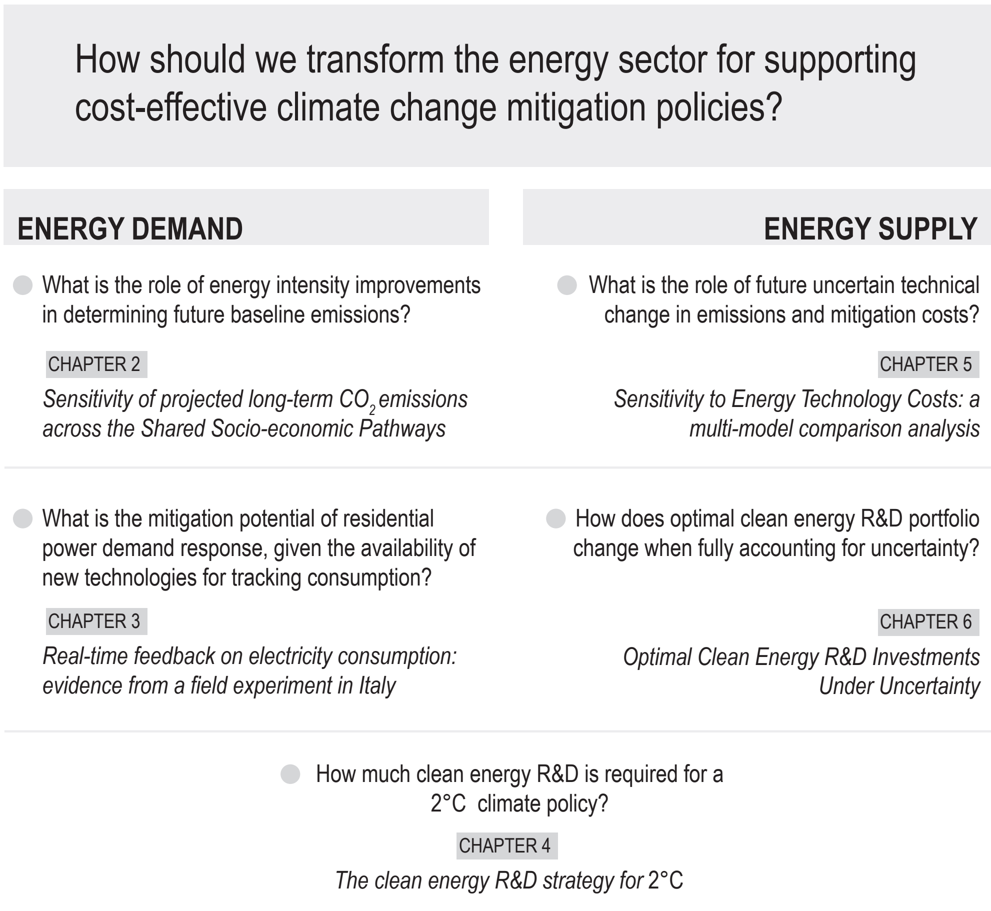

Figure 1.1: *Overarching structure of chapters and related main questions.*

Starting with the energy-demand side, chapter 2 investigates the role of energy efficiency improvements in affecting baseline emissions. The analysis takes also into account interactions with changes in other important factors across meaningful future scenario alternatives. As reduction of energy intensity turns out to be among the key drivers of unconstrained CO_2 emissions, it is worth exploring what mitigation options are available in this sector due to innovative technologies. Chapter 3 casts some light on the potential of energy conservation from the digitalization of the residential power sector. Smart-meters, consumption tracking devices and demand response programmes resulting from this information are becoming more and more common among utilities

R&D agenda. In particular, we focus on the impact evaluation of a real-time feedback in-home display deployed in Italy. Passing from a microeconomic to a macroeconomic perspective, Chapter 4 quantifies optimal public R&D expenditures in energy efficiency improvements compatible with an ambitious 2 degrees climate stabilization target. This channel of innovation is juxtaposed with one in a breakthrough clean non-electric technology. This starts our exploration of the innovation possibilities in the energy supply side. Chapter 5 involves a wider set of technologies subject to potential future R&D attention, and questions the role of their future uncertain progress in emissions and mitigation costs. Chapter 6 concludes by considering the joint problem of finding optimal R&D investments and the uncertain technical change resulting from them.

	CHAPTER **2** *Sensitivity of projected long-term CO_2 emissions across the Shared Socio-economic Pathways*	CHAPTER **3** *Real-time feedback on electricity consumption: evidence from a field experiment in Italy*	CHAPTER **4** *The clean energy R&D strategy for 2°C*	CHAPTER **5** *Sensitivity to Energy Technology Costs: a multi-model comparison analysis*	CHAPTER **6** *Optimal Clean Energy R&D Investments Under Uncertainty*
Innovation in					
Energy efficiency	■	■	■		
Advanced biofuels			■	■	■
Batteries for personal transport					■
Solar				■	■
Bio-electricity				■	■
Nuclear				■	
CCS				■	
Methods					
IAM	■		■	■	■
Sensitivity analysis on ensemble of IAMs	■			■	
Experts' elicitation				■	■
Empirical analysis (regression and clustering)		■			
Approximate dynamic programming					■
Climate policy					
Baseline	■	■	■	■	
Copenhagen pledges			■		■
2°C			■	■	
Insights on					
Key drivers of uncertainty	■			■	
Impact evaluation of behavioural programmes		■			
Assessment of public R&D portfolios			■		■
Novel methodologies				■	■

Figure 1.2: *Summary of features included in the research of each chapter.*

1.5 Chapters

1.5.1 Sensitivity of projected long-term CO_2 emissions across the Shared Socio-economic Pathways

Scenarios, showing future greenhouse gas emissions in the absence of climate regulation are needed to estimate climate impacts and the mitigation efforts required for climate stabilization. Recently, the Shared Socio-economic Pathways (SSPs) have been introduced to describe alternative social, economic and technical narratives, spanning a wide range of plausible futures (Riahi et al., 2016). In particular, this work focuses on the first 3 SSPs, which, if they were to be located in a mitigation versus adaptation challenge 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: population, GDP per capita, energy intensity improvements, fossil fuels availability and low carbon energy technology development.

We aim at assessing the sensitivities of future CO_2 emissions from fossil fuels and industry over the next decades to these key drivers characterizing the SSPs. We focus on energy-related emissions given their predominant role in future GHG atmospheric concentrations (which are in turn directly related to changes in relevant climate variables), and their ease of comparability the differently structured models.

A recently developed decomposition algorithm (E. Borgonovo, 2010) allows us to parsimoniously compute both the direct and total effect of each of these drivers on cumulative emissions. This method involves changing the factor of interest from a reference to an alternative value, as well as changing all of the other factors except the one of interest. The resulting scenario protocol, for a total of 46 scenarios, is implemented by six state-of-the-art integrated assessment models (IAMs) with different structural characteristics.

The results of this multi-model, global sensitivity analysis reveals that the SSP assumptions about energy intensity and economic growth are by far the most important determinants of future CO_2 emissions from energy combustion, both with and without a climate policy. Interaction terms between parameters are shown to be important determinants of the total sensitivities. For example, assumptions of higher sustainability are synergistic with the availability of higher wealth per person, leading to a lower emission increase than the one produced by the same increase in income in a less sustainable scenario. Neglecting these interactions may lead to over- or under-estimations of the effects of factors when analyzed individually. Looking at the full century, fossil fuels availability become slightly more important, while the contribution from low carbon technologies availability and the population factor remain marginal.

Results are conditional to the width of uncertainty spanned by SSP story-lines (e.g. the expected limited variation in population in demographic porojections in general up to 2050 reduces automatically its impact), the specific modelling choices in implementing the story-lines 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. Nonetheless, the top two drivers in the ranking tend to remain so across models, over different time horizons, and with or without a carbon price.

1.5.2 Real-time feedback on electricity consumption: Evidence from a field experiment in Italy

Smart meters offer the potential to help consumers optimize energy consumption patterns. However, mixed evidence exists on their effectiveness in reducing energy consumption and especially on leveling off the daily peaks of electricity load curves. Here, we assess the role of real time feedback on electricity consumption on a large scale trial in Italy. We use a combined approach of standard regressions and machine learning techniques on high frequency data.

Enel Info+ is a kit distributed by Enel (the largest electricity company in Italy) to thousands of households in the province of Isernia, as part of a project on customer engagement and demand response. The main interaction with *Enel Info+* occurs via an in-home display, informing users about instantaneous consumption, as well as daily, weekly and monthly summaries. Three datasets were collected for three samples of households involved. The *Client* sample contains those who adhered to the initiative and had the in-home display active at the end of the test period, in December 2014. We focus only on domestic resident consumers with a 3kW or 4.5kW power contract. The *Survey* sample is a subset of *Client* households that agreed to provide further information on the family and dwelling characteristics. The *Curves* sample is another subset of *Client* households, for whom it was possible to obtain readings of energy consumed every 15 minutes.

We begin by assessing the impact of the in-home display on average power conservation effect. Impact is usually evaluated against a counterfactual consumption, in this context the hypothetical one of those who already received the display if they hadn't received it. Ideally, a control group is sampled to provide such counterfactual. We do not have access to the latter, since the company did not ask for informed consent and refused to give us private information. As an alternative we exploit the gradual phase-in of the experiment, building the counterfactual on the basis of the consumption of those who haven't received the display yet at any point in time. We cast the impact evaluation problem as an OLS regression, either in a pooled, fixed effects or diff-in-diff setting, considering the different samples mentioned above, along with their different sets of available variables.

High-frequency data of the *Curves* sample can be used to assess not only changes in overall electricity consumption, but also in shifts of consumption throughout the day. We rely on a K-Means clustering algorithm to find a limited set of prototypical days of consumption pattern. After having identified these representative patterns, their frequencies of occurrence are calculated for each client, distinguishing the days before and after the arrival of the in-home display. If any behavioral change happened in the patterns of daily consumption due to the in-home display, this should be reflected in the before-after difference of such vectors.

Results indicate that real-time feedback can moderately decrease electricity consumption (by 1-2% on average), but that it is does not promote load shifting throughout the day. We find evidence of significant household heterogeneity. Such a small average conservation effect can have several explanations. The in-home display alone did not provide any monetary incentive or direct message promoting energy conservation, which are documented to be more effective means than information feedback alone. The geographical area of interest is relatively mountainous, with a climate not requiring air conditioning. Heating on the other side is rarely done via electricity. Power demand is mostly related to lighting and other low-consumption appliances, making it harder to save more energy.

Several limits and specificities of the experiment constraint the generalizability of the results to a wider population sample. In particular, families participating in the trial are more numerous than the population average, even though consumption per capita is in line with the official statistics of the municipality.

1.5.3 The clean energy R&D strategy for 2°C

After describing the challenge for the economy and the energy systems to stabilize the climate to non-dangerous levels, the R&D investment gap is quantified for what can be considered as first-best settings, where mitigation action, even if fragmented, starts immediately, and global cooperation starts in 2020 or in 2030. Then, R&D figures are analyzed in a class of second-best scenarios, in order to see if other sub-optimal policies, where the regional emission reduction efforts of the Copenhagen pledges are replaced by high energy R&D investments and global cooperation is delayed up to 2030, could constitute viable cost-effective alternatives.

We implemented these scenarios in the WITCH model, accounting for two channels of endogenous technical change. One type of formulation of technical change affects the investment costs of an alternative, carbon-free technology in the non-electric sector. This ‘backstop’ zero-emission fuel can be thought of as an advanced biofuel mitigation option whose costs are currently much higher (e.g. 10 times) than oil, due to lacking of sufficient knowledge. With sufficient R&D and physical investments, the low carbon backstop can become a viable substitute to low carbon fossils. The externality nature of the backstop innovation process is modelled via international spillovers of knowledge and experience across countries and time. The other main channel of technical change in WITCH is about energy savings. Energy efficiency is modelled through improvements in the productivity of the energy input in the production of the final good sector, via a constant elasticity of substitution production function. Innovation in this case is subject only to knowledge externalities through a single factor learning curve.

We find that in order to attain 2°C with sufficiently high probability, a strong decarbonisation of the energy system is required, and mitigation actions call for an increased financing in climate R&D. We quantify the global climate mitigation R&D investment needs for attaining 2°C is approximately 1 USD Trillion cumulatively over the period 2010-2030, and 1.6 USD Trillions in the period 2030-2050. The investments would be initially concentrated in the industrialized countries, but would balance off with those of developing economies after 2030. The largest share of investments would be concentrated for the development of low carbon alternative fuels, though energy efficiency investments would also play an important (and growing) role. We find that focusing on an international clean energy R&D effort slightly underperforms a continuation of the fragmented mitigation effort outlined by the Copenhagen pledges for the sake of climate stabilization, but it might prevent a potential lock-in to current carbon-intensive energy technologies. An exclusive focus on R&D at the expenses of mitigation is however incompatible with climate stabilization if maintained for too long. Specifically, R&D deals to 2030 and 2040 do not attain 2°C with likely (e.g. 450ppm-eq) and as likely as not (e.g. 500ppm-eq) probabilities respectively.

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

In this chapter 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.

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, we obtain eight probability distributions representing the values of these uncertain metrics. 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. The 740 runs are 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, in line with scenarios imposing a radiative forcing of 2.6 and 4.5 W/m2 by 2100.

By means of this large set of simulations, we aim to assess the implications of these subjective distributions of technological costs over key model outputs. In particular, we inspect two sensitivity insights: key-uncertainty drivers and sign of change. Regarding the former, we use three global sensitivity measures, each considering a different property of the influence of model uncertain inputs distributions on model output distribution. Regarding the latter, we rely on the first order effects of the functional ANOVA expansion of the model output, representing the expected variation of the output as a function of each individual model input.

We are then 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, 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 this 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.

1.5.5 Optimal Clean Energy R&D Investments Under Uncertainty

In this chapter we evaluate optimal near-term innovation investments portfolios in solar, biofuels, bioelectricity and personal electric vehicles battery technologies under uncertainty in the learning rates of these technologies. The integrated techno-economic assessment of the WITCH model is combined with a recent expert elicitation on expectations of future costs for the above-mentioned technologies (the ICARUS project). This survey could focus only on a limited amount of R&D budgets for each technology, while in our framework we want to be able to search for the optimal budget allocation in a continuum of possibilities.

We cast this optimization problem as a two-stage stochastic program. Optimal near-term public R&D investments maximizes the sum of two terms: the present discounted value of future utility over the near-term (first stage), which decreases deterministically with R&D investments; and the net present value of future (second-stage) welfare, which depends on the uncertain realizations of future costs, as the benefits of R&D investments materialize with uncertain effectiveness. We link R&D investments and future cost of technologies through a one-factor learning curve, where costs with knowledge capital stock conditionally to a given learning rate. The uncertain effectiveness of R&D investments is described by treating the learning rates as stochastic parameters. Optimal energy R&D investments trade off the benefits of shifting distributions of future costs towards the lower end, with the burden on today utility of sustaining such investments.

Thanks to the application of Approximate Dynamic Programming, it is possible to keep the IAM complexity intact, while endogenously accounting for uncertainty in the R&D strategy problem. In particular, we build an approximating continuous function of the WITCH regional welfare response to future costs realizations over ranges consistent with experts' expectations. Ten samples are pick along each of the four technological cost dimensions, for a total of 10,000 runs of WITCH. The resulting welfare outputs are fit to a Chebysev interpolating polynomial function, with input costs as variable arguments.

Focusing on Europe and its near-term climate policy commitments, we find that batteries in personal transportation dominate the optimal public R&D portfolio both with and without uncertainty. Several reasons may justify this result. First, the model future utility is much more sensitive to changes in future costs of batteries than in all the other costs. The non-electric sector, and in particular the personal transport sector, is traditionally considered one of the most difficult and expensive to decarbonize. Through electrification of vehicles, Europe can benefit from all the efforts already diffused in supporting clean power generation also for reducing transport emissions. Its stringent climate policy commitments can then be achieved at contained costs. Such an electrification is possible only with an adequate battery technology in place, which requires a considerable amount of R&D from the status quo. Second, the probabilistic distribution of future battery costs seems to have more inertia to investments upscaling with respect to other technologies. Finally, batteries has received a marginal attention in terms of European R&D funds in the recent past, making the initial cost quite high.

While uncertainty seems to have a minor effect on the shares of the portfolio, its role is clear in doubling the level of optimal battery R&D investments with respect to a certainty-equivalent case. A precautionary mechanism emerges from the optimization, where the risks of low learning in batteries are strongly hedged against by increased investments.

The resulting ranking across technologies is robust to changes in risk-aversion, R&D budget limitation and assumptions on crowding out of other investments. This results suggest an important upscaling of R&D efforts compared to the recent past.

1.6 Conclusions

We think studying how we should bring innovative changes in the way we produce and consume energy under sustainable concerns is an actual and relevant point in the research agenda for supporting climate change mitigation policies. The output of this thesis is hopefully of use to both the policy and the research world, as well as industries involved in the innovation of clean energy technologies and energy conservation services.

In a multi-model sensitivity analysis, we show that the assumptions about energy intensity improvements, along with per capita income, appear to be the most influential factor in explaining the projected change in future cumulative CO_2 emissions. Results are conditional to the width of uncertainty spanned by the Shared Socio-Economic pathways SSP story-lines, which have been recently introduced to describe plausible alternative social, economic and technical narratives.

One innovative way of improving energy intensity consists in leveraging on the massive future deployment of smart meters, both for power and heat end uses. In-home displays communicating with smart meters might provide to consumers the missing knowledge or salience needed for optimal consumption behavior, potentially promoting energy conservation. Nonetheless, an empirical study on a field experiment in Italy brought evidence that consumption quantity feedback alone has a minor conservation effect. Changing inefficient life-style, or appliances, might require deeper behavioral interventions, for example providing targeted suggestions at the appliance level, or resorting to other economic, moral or social-norm-based incentives. Still, even a 1% reduction, if brought to a large-scale may matter to the power industry.

Gradual innovation in energy efficiency improvements might also be crucial, along with breakthrough innovation in low-carbon technologies, especially if we want to pursue ambitious climate stabilization goals like the 2 degree one. The gap between optimal energy R&D investments of a world with stringent climate concerns and current Copenhagen commitments lies in the order of $30 billions per year for the first half of the century. This projected effort asked to clean energy investors is 3 to 6 times the total annual amount of R&D, averaged in the period 2005-2010, spent by almost all of the OECD (and global) R&D spending in that period. These figures roughly double when considering the second half of the century. A short-term international clean energy R&D effort might be preferred to a continuation of the current fragmented mitigation effort for the sake of climate stabilization after 2020, if legislators value the future enough and prefer to avoid a potential carbon lock-in. These policy findings are already quoted in the chapter "Assessing Transformation Pathways" of the last IPCC report on mitigation, discussing optimal rates of clean energy R&D expenditures to stabilize GHG concentrations.

In one of the first integrated assessment model comparison to look at an extensive sensitivity analysis of technology costs, we tried to understand how the uncertainty in future technical change may affect models results. Across three different models, the uncertainty in future cost of nuclear is shown to dominate in affecting future baseline emissions, while biofuels and bioenergy costs, in addition to nuclear ones, determine abatement costs the most in climate constrained scenarios. 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. Beyond policy implications, this type of analysis emphasizes the importance of underlying assumptions of IAMs, and helps improving the reliability and transparency of these models.

As uncertainty plays an important role in innovation decision-making, we proposed one way of including this element endogenously in the optimization problem of a complex IAM used for climate policy assessment. Due to the additional computational burden and to the limited data availability on distributions of future costs, we focus on a smaller set of promising low-carbon technologies, and consider the R&D investments only for Europe in a "Copenhagen world". The resulting optimal R&D allocation is dominated by the sector of batteries for personal electric vehicles. Batteries seem to have a great potential in supporting the required decarbonization, and are characterized by low expected learning rates that need to be hedged against. Compared to the past, a significant upscaling of investments is suggested: 10-fold for the total budget and 100-fold concerning batteries, with half of the up-scaling due to the inclusion of uncertainty. The share of batteries in the portfolio is robust to different assumptions of risk-aversion, R&D budget limitation and crowding-out effects. These results remark the importance of taking R&D investments actions in the imminent decades to pave the way for a more cost-effective transition to a low-carbon future, especially when considering the risky nature of these investments.

Why considering so many topics and methods at once? The problem of innovating the energy sector towards more sustainable alternatives in a cost-effective way is complex and multi-faceted. The solution to this problem asks for increasingly complicated decision-support models. As models grow in size and complexity, it is important to keep a clear understanding of the robustness and dynamics of their outputs, as critical uncertain inputs and parameters may and will change from our current empirical evaluations. Along with size and complexity, also the computation burden increases, with a necessary attention to approaching the problem in parsimonious ways. Hence the benefits of being able to operate a varied toolkit of methods and tackling the problem from different angles, which can concur in synergy to provide part of the answers sought with a certain urgency by climate policy stakeholders.

1.7 Future work

Several inputs could be taken from this work to expand the agenda for future modelling and experimental research at the intersection of innovation and climate change mitigation.

The relevance of energy intensity in determining baseline emissions goes together with the recognition of the currently limited capability to model energy demand by IAMs, making it a focus of priority for future model development. Including current and future empirical works on energy demand response through behavioral interventions in such models would augment the set of options available for designing optimal mitigation strategies. Welfare implications of these behavioral levers in an integrated assessment framework are still largely unexplored.

On the R&D side, further investigations could be performed on the policy instruments that governments can implement to realize the idea of R&D cooperation (e.g. multilateral financing programs like the Clean Technology Fund). As the policy context evolves, with the Paris agreement and with those to come, more empirical and modelling work is needed to keep policy realism updated in the model, as well as to validate parameters related clean energy innovation, as new evidence unfold and new technologies become more mature.

The sensitivities performed were done focusing either on broad techno-economic assumptions, or on specific technology cost and efficiency parameters. In the perspective of further unpacking the black boxes that IAMs are becoming, it would be interesting to augment the space explored, ideally combining both type of parameters in one sensitivity. A greater number of sampled scenarios would enable a deeper understanding of sensitivities of individual factors, and could allow for a better exploration of the synergies across pairs of inputs.

Finally, it would be desirable to evaluate the optimal R&D portfolio under uncertainty for a wider set of technologies and climate policies. Also, one important ingredient could be added to the current formulation, which is the game across multiple regions and the interplay between uncertainty and the strategic interactions which would occur in terms of international knowledge spillovers.

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CHAPTER 2

Sensitivity of projected long-term CO_2 emissions across the Shared Socio-economic Pathways[1]

2.1 Motivation and contribution

Counter-factual or baseline scenarios - that is scenarios mimicking what would happen in the absence of climate regulation - play a crucial role in the scientific analysis of climate change, but they also increasingly matter in the political debate. Long term projections of socio-economic and emission scenarios are needed to be able to assess future climate change, and its physical and economic impacts. Emission reduction policies, including several of the Nationally Determined Contributions (NDCs) are expressed as emission reductions relatively to a baseline projection. Moreover, baseline emissions are one of the most important drivers of mitigation policy cost assessment (Blanford, Rose, and Massimo Tavoni, 2012; Edenhofer et al., 2014; Stern, Pezzey, and Lambie, 2012): the higher the expectations of future emissions in the absence of climate policy, the greater the mitigation effort for a given climate target, which translates in higher policy costs and technological transformation requirements.

Several emission scenarios have been generated by the research community over the years. The IPCC Special Report on Emission Scenarios (Nakicenovic et al., 2000) described scenarios (SRES) which have been used since the third IPCC assessment report. SRES have been very influential, accumulating almost 3000 citations (according to Google Scholar). However, by now the SRES (published in 2000) are outdated. A

[1] This chapter is drawn from an early draft of the paper "Sensitivity of projected long-term CO_2 emissions across the Shared Socio-economic Pathways" by G. Marangoni, M. Tavoni, V. Bosetti, E. Borgonovo, P. Capros, O. Fricko, D. Gernaat, C. Guivarch, P. Havlik, D. Huppmann, N. Johnson, P. Karkatsoulis, I. Keppo, V. Krey, E. Ó Broin, J. Price, and D. P. van Vuuren, to be published in *Nature Climate Change*. P. Capros and P. Karkatsoulis provided results for the GEM-E3 model. O. Fricko, P. Havlik, D. Huppmann, N. Johnson and V. Krey provided results for the MESSAGE model. D. Gernaat and D.P. van Vuuren provided results for the IMAGE model. C. Guivarch and E. O Broin provided results for the IMACLIM model. I. Keppo and J. Price provided results for the TIAM-UCL model.

new set of future scenario narratives has been recently developed to be used as baseline scenarios. These scenarios, called Shared Socio-economic development Pathways SSPs (O'Neill, Kriegler, Riahi, et al., 2013), describe five future evolutions of the world spanning different challenges to mitigation and adaptation. A set of process-based[2] have interpreted and implemented the SSPs storylines, generating new long term projections of GHG emissions scenarios (Fricko et al., 2016; Fujimori et al., 2016; D. P. v. Vuuren, Elke Stehfest, et al., 2016).

Building baseline scenarios is a daunting task as it requires projecting forward multiple factors driving emissions and accounting for the large uncertainties characterizing them. To date the research community has relied on multi-scenario and multi-model comparisons to help quantifying the uncertainties surrounding baseline scenarios. As no single model projection nor individual scenario will likely be exactly true, it is extremely useful to gauge the relative importance of drivers of these scenarios and allocate research efforts to strategically minimize uncertainties. In such exercise, it is worth also to design additional scenarios that are not necessarily self-consistent with the narratives of the original ones, but still may bring important insights on surprises and risks we might want to hedge against. However, limited attention has been given to the understanding of the sensitivity of projected emissions to the underlying drivers that together define a specific narrative. The aim of this paper is to fill this gap by using a suite of integrated assessment models to systematically decompose the individual and combined influence of each driver on GHG emissions in a multi-model perspective. Varying just one factor at a time (OFAT) only allows for the computation of the individual effects of a particular factor change. A more refined methodology is employed here to also capture non-linearities and interactions across factors at limited computational cost.

IAMs have been subjected to sensitivity analyses in the past. However, most of these analyses have focused on either a small set of models, or focused on individual sensitivities. Nordhaus (2008) assessed the sensitivity of the social cost of carbon and GHG emissions to 8 exogenous inputs in the DICE model, a simple and one of the most popular IAMs. D. P. v. Vuuren, Vries, et al. (2008) explored the uncertainty of baseline emissions as the result of the uncertainty of several inputs conditionally to story-based scenarios. Differently from this work, the authors consider only one model and focus on SRES instead of SSPs. Kriegler, Mouratiadou, et al. (2016) and Gillingham et al. (2015) provide some recent multi-model sensitivity analyses, focusing on direct OFAT impacts alone. Anderson et al. (2014) and Butler et al. (2014) provide a large-scale model diagnostic evaluation that explicitly accounts for the parametric interactions and dependencies between DICE coupled climate and economic components. Valentina Bosetti et al. (2015) carry out one of the few multi-model global sensitivity study focusing on costs of low carbon technologies. Rozenberg et al. (2013), using the IMACLIM-R IAM, questioned the definition of SSPs and identified energy efficiency, equity and convergence as the most important factors in explaining future differences in challenges to climate change adaptation and mitigation. We go beyond the existing literature by focusing on the SSPs in a multi-model, global sensitivity comparison exercise.

[2] As opposed to stylized, reduced-form approaches of another class of IAMs, often used for cost-benefit analyses.

2.2 Approach

The SSP framework has identified five main narratives, which span the mitigation and adaptation challenges space (Figure 2.3 in the SI). In this paper we focus on the diagonal scenarios, namely SSP1, SSP2 and SSP3. These three scenarios represent low, intermediate, and high challenges to both mitigation and adaptation. Our variable of interest is the cumulative CO_2 emissions from fossil fuels and industry over the next decades, a good proxy for changes in relevant climate variables, such as global average temperature (Allen et al., 2009; Matthews et al., 2009). We focus on energy-related emissions given their predominant role in future GHG atmospheric concentrations, and their ease of comparability across the differently structured models. Six IAMs have participated in the study: GEM-E3-ICCS (Capros et al., 2013), IMAGE (E. Stehfest et al., 2014), IMACLIM (Waisman et al., 2012), MESSAGE-GLOBIOM (Fricko et al., 2016), TIAM-UCL (Anandarajah et al., 2011) and WITCH-GLOBIOM (Emmerling et al., 2016).

These models have previously contributed to major scientific and policy evaluations such as the IPCC 5th assessment report (Change, 2015) and the Impact Assessments of the EU energy and climate policies. The ensemble of models includes computable general equilibrium models with detailed representation of economics sectors, technology rich models, as well as hybrid models, thus collectively encompassing different modeling paradigms (see SI for details). Three of the six models (IMAGE, MESSAGE-GLOBIOM and WITCH-GLOBIOM) have been directly involved in the SSP process, and two of them were selected as 'marker' models, i.e. providing a preferred quantification for a selected SSP (Fricko et al., 2016; D. P. v. Vuuren, Elke Stehfest, et al., 2016).

SSPs narratives differ in many regards. SSP1 can be described as a scenario with low population growth, high economic growth, high energy efficiency improvements, low fossil fuels availability and high preference for renewable energy. SSP3 has a specular characterization, with SSP2 lying in the middle. Some of these aspects include variables which have been precisely quantified, such as population, and economic growth. Other variables - such as household preferences, technical progress, or technology availability - have been more qualitatively defined. In order to implement our analysis, we consider five main factors: population (POP), GDP per capita (GDPPC), energy intensity improvements (END), fossil fuels availability (FF) and low carbon energy technology development (LC). The resulting quantification of key emissions drivers and their comparison with the SSP markers are shown in Figure 2.1[3].

[3] In the SI, Figure 2.5 further expands the decomposition of the SSPs as quantified by the marker models, Figure 2.6 shows emissions time profiles across SSPs, with differences with SSP2 highlighted in Figure 2.7, while more details on the implementation by the models of this study can be found in Table 2.2.

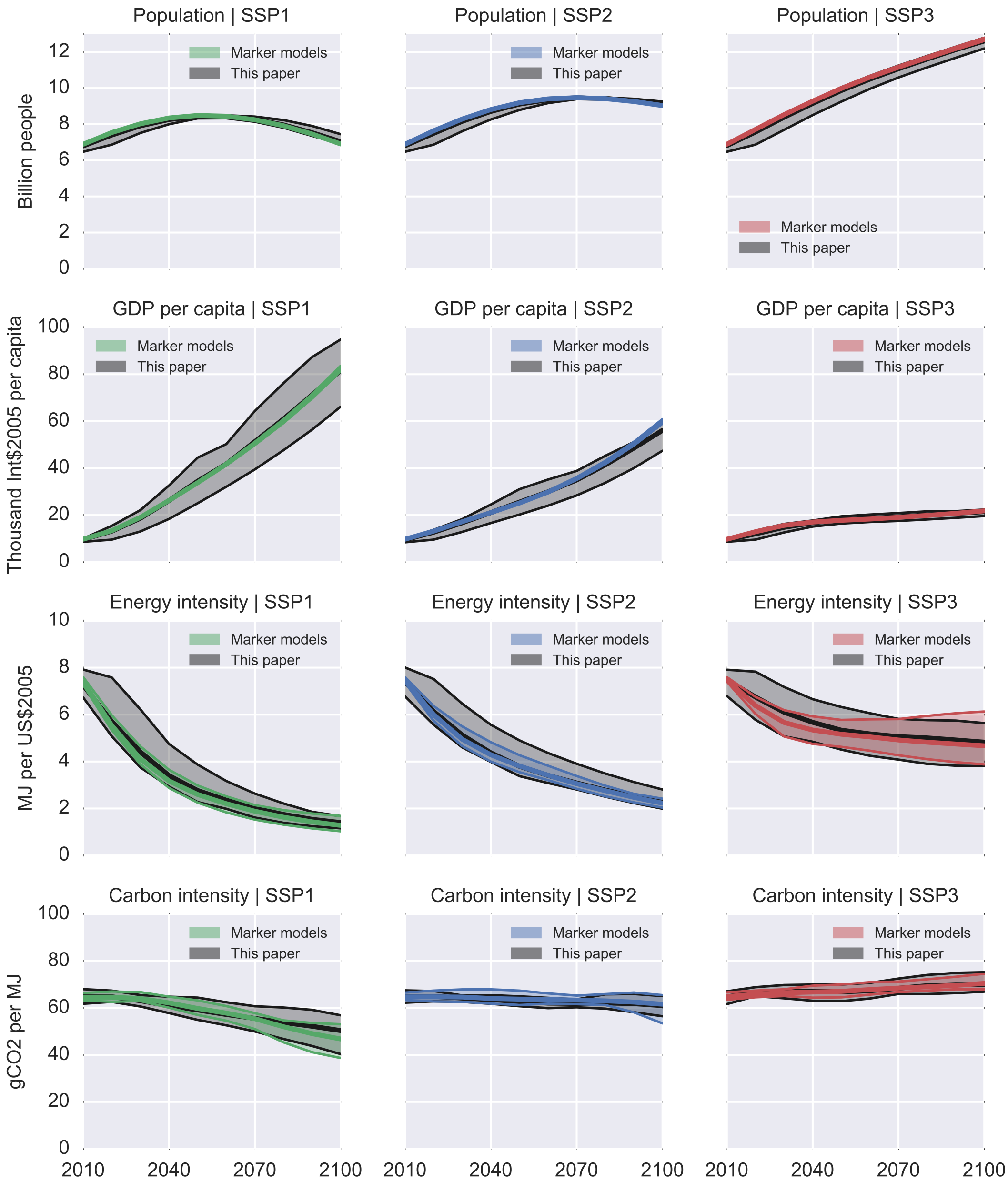

Figure 2.1: *Decomposition of CO_2 emissions from Fossil Fuel and Industry for the 3 SSP scenarios, as implemented by the set of SSP marker models (in color) and by models involved in this sensitivity analysis (in gray). First row: yearly world population. Second row: yearly world GDP (PPP) per capita. Third row: yearly world primary energy supply per unit of GDP (PPP). Fourth row: yearly world CO_2 FFI emissions per unit of primary energy supplied. Thicker lines are means across models.*

Given this setup, we have designed a scenario protocol such that when deviating from the central SSP2 case to either SSP1 or SSP3 it is possible to attribute the observed change in output to changes in each of these five groups of inputs. Since we are interested in determining also the relevance of parameter interactions, we employ a recently developed scenario decomposition algorithm (Borgonovo, 2010). The method is illustrated in Figure 2.4 in the SI, and involves changing the factor of interest from a reference to an alternative value, as well as changing all of the other factors except the one of interest. The first set of model runs provides the individual effect. The second - with a change in sign - gives us the total effect of that same factor, i.e. an effect that contains both the individual effect and the interaction effect. The interaction effect contains all the interactions of the factor at with all the other factors and is the difference between the individual and total effects. We coordinated the work in such a way that the six IAMs ran exactly on the same grid of points. The full matrix of scenarios is reported in Table 2.3 in the SI. The design has been chosen to obtain interaction effects with a parsimonious number of model evaluations, an important feature given the complexity of the models involved in the study.

Each of the six IAMs ran the 23 required scenarios for the no climate policy case (referred to as BASE), as well as another 23 scenarios for the climate policy case (referred to as CPRICE). The climate policy scenarios assume a global carbon price starting in the year 2020, equal to 30\$/tCO_2eq, and rising at a fixed rate of 5% per year. This is one of the diagnostic carbon prices recommended by the Integrated Assessment Modeling Consortium (IAMC). Running both cases allows us to test whether the key parameters driving emissions are the same with and without a mitigation policy.

2.3 Methods

2.3.1 Socio-economic pathways.

The narratives behind the SSP scenarios are explained qualitatively in O'Neill, Kriegler, Ebi, et al. (2015). In particular, this work focuses just on the first 3 SSPs, which, if they were to be located in a mitigation versus adaptation challenge 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 (see Figure 2.3 in SI).

- **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 (KC and Lutz, 2014). SSP1 has lower global population growth, while in SSP3 the growth is low in industrialized and high in developing countries, with resulting globally higher levels.

- **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 (Dellink et al., 2015) with the population levels above. SSP1 features 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 and industry 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 aligned 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 the production of 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 aligned 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, specifically wind and solar technologies, 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 aligned 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 may slightly differ in terms of fossil fuels CO_2 emissions from an SSP1 scenario with its comprehensive implementation.

2.3.2 Design of Experiment and Finite Change Decomposition

In this analysis, we are dealing with M models, where each model, in principle, has its own input space and input-output mapping. Then, we write $\mathbf{y} = h_m(\boldsymbol{x})$, $\mathbf{y} : \mathcal{X}_m \mapsto \mathcal{Y}^m$, where $\mathcal{X}_m \subseteq R^{n_m}$, and $\mathcal{Y}^m \subseteq R^{q_m}$ are the model input space and model output spaces, and n_m and q_m the number of model inputs and model outputs of model m, respectively. To illustrate the method, let us 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, which is computed by all models and for all values of $\boldsymbol{x} \in \mathcal{X}_m, m = 1, 2, ..., M$.

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 $\boldsymbol{z} = [z_1, z_2, \ldots, z_n] \in \{0, 1\}^n$. Each component z_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. Then, a map is needed to translate these common scenarios to implementable model inputs combinations. We denote this function through $t_m(\cdot) : 0, 1^N \mapsto \chi_m$ for each model. That is $\boldsymbol{x} = t_m(\boldsymbol{z})$. Hence, we can associate each scenario $\boldsymbol{z}$ with a model response $y_m = h_m(t_m(\boldsymbol{z})) = g_m(\boldsymbol{z})$.

When moving from the nominal scenario $\boldsymbol{z}^0 = [0, \ldots, 0]$ to its alternative counterpart $\boldsymbol{z}^1 = [1, \ldots, 1]$, we observe a finite change in the output $\Delta y = g_m(\boldsymbol{z}^1) - g_m(\boldsymbol{z}^0)$. To understand the contributions of the i-th scenario feature z_i to this change, we exploit the link between Placket-Burmann design of experiments and finite change decomposition (Borgonovo, 2010). Dropping the model index m for brevity, we have:

$$\Delta y = g(\boldsymbol{z}^1) - g(\boldsymbol{z}^0) = \sum_{i=1}^{n} \Delta_i g + \sum_{i<j}^{n} \Delta_{i,j} g + \cdots + \Delta_{1,2,\ldots,n} g \tag{2.1}$$

where:

- $\Delta_i g = g([z_1^0, z_2^0, \ldots, z_{i-1}^0, z_i^1, z_{i+1}^0, \ldots, z_n^0]) - g(\boldsymbol{z}^0)$ is the observed change in output due to the individual change in the i-th scenario input;
- $\Delta_{i,j} g = g([z_1^0, z_2^0, \ldots, z_{i-1}^0, z_i^1, z_{i+1}^0, \ldots, z_{j-1}^0, z_j^1, z_{j+1}^0, \ldots, z_n^0]) - \Delta_i g - \Delta_j g - g(\boldsymbol{z}^0)$ 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 higher order terms such as $\Delta_{i,j,k} g$.

One then summarizes the individual, interaction and total effect of each model input in the following sensitivity indices:

- $\phi_l^1 = \Delta_l g$ and its normalized version $\Phi_l^1 = \dfrac{\phi_l^I}{\Delta y}$ will be referred to as the *individual effect* of input l;
- $\phi_i^T = \sum_{k=1}^{n} \sum_{i \in i_1, i_2, \ldots, i_k; i_1 < \ldots < i_k} \Delta_{i_1, \ldots, i_k} g$ 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;
- $\phi_i^{\mathcal{I}} = \phi_l^T - \phi_l^1$ 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 model input i.

The number of interacting terms determining the total effect is exponential in the number of inputs (equal to $2^n - 1$, in principle). 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 (ibid.):

$$\phi_i^T = g(\boldsymbol{z}^1) - g([z_1^1, z_2^1, \ldots, z_{i-1}^1, z_i^0, z_{i+1}^1, \ldots, z_n^1]) \tag{2.2}$$

Then, it is possible to compute all ϕ_i^1, ϕ_i^T and $\phi_i^{\mathcal{I}}$ at $2n + 1$ model evaluations. This design motivates the table of runs of each model (see Supplementary Table 1).

2.3.3 Integrated Assessment Models.

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

- **GEM-E3-ICCS** is a computable 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** 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** is a recursive dynamics model that can be described as a geographically explicit assessment, integrated assessment simulation model, focusing on 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 analyze 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-GLOBIOM 1.0** integrates the energy-engineering model MESSAGE and the land-use model GLOBIOM into a consistent integrated assessment framework. To account for general equilibrium effect MESSAGE-GLOBIOM also soft-links to the aggregated macro-economic model MACRO.

- **TIAM-UCL** is an energy systems focused partial equilibrium model. It uses the TIMES modelling platform, extended with a stylized representation of non-energy emissions and a simple climate module. 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-GLOBIOM** 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.

2.3.4 Climate policies.

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

- **BASE**: global carbon price equal to 0.

- **CPRICE**: global carbon price equal to 30 US$2005/tCO2eq in 2040, starting in 2020 and increasing at 5%/yr.

2.4 Results

The main results of the decomposition analysis of emissions for the no climate policy case and the first half of the century are shown in Figure 2.2. The left hand side panel reports results when moving all scenarios drivers from the parameterization of the SSP2 scenario, the "middle of the road", to those of SSP1, the more sustainable scenario. The overall reduction in emissions is 12% on average across the models. GDP per capita and energy intensity improvement (END in Figure 2.2) appear to be the most important drivers, with an absolute median impact on emissions of 5% (full model range: 3 to 8%) and 10% (6 to 18%), respectively. These two factors have opposite sign and thus partly offset each other. SSP1 is assumed to be a wealthier, but more efficient world than SSP2. Low availability of fossil fuels resources (FF) and high deployment of low-carbon technologies (LC) contribute in lowering SSP1 emissions with respect to those of SSP2 by 2% (-0.1 to 8%) and 2% (-1.9 to 6%), respectively. Assumptions about population appear to have the lowest impact on emissions to 2050 across all models, with a median reduction of 1%. Although this might appear surprising, one has to bear in mind that population assumptions across SSPs tend to diverge gradually over time, and differences are more visible especially mid-century, as shown in Figure 2.1.

The chart reports both individual and interaction effects that sum up to the total effect. The interaction effect can either amplify or dampen the changes resulting from individual effects. The assumptions of higher sustainability in SSP1 are synergistic with the availability of higher wealth per person, leading to a lower emission increase than the one produced by the same increase in income in the less sustainable SSP2 scenario. As a result, the median impact of larger income per capita on emissions is reduced from 8% - had we changed the factor in isolation - to 5%. For other parameters, the direction of individual and interaction effects is less clear-cut, showing model dependent behaviors.

The right hand side panel of Figure 2.2 reports results when moving all scenarios drivers from SSP2 to the more challenging world of SSP3. In general, emissions are higher in SSP3 than in SSP2, in line with the SSP3 narrative, and changes are bigger than in the movement between SSP2 and SSP1, although the magnitude is model dependent. The decomposition allows us to appreciate which drivers amplify this divergence. Again, income and energy efficiency emerge as key determinants. The magnitude of these two drivers is even larger than for the SSP1 case. When moving from SSP2 to SSP3, specularly to the SSP1 case, we find that interaction effects amplify the emission reductions associated to the GDP decrease, and mitigate the increase in emissions associated to higher energy end use. On the one hand, income reduction in a more energy and fossil intensive economy leads to a larger drop in emissions. On the other hand, lower efficiency in a poorer world yield a smaller increase in emissions. Absolute levels of cumulative emissions and total effects in $GtCO_2$ can be found in Figure 2.8 in the SI.

Table 2.1 provides a robustness test over different time horizons (e.g. till the end of the century) and under the carbon price case. Overall, results hold across scenarios.

Figure 2.2: *Generalized tornado plot of cumulative CO_2 emissions (2010-2050) change from SSP2 to either SSP1 (left) or SSP3 (right) without climate policies, for each of the 6 IAMs. TOTAL refers to total emission changes, and the rows below show emission changes for each of the five factors. Individual effects are reported with transparent thicker bars, total effects with solid thinner bars and interaction effects with striped bars.*

In the medium term, i.e. up to 2050, the results shown in Figure 2.2 are confirmed in the case of the carbon price policy. Looking at the full century, fossil fuels availability become slightly more important, while the contribution from low carbon technologies availability and the population factor remain marginal. Full tornado plots with single model values are reported in Figure 2.9 (CPRICE 2050) and 2.11 (BASE 2090) in the SI, with further highlighted in Figure 2.10 and 2.12 also in the SI.

Deviation	SSP2 → SSP1							
Year	2010-2050				2010-2090			
Policy	BASE		CPRICE		BASE		CPRICE	
Input								
TOTAL	-12	[-20,-5]	-9	[-17,-0]	-21	[-28,-15]	-13	[-21,-3]
END	-10	[-18,-6]	-8	[-18,-6]	-17	[-30,-7]	-19	[-33,-6]
GDPPC	5	[3,8]	5	[4,7]	9	[6,13]	7	[6,13]
FF	-2	[-8,0]	-1	[-7,1]	-3	[-16,0]	-0	[-12,2]
LC	-2	[-6,2]	-0	[-6,2]	-2	[-11,3]	2	[-3,4]
POP	-1	[-2,-0]	-1	[-2,-0]	-3	[-8,-1]	-4	[-5,-1]

Deviation	2 -> 3							
Year	2010-2050				2010-2090			
Policy	BASE		CPRICE		BASE		CPRICE	
Input								
TOTAL	13	[-3,31]	8	[-5,31]	9	[4,31]	6	[-13,50]
END	9	[2,29]	7	[2,30]	18	[4,39]	11	[4,52]
GDPPC	-9	[-21,-3]	-9	[-20,-3]	-30	[-57,-23]	-24	[-65,-16]
FF	4	[-0,8]	2	[-1,6]	12	[-0,15]	1	[-0,6]
LC	2	[0,6]	2	[0,6]	3	[2,7]	1	[-2,8]
POP	-0	[-1,1]	0	[-2,1]	1	[-3,5]	3	[-3,7]

Table 2.1: *Median percentage change in cumulative CO_2 fossil fuels emissions from SSP2 base scenario under 4 configuration (BASE or CPRICE, cumulative to 2050 or 2090). Model ranges are in brackets.*

2.5 Conclusions

Overall, this analysis has shown that the assumptions about energy demand and per capita income underlying the SSPs appear to be the most influential factors in explaining the projected change in future cumulative CO_2 emissions. Results are conditional to the width of uncertainty spanned by SSP story-lines (e.g. the expected limited variation in population in demographic projections in general up to 2050 reduces automatically its impact), the specific modelling choices in implementing the story-lines 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.

Further research is needed to cast light on the mechanics of interactions and on the correlations between deviations from means and specific models characteristics. Expanding the analysis to additional factors, such as land use emissions, could also provide additional insights, especially in stringent mitigation scenarios. Assessments aiming at quantifying uncertainty, exploring surprise scenarios (Lempert, 2007), and design hedging strategies in the face of both parametric and model uncertainty (Drouet, V. Bosetti, and M. Tavoni, 2015) are needed to inform climate policy, including the upcoming reports of the IPCC. Such efforts, along with those undertaken in this paper, can provide important insights in the nascent literature on IAMs diagnostics (Kriegler, Petermann, et al., 2015). In addition to unpacking model results, it can also provide guidance in terms of research directions: our results on energy intensity together with the recognition of the currently limited capability to model energy demand (Wilson et al., 2012) indicates this a focus of priority for future model development.

2.6 Acknowledgements

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2.A Appendix

2.A.1 Supplementary Figures

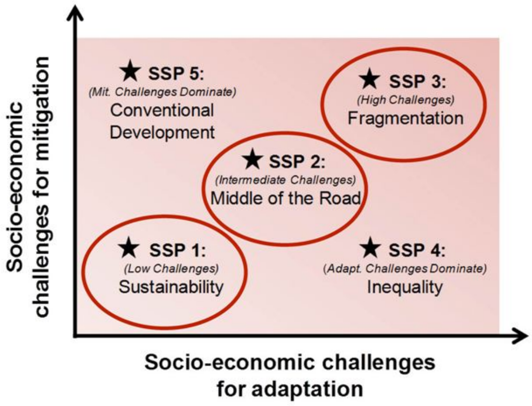

Figure 2.3: *Diagram of SSP scenarios in the mitigation/adaptation challenges space.*

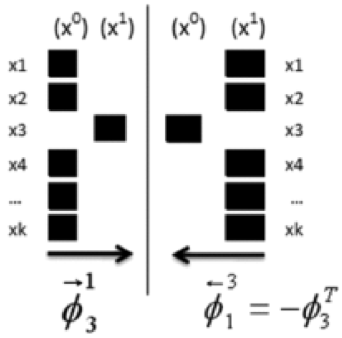

Figure 2.4: *Logic underlying the scenario protocol design for decomposition analysis. Left: a given input x_i (e.g. POP) among the k considered (i.e. the 5 factors) is moved from a reference level x^0 (i.e. SSP2) to an alternative level x^1 (i.e. SSP1 or SSP3). The difference in outputs yields the individual effect $\vec{\Phi}_i^1$ of that input on the output. Right: all parameters but one input x_i are moved to the alternative level from the reference level. With a change in sign, the difference in outputs $\vec{\Phi}_1^i$ yields the total effect Φ_i^T. The different between total and individual effects are the interactions.*

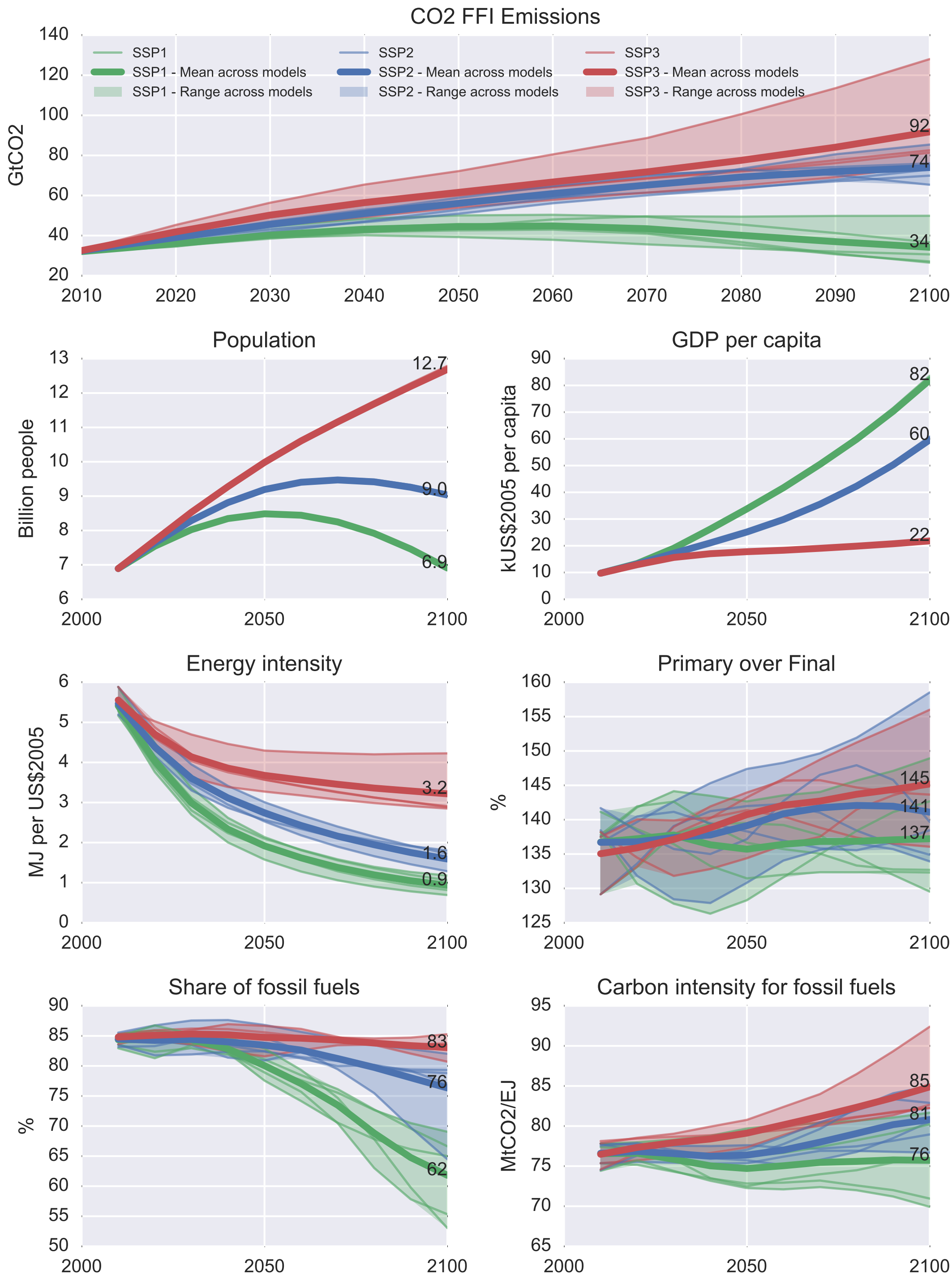

Figure 2.5: *CO_2 emissions from Fossil Fuel and Industry with potential drivers as quantified by the 5 SSP marker models and reported in the SSP online database. First row: yearly CO_2 FFI emissions throughout the century. Second row: yearly world population (left); yearly GDP (PPP) per capita (right). Third row: yearly final energy per unit of GDP (PPP) (left); yearly primary energy over final energy (right). Fourth row: yearly share of primary oil, coal and gas supply over all primary energy supply (left); yearly CO_2 FFI emissions per unit of primary fossil supply (right).*

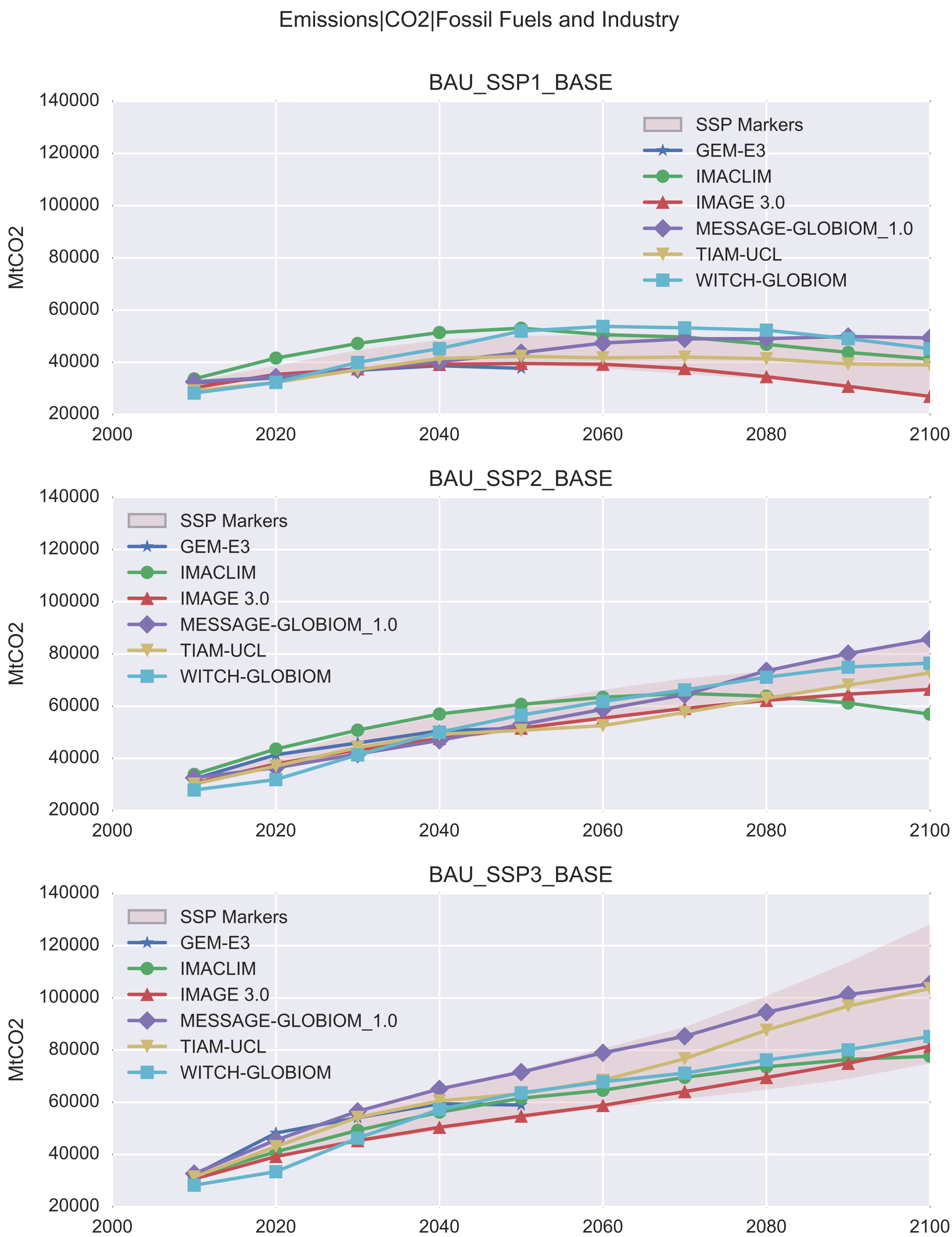

Figure 2.6: *CO_2 emissions from Fossil Fuel and Industry across BASE SSP1, SSP2, SSP3 scenarios, as implemented in this exercise.*

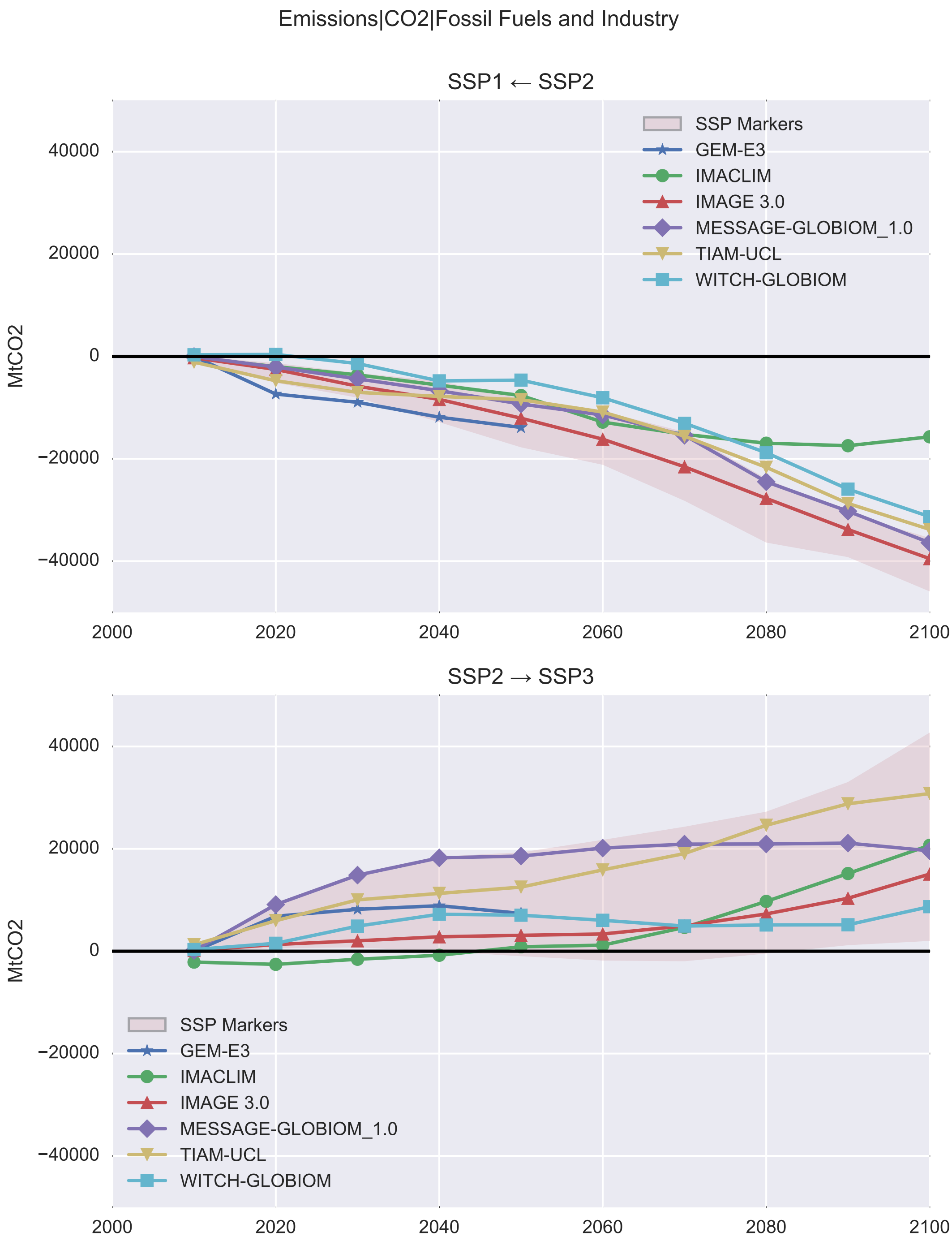

Figure 2.7: *CO_2 emissions from Fossil Fuel and Industry difference between BASE SSP2 and either SSP1 or SSP3 scenarios, as implemented in this exercise. With solid colored lines: results from the 6 models. Black line: 0 difference with SSP2. In pale red: min-max range for the SSPDB.*

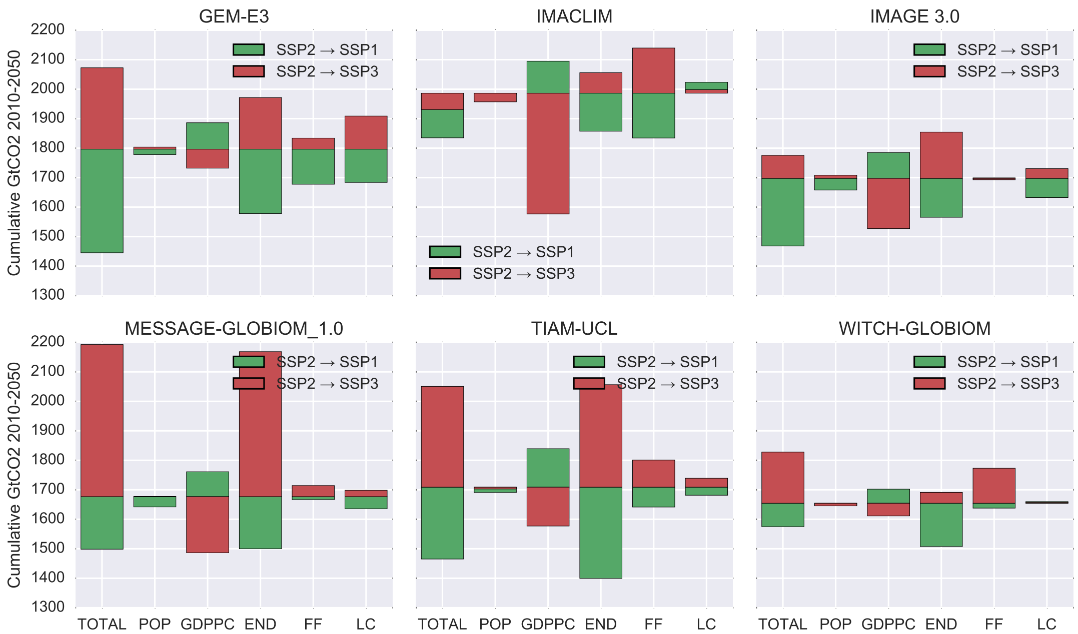

Figure 2.8: *Total effects on cumulative CO_2 FFI till 2050 under BASE, in $GtCO_2$, for each model.*

Figure 2.9: *Generalized tornado plot of cumulative CO_2 emissions (2010-2050) change from SSP2 to either SSP1 (left) or SSP3 (right) under CPRICE, for each of the 6 IAMs. TOTAL refers to total emission changes, and the rows below show emission changes for each of the five factors. Individual effects are reported with transparent thicker bars, total effects with solid thinner bars and interaction effects with striped bars.*

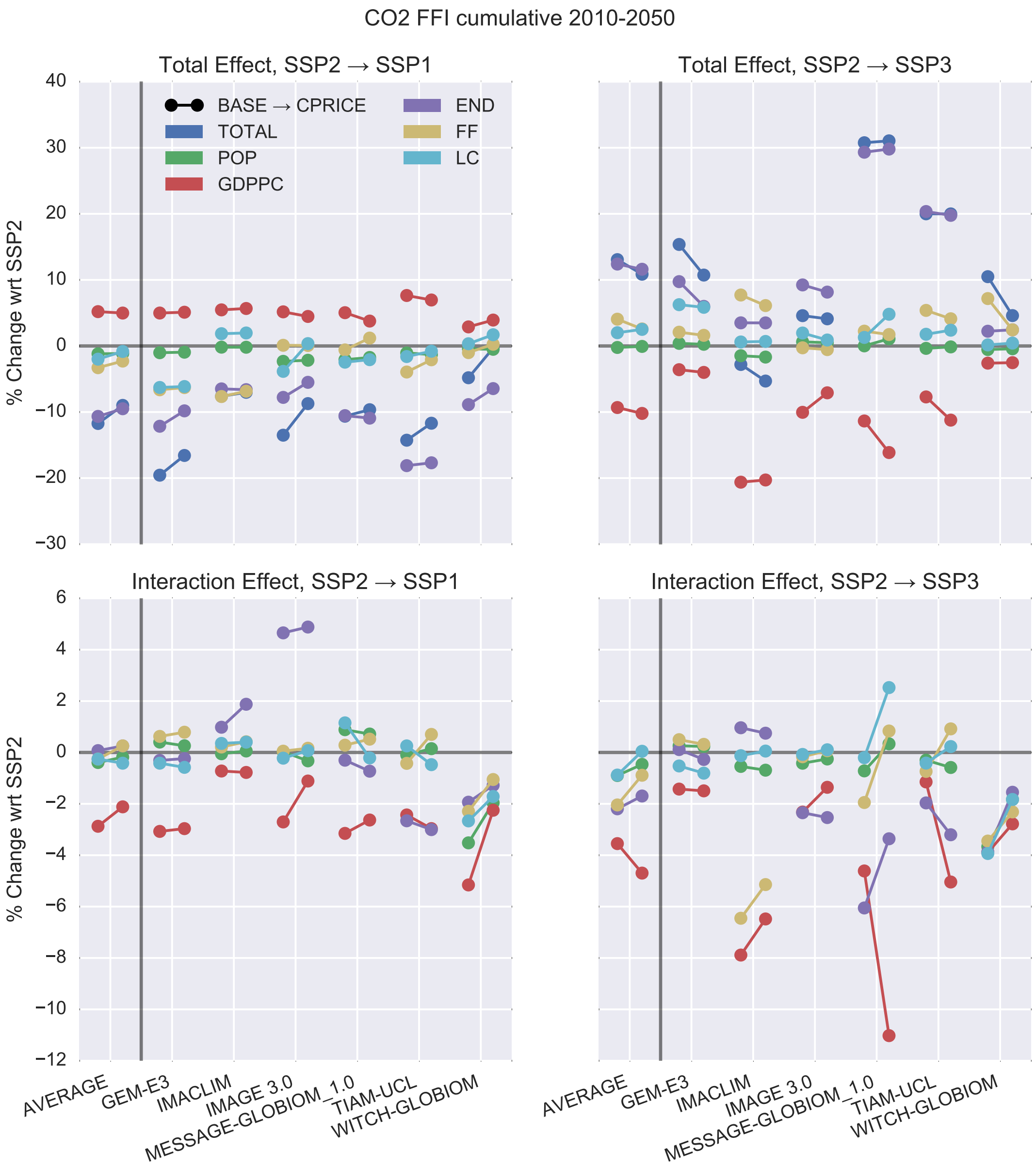

Figure 2.10: *Total and interaction effects on cumulative CO_2 FFI till 2050, when moving from BASE to CPRICE case, for each model. Average effects across models are on the left of each subplot.*

Figure 2.11: *Generalized tornado plot of cumulative CO_2 emissions (2010-2090) change from SSP2 to either SSP1 (left) or SSP3 (right) under BASE, for each of the 6 IAMs. TOTAL refers to total emission changes, and the rows below show emission changes for each of the five factors. Individual effects are reported with transparent thicker bars, total effects with solid thinner bars and interaction effects with striped bars.*

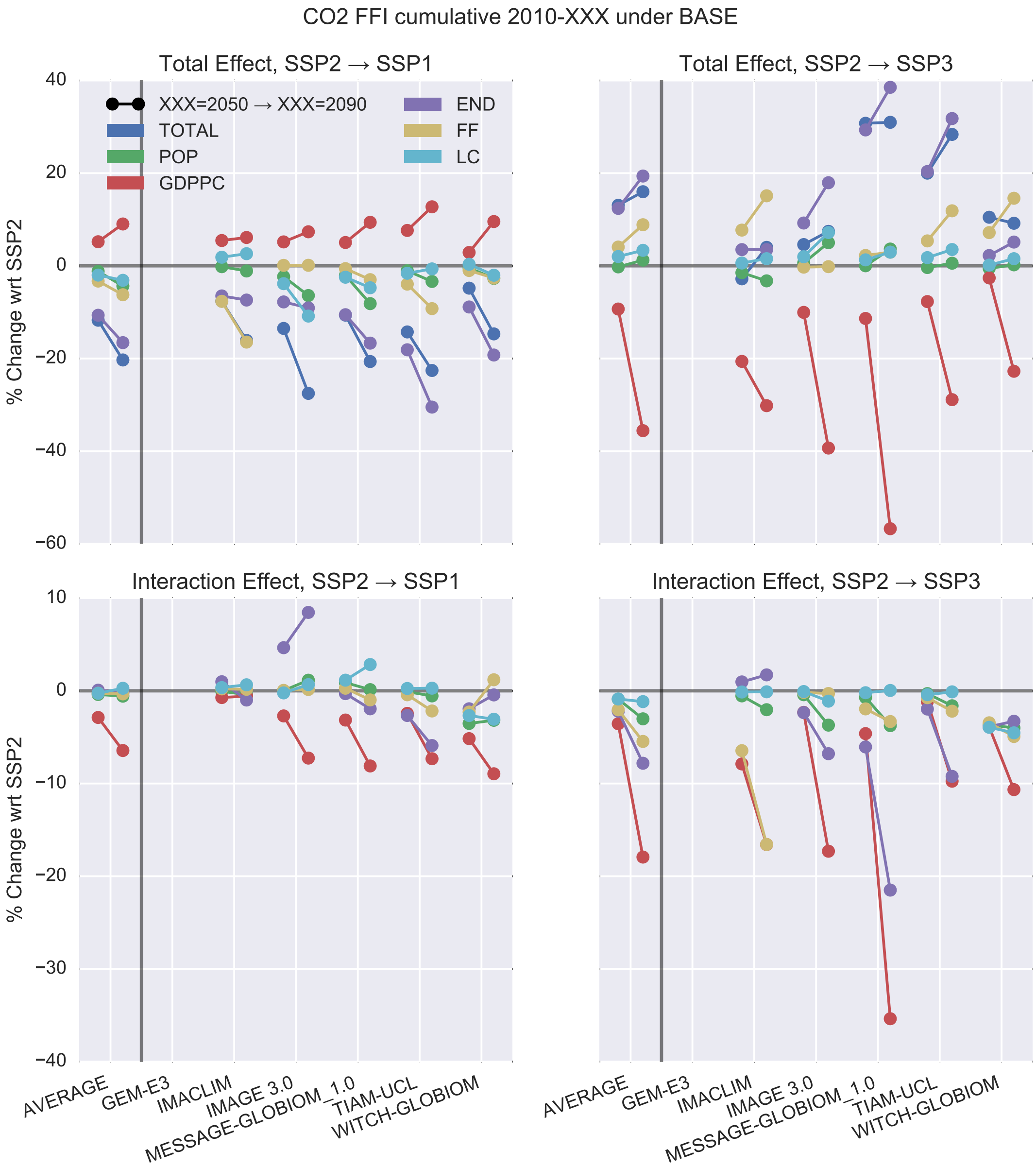

Figure 2.12: *Total and interaction effects on cumulative CO_2 FFI under BASE, when moving from 2050 to 2090 as terminal year for the cumulative calculation, for each model. Average effects across models are on the left of each subplot.*

2.A.2 Supplementary Tables

Model	POP	GDPPC	END	FF	LC
GEM-E3	Total population; subsistence minima parameters.	Technical change factors of skilled and unskilled labor (adjusted to get target GDP per capita).	Technical change and energy intensity factors in firms and households.	Reserves of crude oil; regional prices of coal and gas (adjusted to different levels starting from ROSE project estimates).	Maturity and learning-by-doing rates of renewable energy technologies.
IMACLIM	Total and active population.	Labor productivity growth.	Motorisation rate; residential space; industrial goods consumption increase with wealth.	Extraction costs and availability of unconventional oil/gas.	Learning-by-doing rates and maximum potential of renewable energy technologies (changed in the opposite direction for nuclear).
IMAGE	Total population.	GDP.	Preference factor for low carbon or traditional fuels; energy intensity for services.	Learning factors; trade barriers.	Learning factors of renewable energy technologies and hydrogen (opposite preference for nuclear); support for renewables capacity.
MESSAGE-GLOBIOM	Total population (directly used in the parameterization of energy demands).	Growth rates of total labor in MACRO (macroeconomic model soft-linked with MESSAGE), representing the combined effect of labor force and labor productivity growth (recalibrated in the scenarios that directly influence energy demands by changing POP, GDPPC, END, also using sector-specific AEEI coefficients in addition to labor productivity change parameters).	Energy intensity improvement; maximum fuel shares (e.g., rate of electrification in transport); availability and cost of end-use technologies (e.g., hydrogen fuel cell availability, cost of industrial boilers).	Extraction costs and availability of oil/gas/coal; cost and availability of fossil conversion technologies (including technologies with carbon capture and storage).	Investment, operation and maintenance costs renewable energy technologies, as well as resource availability; plant load factors of nuclear power plants.
TIAM-UCL	Total population.	GDP.	Demand curves exponents.	Extraction costs for fossil fuels; temporal trajectory of the cost trends (without changing total cumulative availability).	Maximum annual nuclear growth rate; capital costs of non-biomass renewables; biomass availability and supply costs.
WITCH-GLOBIOM	Total population.	Labor productivity growth.	Factor productivity of energy in final good production; transport fuel efficiency; travel intensity.	Reserves and extraction costs of fossil fuels.	Learning-by-doing rates of renewable energy technologies and battery; investments, operation and maintenance costs of nuclear.

Table 2.2: *List of parameters belonging to the five factor changed across SSP levels, according to the implementation of each modelling team.*

Remark for MESSAGE-GLOBIOM in Table 2.2. In all scenario variants explored in this global sensitivity analysis, the GLOBIOM land-use representation from SSP2 has been used. As a result, only SSP2 BASE is consistent with the SSP implementation of MESSAGE-GLOBIOM while SSP1 and SSP3 are by design deviating from the official SSP implementations as documented in Fricko et al., 2016 and Riahi et al., 2016. While the internal consistency of the SSPs is affected by this approach, a systematic comparison of these scenarios with the original SSP implementation show that impacts on overall fossil fuel use in baseline scenarios is very modest and also the resulting changes in fossil fuel and industrial CO2 emissions, the primary variable of interest in this study, are small (some 2% by 2100). By contrast quite significant impacts on biomass use are observed for two reasons, (i) the traditional biomass potential is factored into the cheapest category and when pairing this with higher/lower traditional biomass demand the remaining biomass for commercial applications change, and (ii) in particular in the long run the demographic effect and the resulting difference in pressure on land are quite significant in the SSPs.

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

Table 2.3: *Names and details of the scenarios needed for the decomposition analysis and implemented by modellers. Each number under an input column refers to the SSP base scenario from which the setup for that input is taken.*

CHAPTER 3

Real-time feedback on electricity consumption: Evidence from a field experiment in Italy[1]

3.1 Introduction

Europe has set ambitious policy targets for energy and climate, with the aim of developing a sustainable, low-carbon society. Existing policy packages such as the 20-20-20 objectives for year 2020, and new policy objectives, such as the 2030 energy and climate strategy, have emphasized a variety of proposed tools. These include carbon pricing, incentives to renewable and other low-carbon energy, as well energy efficiency measures. These policies pushed together with the liberalization of the EU electricity markets, are having profound repercussions on the energy industry. While our energy supply systems undergo a necessary transition towards lower carbon-emitting alternatives, power utilities are also considering the potential coming from the demand side. Utilities do no longer provide electricity or gas alone, but are now providers of energy services, aimed at improving customer experience.

Power consumers, by changing inefficient behavior and/or appliances, can reduce their energy consumption, as well as the need for potentially costly and carbon-intensive on-peak production, and for investments in networks and plants to sustain future peak demands. Since power consumers are often unaware of their precise consumption levels over time, one way of engaging them is via frequent information feedback on their consumption. Thanks to the increasing deployment of smart meters, i.e. electronic devices that record consumption of electric energy sub-hourly for monitoring and billing purposes, real-time feedback is now a viable and affordable option. Smart meters are indeed being deployed at a very fast rate, with almost 200 million devices operational

[1] This chapter is drawn from the paper "Real-time feedback on electricity consumption: Evidence from a field experiment in Italy" by G. Marangoni and M. Tavoni, to be submitted.

in the EU. Such technology has the capability of registering and communicating energy consumption at a high temporal resolution (e.g. 15 minutes or less), thus enabling to empower consumers with a on hand grasp of their energy bills.

Policy makers have promoted information programs, claiming their high potential and cost effectiveness for energy conservation. The rationale for this policy intervention is that users are often unaware of their energy footprint, either because of the high costs of acquiring this information, or because of behavioral factors such as limited attention, present bias and limited salience (Allcott and Mullainathan, 2010). However, critics remain due to mixed empirical findings.

This paper aims to contribute to this literature, trying to understand how much real-time feedback of power consumption can promote energy conservation behaviors, specifically in the residential sector. We use an original dataset coming from a pilot project carried out by a major energy utility in Italy. The high-frequency dataset allows us to also address the issue of load shifting, namely the redistribution of electricity consumption throughout the day. This is a major policy and economic issue, given the hardly storable nature of electricity and the increased share of intermittent energy sources, such as wind and solar power, in the electricity mix.

3.2 Real time electricity feedback project

In 2011 Enel Distribuzione S.p.A. (the largest electricity company in Italy, and one of the largest in Europe) started a 3-years-long pilot project in the area of Isernia (mid-south Italy) to test new smart-grid-related technologies and inform future network restructuring plans. One part of the project dealt with customer engagement for demand response. In this context, a kit called "Enel Info+" was distributed to thousands of end users to enable active participation by making people aware of how much electricity was being consumed.

The main interaction with "Enel Info+" occurs via a display installed in the house informing users about instantaneous consumption, as well as daily, weekly and monthly summaries (Figure 3.1). The display also provides information about the current billing slot (days are partitioned in 3 billing periods, peak (F1), intermediate (F2) and off peak (F3)) and the time at which the next slot will enter into force. If users enter information about their billing tariffs, they also get feedback on monetary expenditures. Users can set goals, and are also warned by an acoustic signal whether their power consumption exceeds the contractual obligation (set at 3kW for most of the customers).

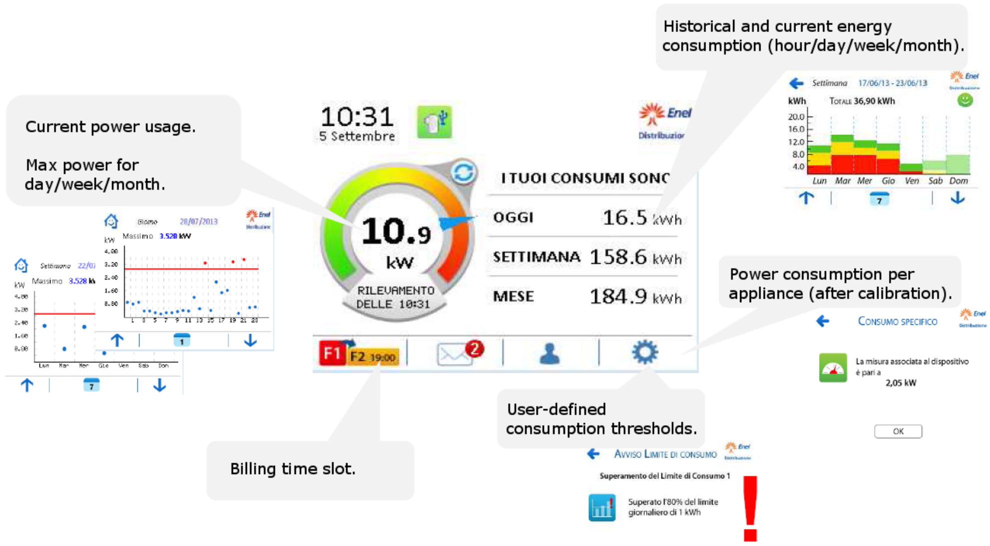

Figure 3.1: *Features of the in-home display for real-time power consumption information feedback, distributed by Enel Distribuzione S.p.a. to households in the province of Isernia.*

The display was distributed for free to residents of Isernia city and surrounding municipalities. The company focused on this area for technical reasons related to the feasibility of high-frequency consumption data measurement and transmission. The display was not randomly allocated: it was first distributed outside the city, and subsequently in the city. The company advertised this opportunity through media campaigns. They faced initial difficulties in recruiting sufficient candidatures, possibly for concerns about privacy or simply lack of knowledge. They subsequently intensified the promotional campaign, by hosting meetings with the local population in schools and other public spaces. This had the effect of increasing participation quite rapidly. Overall, the trial was not carried out according to the golden rules of randomized controlled trials. The design is subject to possible self selection which can hinder the external validity of the programme impact. Nonetheless, the trial provides useful information on energy consumption behavior, and is the first one carried out in Italy on a large sample. We discuss more in detail below the measures we have taken to try to mitigate the imperfect (from a research stand point) implementation.

3.3 Relation to the Literature

People's perceptions of energy consumption can have significant discrepancies with reality (Attari et al., 2010). In particular, low-energy activities tend to be overestimated and high-energy activities tend to be largely underestimated. This justifies the potential for information feedback programmes.

Several field experiments have been conducted to study the causal impact of such programmes. Regarding relative average consumption reductions, two recent papers performed a meta-analysis of the many available studies. We refer to these given the large literature on the topic. Karlin, Zinger, and Ford, 2015 consider 42 studies with an effect size on power consumption ranging from -8% to above 20%. Their meta-model estimate an overall reduction between 4% and 12%, depending on different aggregation schemes. Several treatment variables moderate this relationship, including frequency of feedback, medium, comparison message, duration, and combination with other interventions (e.g., goal, incentive). Feedbacks turn out to be more effective especially when combined with goal-setting or external incentive interventions, and is somewhat brief (e.g., less than 3 months) or quite long (e.g., longer than 1 year). McKerracher and Torriti, 2013 come up with more conservative estimates in their meta-analysis. Especially focusing on the lower estimates of more recent studies with larger sample sizes and more representative sample selection and recruitment methods, the authors argue that a realistic, large-scale conservation effect from feedback is in the range of 3-5%. These estimates are significantly lower than what suggested in earlier studies, but are supposed to be more robust, given the very large sample sizes of recent trials. It should be remarked that even if relative reductions do not appear to be large, they are in fact considered very significant from the industry view point. If these results are generalizable, given the large share of energy consumed in the residential and commercial sector, they can go a long way in improving energy efficiency, especially in the light of the very low price elasticities observed in residential energy.

Houde et al., 2013 take advantage of hourly data from a long-lasting real-time feedback field experiment and look also into time-of-day reduction effects and persistence of the effect over time. In this case, access to feedback leads to an average reduction in household electricity consumption of 5.7%, persisting for up to four weeks. The largest reductions were observed initially at all times of the day but as time passes, morning and evening intervals show larger reductions. No particular demographics, housing and psychological variable seemed to explain the heterogeneity in treatment effects.

Availability of hourly consumption data can provide further insights on how people behave. Machine learning, and in particular clustering, has been applied in the past to better understand patterns of consumption. Although several approaches are documented (Wang et al., 2015), some are of more immediate application and interpretation, like the one by Kwac, Flora, and Rajagopal, 2014, focusing on the direct clustering of normalized load shapes. These methods have been used in the context of static load profiling, and are not yet exploited, to the best of my knowledge, for detecting behavioral changes.

This work tries to combine the classical regression approach, as in (Houde et al., 2013), with a machine learning approach, as in (Kwac, Flora, and Rajagopal, 2014), to better understand if and how power consumption behavior changed concurrently with the installation of in-home displays providing real-time feedback in a sample of Italian households.

3.4 Methods

The "Enel Info+" kit, containing the in-home display used for consumption feedback testing, was distributed by Enel to thousands of households in the province of Isernia in Italy. Recruitment occurred on a voluntary basis, and was supported through several initiatives. Between June and September 2012, Enel promoted the kit through informational days at schools, mass marketing, and collaborations with public authorities and institutions. The official recruitment started in November 2012, while friendly tests were running since August. Among those who adhered to the initiative, only a sub-sample, which will be called the "Client" sample, had the in-home display still active at the end of the test period, namely December 2014. For each of these clients, Enel provided monthly energy consumption data between January 2012 and December 2014, divided per billing time slot [2]. Extra information is available for each of these clients, like contractual power and municipality at the moment of joining the program, as well as date of delivery and version of the display. For the sake of this analysis, we focus only on domestic resident consumers with a 3kW or 4.5kW power contract. We exclude non-resident or non-domestic clients, who may have very different patterns of consumption. With "Survey" sample, we denote a subset of "Client" households that agreed to provide also information on the demographics of family members, the number of appliances available in the house, and some characteristics of the dwelling.

For another subset of the "Client" households, which will be referred to as the "Curves" sample, it was possible to obtain higher frequency readings of energy consumed, i.e. every 15 minutes, at least for a fraction of the full 3 years span. The collected load curves are re-sampled to 1-hour time steps for the purposes of this analysis. To filter outliers on the higher end, we assume that electricity can be withdrawn at most with power exceeding 10% the contractual value. Hourly readings exceeding 3.3kWh or 4.95kWh are thus removed for 3kW or 4.5kW contracts households respectively. These thresholds represent the same power levels above which service would generally be discontinued after a while. Still, only a tiny fraction of observations exceed these extremes, corresponding to around 99.999% quantiles of their respective datasets. A slightly more restrictive threshold is assumed on the lower end, removing data below the 0.1% quantile (i.e. 4Wh). This should filter very low readings which might correspond to either faulty sensors, blackouts or empty houses, i.e. not interesting cases for the analysis. Gaps up to 2 hours of missing data are interpolated linearly from available values. Days remaining with missing points after this interpolation are removed.

Table 3.1 reports the main variables available for the "Client", "Curves" and "Survey" samples, along with some summary statistics. Table 3.2 compares part of these variables, conditionally to each sample, with 2012 statistics at the province, region ("Molise") and national ("Italia"). The "Client" and "Curves" samples can be compared only on the basis of 2012 average yearly consumption. Households who joined and stick to the experiment seem to have consumed much more than the average family in Isernia in 2012, both when considering the estimate from ISTAT of 1973 kWh and the one from TERNA of 2248 kWh (not reported in the table). Both average and standard deviation of consumption across households do not change much between the sub-samples considered. When looking at survey data, we observe that the program involved families with above-average number of members and rooms in the house. Ownership of washers, dryers, dishwashers, electric boilers is also above the regional average, while the presence of air conditioning is more marginal. This holds also when considering the intersection of the "Survey" and "Curves" samples. Thus, it appears that the sample of our analysis is not fully representative, pointing to selection bias. The bias was not apparently driven by higher per capita energy consumption: this matches quite well the official statistics of the Isernia municipality. However, families partic-

[2]Time of use is classified by Enel into 3 categories: F1 (on-peak), from Monday to Friday 8am-7pm, national holidays excluded; F2 (intermediate), from Monday to Friday 7am-8am and 7pm-11pm, plus Saturday 7am-11pm; F3 (off-peak), on Saturday 11pm-7am, Sunday and national holidays. Depending on the contract, different time slots may have different prices, with the most popular billing having a higher price for F1 and a lower price both for F2 and F3.

ipating in the trial are more numerous, with 3.2 persons per family as opposed to the population average of 2.4. Following discussion with Enel, this might be attributed to the campaigns the company did in schools to help getting the programme going, which apparently were the most successful ones.

Table 3.1: *The different datasets collected during the experiment.*

Main Variables	Summary statistics
Client dataset	1834 households
Date of delivery of the display	2012 (2%); 2013 (66%); 2014 (32%)
Version of the display	I (27%); II (73%)
Municipality	Isernia (63%); Other (37%)
Contractual power	3kW (94%); 4.5kW (6%)
Monthly energy consumption divided by billing time slots in 2012-2014	Total Yearly Avg. (Std.): 2814 (1103) kWh in 2012, 2739 (1069) kWh in 2013, 2614 (998) kWh in 2014
Survey dataset	804 households
Number of family members	<3 (26%); 3 (26%); 4 (37%); >4 (10%)
Age of family members	Head of family, age class: 18-30 (3%); 31-50 (37%); 51+ (54%)
Sex of family members	Head of family, sex: Male (85%); Female (14%)
Number of TVs per HH	1 (27%); 2 (31%); 3 (23%); >3 (18%)
Number of fridges/freezers per HH	<2 (32%); 2 (56%); >2 (12%)
Number of ovens/stoves/microwaves per HH	1 (39%); 2 (40%); >2 (16%)
Number of washers/dryers per HH	0 (1%); 1 (84%); >1 (15%)
Number of ACs per HH	0 (81%); 1 (14%); >1 (5%)
Number of boilers per HH	0 (86%); >0 (14%)
Number of heaters per HH	0 (78%); 1 (21%); >1 (2%)
Number of rooms	3 (6%); 4 (13%); 5 (26%); 6 (55%)
Load curves dataset	966 households
15min time-step energy consumption	On median, tracked: 62% over 3 years; 456 days before display; 194 days after display

Table 3.2: *Comparison of variables between different sub-samples from this study and official historical statistics for year 2012.*

	Client	Curves	Survey	Survey + Curves	Isernia	Molise	Italia
Number of HHs	1834	966	804	439	36563	131059	25872613
Avg. Domestic Power Consumption in 2012 [kWh/HH]	2814 (1103)	2715 (1046)	2831 (1076)	2772 (1069)	1973		2299
Avg. Domestic Power Consumption in 2012 [kWh/-Capita]			960 (515)	992 (574)	954		1186
Avg. Number of Family Members			3.3 (1.2)	3.2 (1.2)	2.4	2.4	2.3
% Females in Families			49.1 (22.0)	49.4 (23.3)	51.0	51.2	51.5
Avg. Age			42.1 (15.6)	44.4 (16.6)		44.9	43.8
Avg. Number of Rooms per HH			5.3 (0.9)	5.3 (0.9)	4.6	4.5	4.2
% HHs w/ Fridge			99.4	98.9		99.8	99.6
% HHs w/ Washer			99.0	98.9		98.1	96.2
% HHs w/ Dishwasher			62.3	61.7		35.9	39.3
% HHs w/ Freezer			65.4	64.5		25.8	25.3
% HHs w/ Dryer			12.4	11.4		3.0	3.3
% HHs w/ Electric Boiler			13.8	14.4		8.6	13.6
% HHs w/ Air Conditioning			18.9	18.7		23.5	28.0

Hourly The "Curves" dataset appears to have a log-normal distribution (see Figure 3.2), in agreement with the literature (Kwac, Flora, and Rajagopal, 2014). It includes 966 households and 26304 time periods, for a total of 14,805,000 non-null observations (i.e. ~60% of all client-hour combinations).

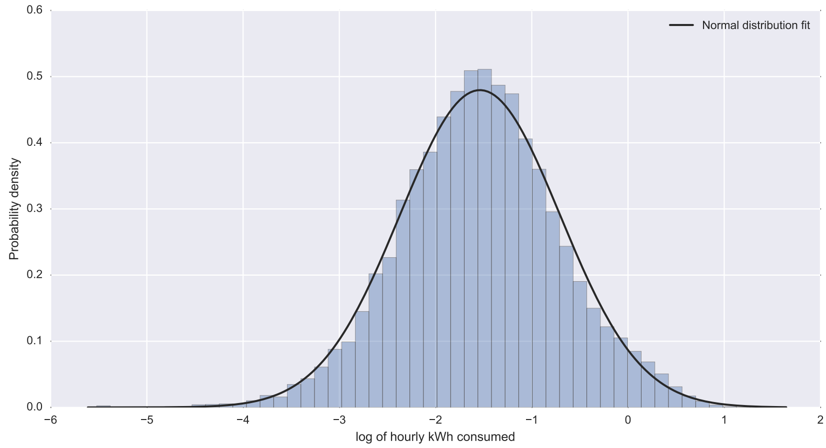

Figure 3.2: *Distribution of hourly power consumption is well approximated by a log-normal distribution.*

3.4.1 Regression of daily consumption

Let us begin by assessing the impact of the in-home display on average power conservation effect. If we were to look only at conditional averages of consumption between those with and without an in-home display over time, we would risk to attribute to the display the merit of an already decreasing trend in demand (~3% reduction per year in 2013 and 2014, based on ISTAT and TERNA data). Hence it is important to rely on some other identification strategies.

Impact is usually evaluated against a counterfactual consumption, in this context the hypothetical one of those who already received the display if they hadn't received it. Ideally, a control group is sampled to provide such counterfactual. We do not have access to the latter, since the company did not ask for informed consent and refused to give us private information. As an alternative we exploit the gradual phase-in of the experiment, building the counterfactual on the basis of the consumption of those who haven't received the display yet at any point in time. Figure 3.3 shows how clients progressively received the display. Although our identification strategy is not ideal, recent research seems to indicate that high frequency data can be used to estimate causal effects in non-experimental research designs[3]

[3] See for example, David Rapson work entitled 'Can high-frequency data and non-experimental research designs recover causal effects? Validation using an electricity usage experiment', with Katrina Jessoe and Douglas Miller, presented at 2015 AERE (`http://aere.org/summer/documents/AERESummerConference2015Program.pdf`)

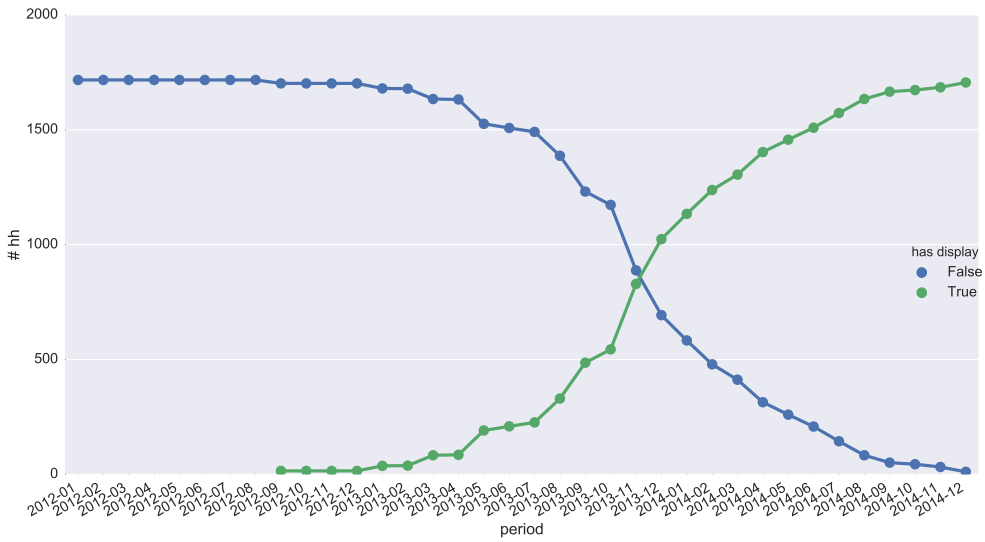

Figure 3.3: *Number of observed clients with and without display at each month in the 3 years of the experiment.*

We can cast the impact evaluation problem as an OLS regression, either in a pooled, fixed effects or diff-in-diff setting. Observations are defined over the set of households and timestamps, which both depend on the sample considered. Timestamps can be represented either (month, year) pairs with low-frequency monthly (LF) datasets, or (day, month, year) triplets with the high-frequency (HF) dataset. The independent variable is log of daily power consumption, obtained by dividing monthly levels, or when available resampling high-frequency data. In the diff-in-diff case, we consider the percentage variation in consumption from one month to the same month in the previous year. As dependent variables, we pick several subsets of the following variables:

- presence of the display (either 0=no display yet, or 1=display received);
- day of the week (from 0=Monday to 6=Sunday, only for high-frequency data);
- month (from 0=January to 11=December);
- year (from 0=2012 to 2=2014);
- municipality of the household;
- household fixed effect;
- time fixed effect (from Jan 2012 to Dec 2014 for LF data, and from 1st Jan 2012 to 31st Dec 2015 for HF data);
- survey variables (family size, average age and sex ownership; appliance ownership; number of rooms in dwelling);
- weather variables (average temperature, both in linear and squared terms).

Aliases and features of the models selected for estimation are reported in table 3.3.

Table 3.3: *Models used for estimating the impact of having a display on daily power consumption levels.*

Model name	Pooled OLS	HH FE	HH FE + Temp	HH FE + Time FE	Diff-in-Diff	HH FE + Time FE F1	Pooled OLS + Survey SURVEY	HH FE + Time FE SURVEY	HH FE + Time FE LOAD	HH FE + Day (HF) + Temp LOAD	HH FE + Time (HF) FE LOAD
Sample											
Client	x	x	x	x	x	x					
Survey							x	x			
Curves									x	x	x
Dependent variable											
log(daily consumption from monthly data)	x	x	x	x			x	x	x		
log(daily on-peak consumption from monthly data)						x					
log(daily consumption from high-freq data)										x	x
% change in daily consumption from last year (from monthly data)					x						
Independent variables											
Display received	x	x	x	x	x	x	x	x	x	x	x
Municipality	x						x				
Year dummies	x	x	x				x			x	
Month dummies	x	x	x				x			x	
Weekday dummies										x	
Avg. Temp. + (Avg. Temp.)^2			x							x	
HH fixed effects		x	x	x	x	x		x	x	x	x
Month/Year fixed effects				x	x	x		x	x		
Day/Month/Year fixed effects											x
Survey variables							x				

Intervals of confidence for the coefficients are consistently estimated with the so-called cluster-robust covariance estimator, treating each individual as a cluster.

Regressions imply a comparison at each time period between the sets of households with and without an in-home display. If the characteristics of these two sets of households are different, the regression may be biased. Thus, we also applied the same models focusing only on central observations (in the period from 2013-05 to 2014-04), where these characteristics are more balanced (see Figures 3.10 and 3.11 in the Appendix). In this case, we suppress municipality and year-related variables, as observations are not enough to provide a valid estimation accounting for these further dimensions.

3.4.2 Clustering of load shapes

High frequency data can be used to assess not only changes in overall electricity consumption, but also in shifts of consumption throughout the day. Reallocating electricity from high peak periods to off peak ones can yield significant economic and environmental benefits, especially in countries - such as Italy - characterized by high penetration of intermittent renewable energy sources. We normalize load curves with hourly resolution by the total daily consumption. Such load shapes represent how households allocate their daily budget of consumption over hours.

We rely on K-Means (MacQueen, 1967), one of the most popular non-hierarchical statistical clustering algorithm, to find prototypical load shapes (or centroids). These represents prototypical days of consumption pattern. The algorithm aims to choose centroids that minimize inertia, i.e. the sum over clusters of the sum of squared distances from a centroid to all members of its cluster. While K-means always converge, it may converge to a local minimum, potentially depending on the initialization of the centroids. To alleviate the problem, the computation is done several times (namely 36), with a re-initialization scheme called "k-means++", with provably better results than random initialization (Arthur and Vassilvitskii, 2007).

K-Means needs an exogenously provided number of clusters to operate. We focus on a range between 8 and 20, spanning reasonable and manageable numbers of prototypical load shapes, already used in the literature (Räsänen and Kolehmainen, 2009). We look at how inertia improves by increasing the number of clusters, and search for a discontinuity in the derivative of such relationship.

After having identified the centroids, frequencies of occurrence of centroids are calculated for each client, distinguishing the days before and after the arrival of the in-home display. 70 days of data are required to build such frequency vectors. If any behavioral change happened in the patterns of daily consumption due to the in-home display, this should be reflected in the before-after difference of such vectors.

3.5 Results

3.5.1 Regression of daily consumption

The coefficient of primary interest in the regressions of this analysis is the one related to having received a display. This coefficient represents the average percentage increase in consumption due to the presence of an in-home display (Figure 3.4).

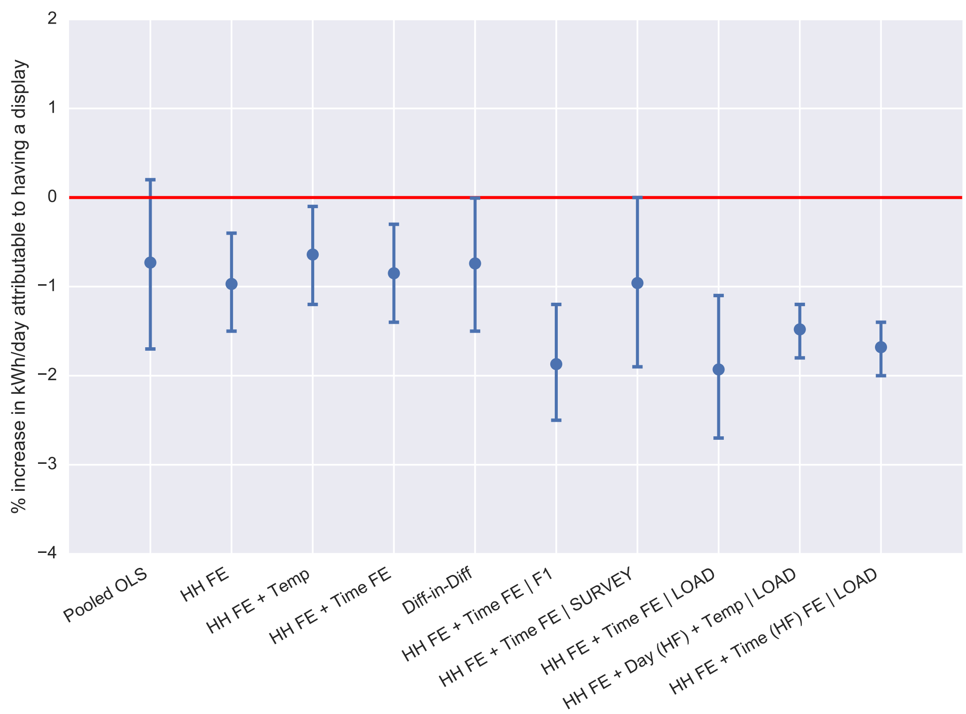

Figure 3.4: *Percentage increase in daily power consumption attributed to having received the in-home display.*

The estimated effect has the expected direction. Although small, it is almost always statistically significant across models, and the magnitude is in line with the most recent studies. It is not significant for the pooled OLS, which is also the model with potentially greater bias. Focusing on the load curves sample, the effect seems greater. In general, the load curves sample may represent households with higher consumption per capita in the first place, hence with more options to reduce consumption (Table 3.2). In the models based on HF data, uncertainty ranges shrunk considerably thanks to the abundance of observations. If we restrict our analysis to observations in the central period, we obtain comparable levels or power reduction attributable to the display, with a decrease in statistical significance for most models (see Figure 3.12 in the Appendix).

Such a small average conservation effect can have several explanations. The in-home display alone did not provide any monetary incentive or direct message promoting energy conservation, which are documented to be more effective means than information feedback alone. The geographical area of interest is relatively mountainous, with a climate not requiring air conditioning. Heating on the other side is rarely done via electricity. Power demand is mostly related to lighting and other low-consumption appliances, making it harder to save more energy. Nonetheless, even a 1% reduction, if brought to a large-scale may matter to the power industry.

A question which recurs in this literature is how long the effect of feedback lasts over time. With this regard, we do not find a clear decreasing trend in effectiveness of the display as months pass by. For some models and sub-samples, reduction in consumption halves after 6 months of having the display (e.g. with HH and time fixed effects focusing on the survey sample), while for other models the effect is the same as in the first month (e.g. with e.g. with HH and time fixed effects focusing on the load curves sample). Overall, on average declining trend in reduction is observable, but it is not statistically significant.

3.5.2 Clustering of load shapes

Figure 3.6 shows how clustering accuracy, as measured by inertia, improves as the number of clusters increase. We pick 14 as the number of centroids to be used on the following analyses, in correspondence with the first local maximum of the derivative.

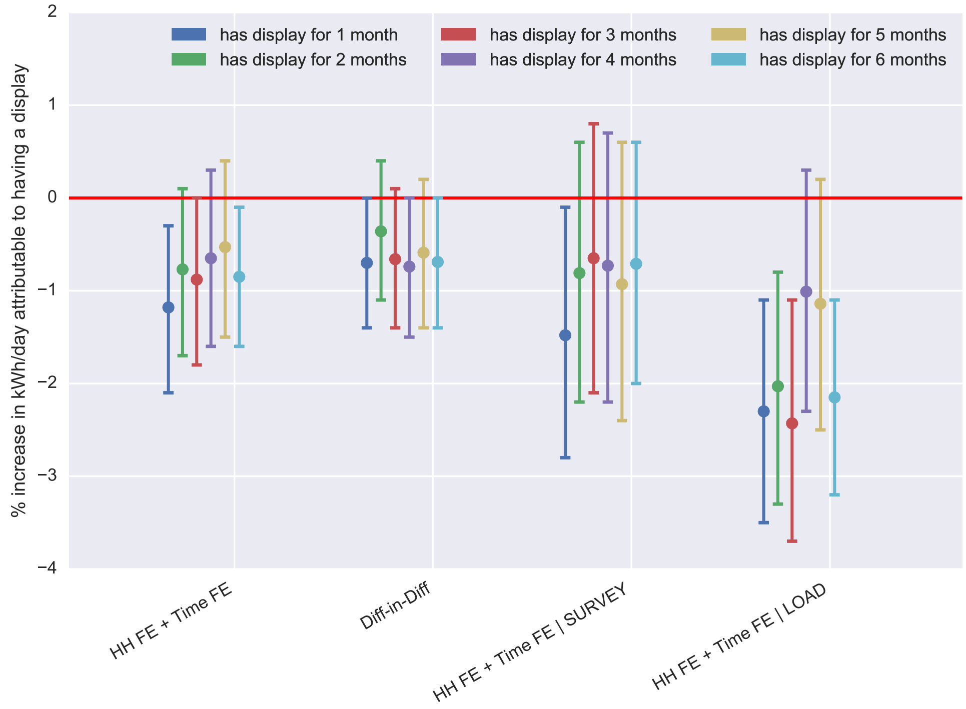

Figure 3.5: *Effect of display over time.*

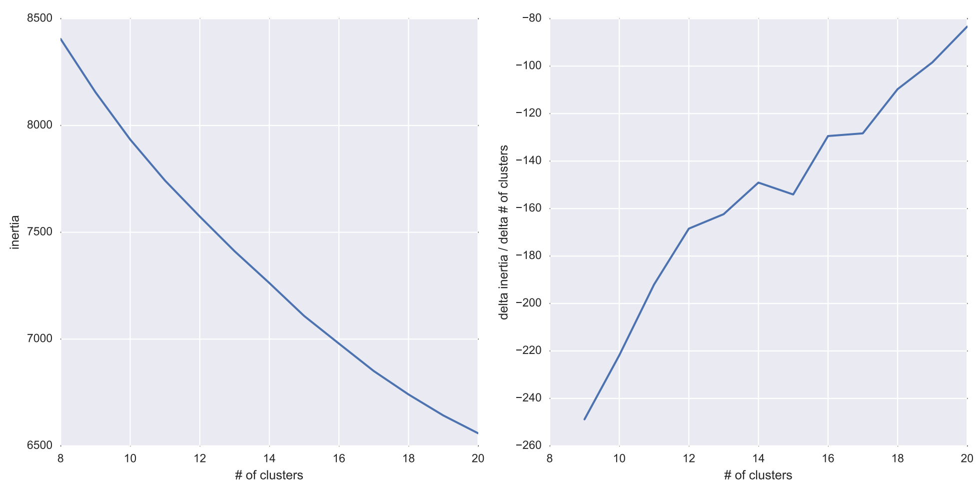

Figure 3.6: *Inertia as a function of number of clusters used in K-Means (on the left), and derivative of the same graph (on the right).*

The 14 centroids representing prototypical days are shown in Figure 3.7. Clusters are sorted by the number of actual load shapes they represent (as shown under N. CURVES in the graphs). Shapes are clearly separated by the characteristics of their peaks, i.e. their relative height and hour of occurrence.

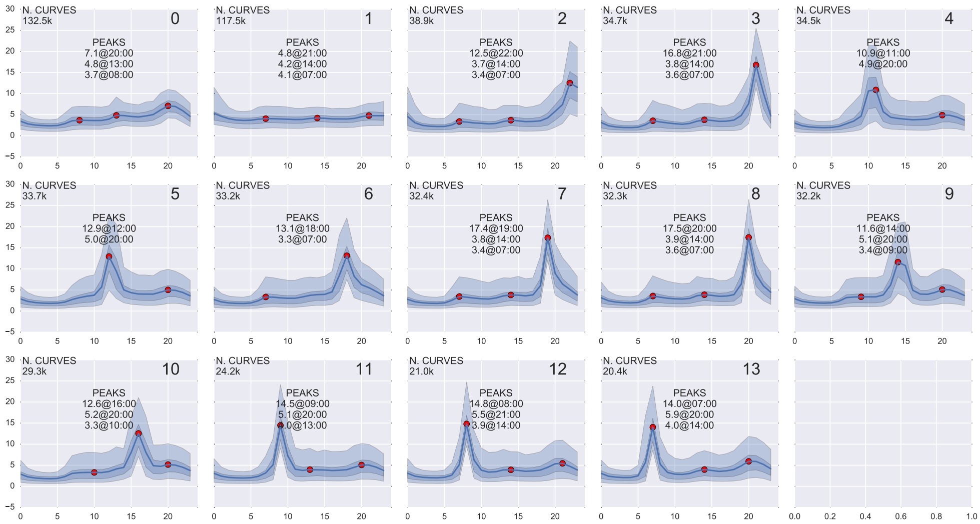

Figure 3.7: *Prototypical load shapes resulting from the K-Means clustering. Primary and secondary peaks are described in each subplot, in terms of % level and hour of occurrence.*

For each client, frequencies of occurrence of centroids are calculated for the days before and after the arrival of the in-home display. If there was a common trend in behavioral change due to the in-home display, we should see a significant change in such frequencies, moving away from some representative shape towards another one. As shown in Figure 3.8, this is not emerging from the data. The average behavior of the sampled clients, as coded in these vectors of frequencies, does not change significantly conditionally on having or not a display.

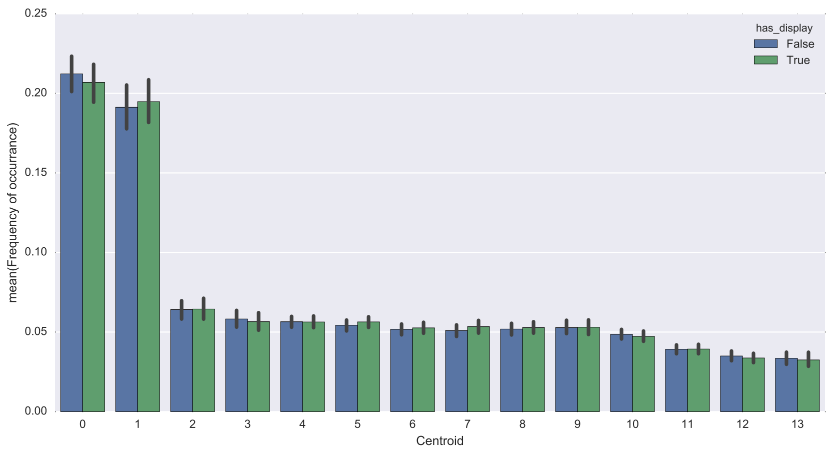

Figure 3.8: *Frequencies of occurrence of centroids, averaged across clients, to which load shapes before and after the in-home display arrival are clustered. Black vertical bars represent confidence interval for the means.*

Nonetheless, if we plot the change in frequencies before and after the delivery of the in-home display for each client, a wide heterogeneity emerges (Figure 3.9). Most households seem to have maintained stable consumption patterns over time, as indicated by the mass of the distributions of frequency gravitating around 0. Still, several households exhibit much more flexibility in consumption, as shown by the long tails of some of the 14 distributions. Overall, the in-home display was not consistently able to provide the incentives required for an average visible shift of peaks over time, but it did work for a subset of the population. This results is consistent with the literature emphasizing the high heterogeneity of households and days.

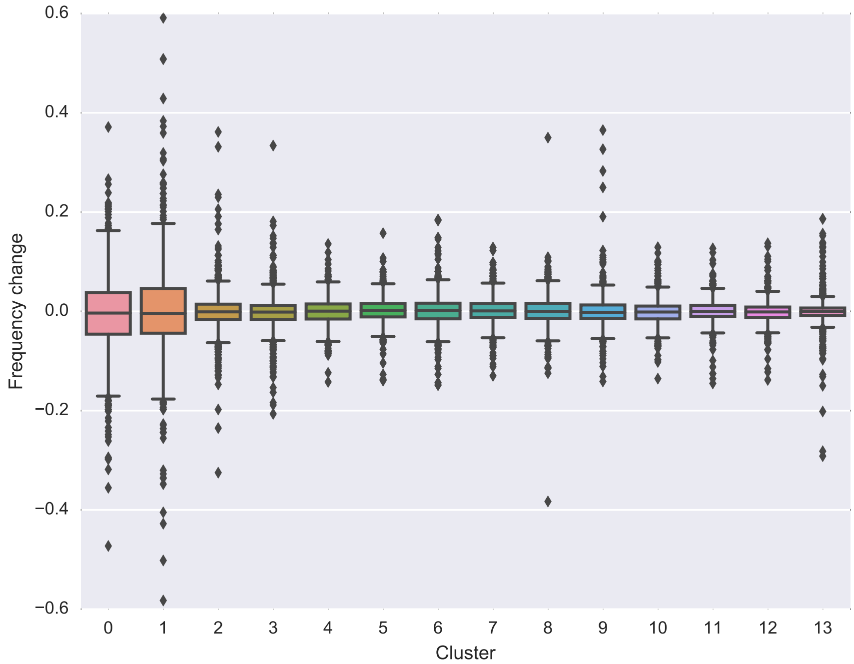

Figure 3.9: *Changes in frequencies of occurrence of centroids, to which load shapes before and after the in-home display arrival are clustered. Each household corresponds to a series of 14 points, one per cluster.*

3.6 Conclusions

Daily behavior of residential power consumption can be modelled as a two-step process: first a daily budget of energy is decided, and then an allocation of consumption over hours is chosen from a finite set of prototypical profiles. How does a real-time information feedback device affect this process? We tried to address this policy-relevant question using data from a recent large-scale trial carried out in Italy.

According to our estimates, an average reduction in daily power consumption of 1.7% can be attributed to such device, even though with marginal statistical significance. This is in line with more recent experimental studies on the topic.

Average hourly power consumption behavior, measured in terms of distributions of preferences for representative load shapes by each user, seems to remain unchanged before and after the arrival of the display. Nonetheless, a wide heterogeneity has yet to be explained.

Further data on the households would be useful to try to segment the analysis in meaningful groups, identifying those customers for which information feedback led to either significantly lower consumption levels or significantly different consumption habits.

Consumption data at the appliance level would provide invaluable information on behavior and behavioral change, even though at the cost of increasing computational tractability.

Results are specific to the group involved in the study, and are not easily generalizable to the wider population. The trial was carried out in an area of the country with lower than average per capita energy consumption, as well as income, allowing for more limited adjustments and investments. On the other hand, the sample households appear to have more family members than average, possibly young children. Future better experimental designs will also help to avoid issues of sample representativeness and absence of control group.

All these potential steps for further research could lead to a better understanding of how such interventions perform at large-scale, and whom these interventions could be most beneficial for.

3.7 Acknowledgements

The research leading to these results has received funding from the European Commission, under the European Research Council (ERC) grant COBHAM.

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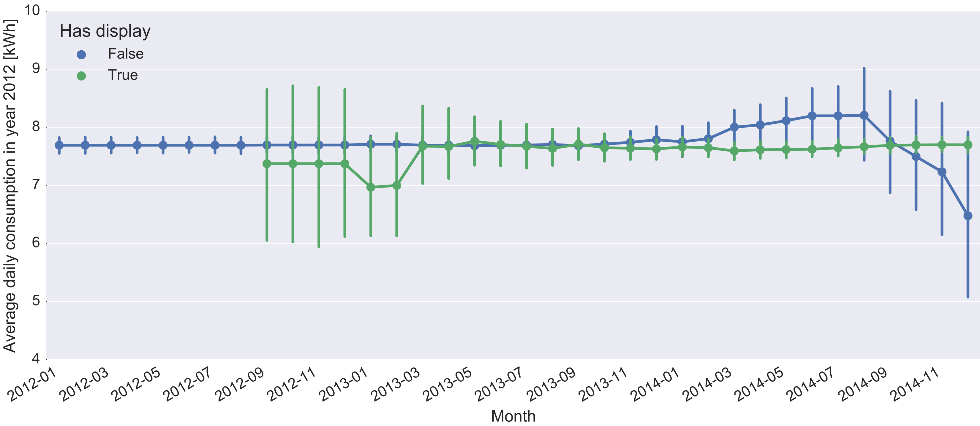
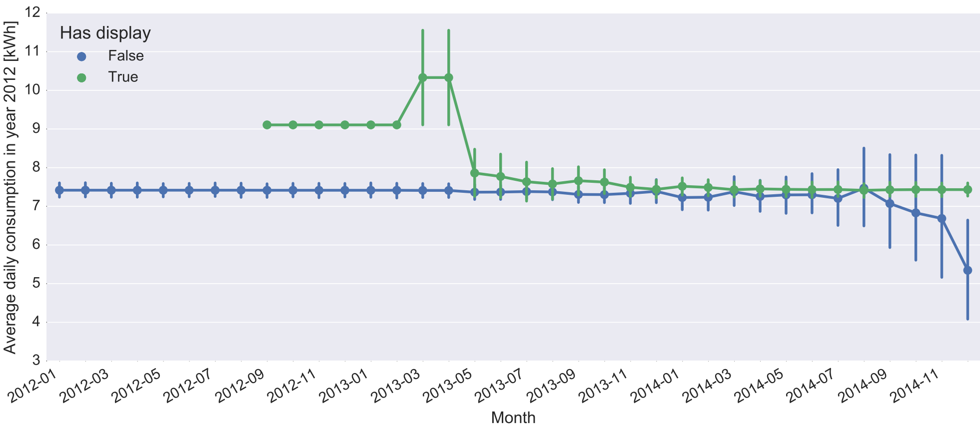
3.A Appendix

3.A.1 Supplementary figures



(a) *Client dataset.*

(b) *Survey dataset.*



(c) *Load dataset.*

Figure 3.10: *Comparison of average daily power consumption in 2012 between households with and without an in-home display for each month of the experiment time horizon. Households belong either to the Client (a), Survey (b) or Load (c) dataset. The average across households is given with a bootstrapped confidence interval.*

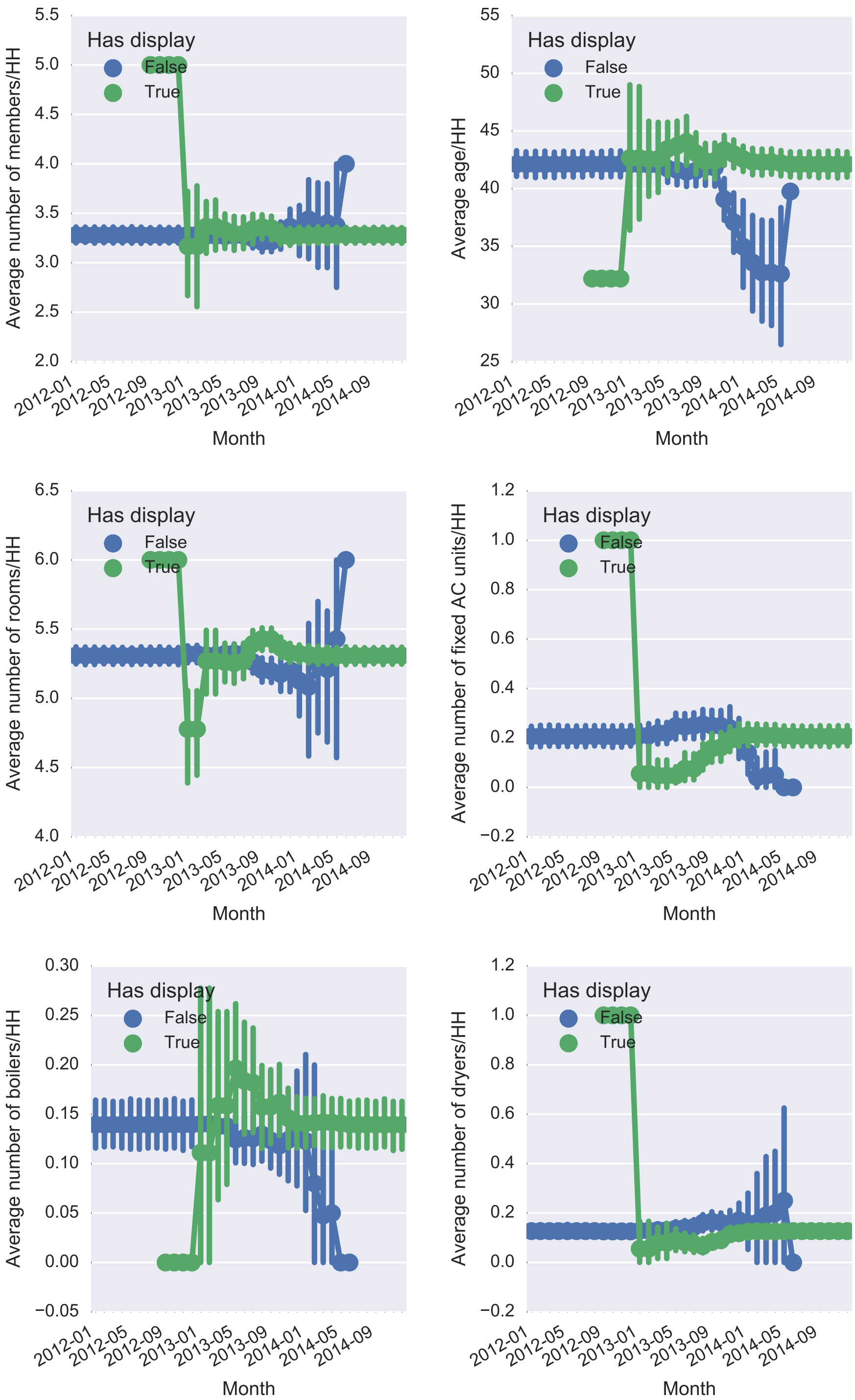


Figure 3.11: *Comparison of survey variables between households with and without an in-home display for each month of the experiment time horizon. Averages across households are bootstrapped.*

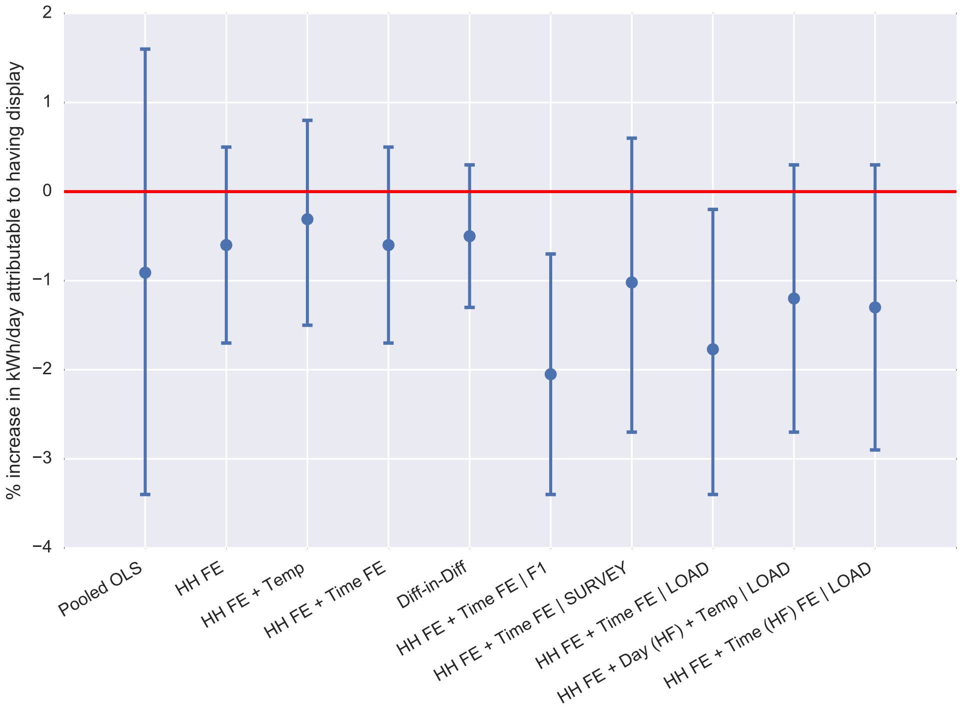


Figure 3.12: *Percentage increase in daily power consumption attributable to having received the in-home display, focusing only on observations belonging to the central period from 2013-05 to 2014-04.*

CHAPTER 4

The clean energy R&D strategy for 2°C[1]

4.1 Introduction

The purpose of this paper is to assess the role of R&D investments in clean energy technologies under the objective of limiting the average global surface temperature increase of 2°C above the pre-industrial average by the end of this century with sufficient probability. 2°C is considered an important signpost for the scientific community as well as for the climate policy debate. The international community has recognized this threshold as the long term goal for the negotiation process which was initiated in Durban, and more recently moved forward in Doha, and which is supposed to lead to a global agreement after 2020. While governments started to acknowledge anthropogenic climate change and the need for action 20 years ago with the first Earth Summit conference, several obstacles have made implementing such a goal very challenging. One of the most important concerns for action is that mitigating emissions, especially at the deep levels required to meet the 2°C objective, could have serious economic repercussions, given that currently available low carbon technologies are costlier than fossil fuel alternatives. A successful climate policy will thus require significant improvement of existing technologies, and invention of new alternatives which can help to reduce energy consumption and emissions at contained costs. Although innovation[2] has been emphasized by many governments in their climate agendas, especially in Europe, the literature that has assessed the clean energy R&D gap remains limited.

The objective of this paper is in line with the main purpose of the LIMITS special issue it belongs to: contributing to a better understanding of the implications of a 2°C stabilization. In order to provide quantitative answers to the problem at hand, this and

[1]This chapter is based on the paper "The clean energy R&D strategy for 2°C" by G. Marangoni and M. Tavoni, published in *Climate Change Econonomics* 05, 1440003 (2014), http://dx.doi.org/10.1142/S201000781440003X.

[2]While innovation is a broad topic, in this paper we will be referring to its R&D component.

most of the other works of the special issue rely on so-called Integrated Assessment Models (IAMs). This family of models is increasingly common in the field of climate policy analysis, since they provide fairly complete descriptions of the problems that climate policy makers are called to decide upon, and present them with sets of possible least-cost solutions. Further information on the broader results obtained with the models involved in the LIMITS comparison exercise can be found in the overview papers of this same special issue (Kriegler et al., and Tavoni et al., this issue). For a focus on how investments related to clean energy technologies are expected to be allocated under a 2°C target, the reader is invited to refer to McCollum et al. in this special issue.

The literature based on multi-model ensembles has indicated that a huge transformation on the way we produce and demand energy, as well as we use and manage land resources, will be required if we want to meet the climatic constraint of 2°C (Calvin et al., 2012; Clarke et al., 2009; Kriegler et al., this issue). This transformation would require emission reductions rates which exceed by far what has been observed historically. Currently available technologies have the potential to initiate the road towards decarbonization (Pacala and Socolow, 2004). Yet, ultimately, groundbreaking technological innovation will be needed to avoid excessive economic losses. Integrated assessment models have indeed shown that technology availability plays a major role on the feasibility and costs of facing the challenge of 2°C (Krey and Clarke, 2011; Kriegler et al., Submitted). The literature thus confirms a deep link between the chances of achieving a low carbon world and the ability to improve the performance of currently known technologies, as well as to create new technologies altogether.

Several policies have been put into place in recent years as a way to promote the development of renewables, with the hope that this would have led to the creation of an industry and would have ultimately profited the manufacturing base they supported. However, incentivizing the installation of currently existing technologies does not necessarily provide the best economic answer (Borenstein, 2012); on the other hand, subsidizing research and development is justified by the innovation market failures arising from property rights protection and knowledge spillovers (Geroski, 1995). Thus, a fundamental research question in the field of climate economics is to what extent climate stabilization can be achieved by just focusing on setting the right carbon price, or by considering also policies aimed at fostering innovation (Jaffe et al., 2005, 2003).

A related question to setting the right levels of R&D subsidies is the assessment of the R&D investments gaps that we need to bridge to get to 2°C. Despite the policy relevance of this topic, only a handful of modeling studies have looked into this issue. This can be partly attributed to the complexity of the topic of technical change, an uncertain process which is difficult to model. Surprisingly, however, these studies (Blanford, 2009; Bosetti et al., 2011, 2008; IEA, 2010; Margolis and Kammen, 1999; Nemet and Kammen, 2007; Popp, 2006) tend to agree on a series of important results. First, R&D plays a fundamental role on the costs and feasibility of climate stabilization policies. Second, the gap in R&D investments between a Business as Usual and a climate policy scenario is substantial, in the order of 50 USD[3] Billions per year.

A further research question pertains to the role of innovation policies in case of fragmented cooperation on climate. Given the difficulties in reaching an inclusive agreement on emissions reductions among the major emitters, it is natural to wonder whether

[3]All monetary values in this paper are given in 2005 US dollars using market exchange rates.

focusing on a technology and innovation agreement could offer better prospects and a more efficient outcome than continuing with a set of uncoordinated efforts to reduce CO_2 emissions (De Coninck et al., 2008; Newell, 2008).

This paper aims at contributing on the latter two lines of research, and thus improving the understanding of the role of innovation and R&D in the clean energy sector. Our study relies on the integrated assessment model WITCH (see next section). The originality of this article is twofold. First, the clean energy R&D gap is quantified with specific reference to the 2°C objective. To this end, we use the set of scenarios developed in the LIMITS project which combines short term policy realism with two different probabilities of meeting 2°C in 2100. The climate outcome of all scenarios has been tested using the probabilistic version of a medium complexity climate model (MAGICC), ensuring that the exceedance probability remains within specified ranges (see Kriegler et al., this issue). Second, we work out the implications of an alternative climate policy agreement based on a concerted international R&D programme. We refer to this policy setting as the 'RD-deal'. This agreement is meant to replace the current fragmented emission reductions pledges in the near-term with near-term high R&D efforts. International technology innovation policies have been widely discussed as alternatives to binding emission reduction targets, but have been rarely assessed by the IAM community.

The paper is organized as follows. We briefly discuss the main features of the WITCH model, and then present the study design. We show the implications of 2°C policies on the transformation of the energy system, and quantify the size and the regional distribution of the R&D investments needed to comply with it. We then assess the R&D climate agreement in relation to the feasibility of the 2°C objective. Finally, we summarize our conclusions.

4.2 Technical change in WITCH

WITCH (World Induced Technical Change Hybrid Model) is an energy-economy-climate model developed within FEEM's Sustainable Development research programme (Bosetti et al. 2006, 2009). The model divides the worldwide economy into 13 regions, whose main macroeconomic variables are represented through a top-down inter-temporal optimal growth structure. This approach is complemented with a compact description of the energy sector, which details the energy production, and provides the energy input for the economic module and the resulting emissions input for the climate module. The endogenous representation of R&D diffusion and innovation processes constitute a distinguishing feature of WITCH, allowing to describe how R&D investments in energy efficiency and carbon free technologies integrate the currently available mitigation options. The different regions can either behave as forward-looking agents optimizing their welfare in a non-cooperative, simultaneous, open membership game with full information, or be subject to a global social welfare planner in order to find a cooperative first-best optimal solution. 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.

For this paper, two channels of endogenous technical change are accounted for in the model. Their characteristics are summarized and compared in 4.1. One type of formulation of technical change affects the investment costs of an alternative, carbon-free technology in the non-electric sector. This 'backstop' zero-emission fuel can be thought of as an advanced biofuel mitigation option whose costs are currently much higher (e.g. 10 times) than oil, due to lacking of sufficient knowledge for transforming cellulose into ethanol. With sufficient R&D and physical investments, the low carbon backstop can become a viable substitute to low carbon fossils. However, we also impose a global constraint on the resource base which can be used to produce the low carbon fuel, as a way to mimic the limitation of land use which can be devoted to growing the bio-feedstock. The global cap is fixed at 150 EJ/yr, in line with available estimates of bioenergy crop potential (see Calvin et. Al, this issue, for a detailed discussion of bioenergy). Thus, although at times we refer to this unnamed technology to as backstop in the paper, its implementation in the model provides a realistic representation of the technology as a bioenergy-based low carbon fuel. While the climate mitigation literature mentions also bioenergy-based systems capable of removing carbon from the atmosphere, by means of carbon capture devices, no negative emissions are envisaged through our backstop technology.

The externality nature of the backstop innovation process is modelled via international spillovers of *knowledge* and *experience* across countries and time. In each country, the productivity of this low carbon technology depend on the region's stock of energy R&D and on the global cumulative installed capacity, two proxies for knowledge and experience respectively. This is modelled via two factor learning curves. The regional R&D stock depends on domestic investments, previous domestic knowledge stock, and foreign knowledge stock through international spillovers. The spillover term for knowledge depends on the interaction between the countries' absorptive capacity, and the distance of each region from the technology frontier. On the other hand, there are complete spillovers of experience across countries.

The other main channel of technical change in WITCH is about energy savings. Following Popp (2006), energy efficiency is modelled through improvements in the productivity of the energy input in the production of the final good sector, via a constant elasticity of substitution (CES) production function. Differently from the previous case, innovation is now subject only to knowledge externalities through a single factor learning curve. The knowledge stock depends on domestic and foreign R&D investments in a similar way than the one used for the backstop, with the only difference that the new additions to the stock of knowledge depend also on the previous domestic stock of knowledge.

Further details for both innovation formulations can be found in (Bosetti et al., 2011) and at www.witchmodel.org. The most relevant equations are reported for convenience in the Appendix.

Table 4.1: *The two channels of innovation in WITCH.*

	Energy Efficiency	Carbon-free Advanced Biofuels (Backstop)
Technological implications of the innovation	Introducing new energy-saving equipment and devices in any of the energy end-use sectors (buildings, industry, and transport).	Introducing advanced carbon-free biofuels as a primary energy supply for non-electric energy end-use sectors (mainly transport).
Economic implications of the innovation	Increasing overall energy efficiency of output.	Reducing the costs of carbon-free non-electric energy supplies.
Integration in the model	As a substitute for energy supply in producing energy services.	As a substitute fuel for oil in meeting the non-electric energy demand.
Technical change drivers	1. Domestic & foreign investments in R&D.	1. Domestic & foreign investments in R&D. 2. Domestic & foreign experience (i.e. amount of advanced fuels already used).
Diffusion limitation	Implicit in the constant elasticity of substitution (CES) production function structure.	Explicit through expansion and total resource constraints.
Knowledge to actual technical change delay	None.	10 years lag.
References in the literature	Jones (1995) for the knowledge formulation, Popp (2002) for the empirical estimation of the parameters, and Popp (2004) for the integration as a CES.	Kouvaritakis et al. (2000) for the knowledge formulation, Bosetti et al. (2009) for further references on the empirical estimation and modeling, Calvin et al. (this issue) for cumulative deployment potential estimates.

When elaborating on regional results, we will be referring to the 13 native regions of WITCH, which are: USA, OLDEURO (Old Europe), NEWEURO (New Europe), CAJAZ (Canada, Japan, New Zealand), KOSAU (Korea, South Africa, Australia), CHINA (including Taiwan), INDIA, SASIA (South Asia), EASIA (South East Asia), LACA (Latin America, Mexico and Caribbean), MENA (Middle East and North Africa), SSA (Sub-Saharan Africa excl. South Africa) and TE (Transition Economies). For the sake of brevity, also the following aggregations will be used: EUROPE (OLDEURO + NEWEURO), OTHER-OECD (KOSAU+CAJAZ), OTHER-ASIA (SASIA+EASIA), and MEA (MENA+SSA).

A distinctive feature of WITCH is the ability to assess the optimal response to climate policies either in a competitive or in a cooperative setting. In the latter, a social planner chooses the optimal financial efforts to allocate in innovation and mitigation, in a way that welfare is maximized conjunctly with the achievement of a given climatic target. This type of optimization can be regarded as a useful benchmark for evaluating the consequences of internalizing the set of externalities which are taken into account in the WITCH model, namely: GHG emissions, dependence on exhaustible natural resources, and technological R&D spillovers. A particular advantage of this setting lies in the ability of estimating the economic benefits of a cooperative world, where classic climate policy instruments are replaced by sets of policy instruments that promote coordinated efforts in achieving the desired climatic targets.

As one could expect, full cooperation scenarios lead to lower consumption losses and higher accumulation of R&D backstop investments compared to the non-cooperative corresponding cases. The results obtained in the context of this paper with the cooperative settings are not reported here, as they are in line with previous studies with this same model (Bosetti et al., 2011), and with the aforementioned literature on R&D subsidies. For the sake of this paper, it is only worth mentioning that cooperation not only affects the global picture (with a general increase of investments), but also the regional contributions to innovation (with a more prominent role for developing countries).

4.3 Study design

To assess the role of energy innovation in decarbonizing the energy system, the 2° degrees target was translated into a set of significant scenarios implementable by the WITCH model. Most of the scenarios we consider here were defined in the context of LIMITS, whose purpose is to explore the implications on feasibility and costs of different policy assumptions, i.e. the probability of achieving the 2° degrees target, the timing and stringency of global and regional mitigation action, and the distribution of regional costs. Further details on the whole scenario framework adopted for this study, as well as on how the economy and the energy system of different IAMs respond to the different scenarios assumptions, can be found in the two overview papers by Kriegler et al. and Tavoni et al. in this issue.

Besides the standard LIMITS scenarios, we have run three additional scenarios to address the specific questions under investigation. Specifically, we have assessed 'second best' policy scenarios in which no agreement is achieved on emission reduction policies, but in which countries decide to cooperate on R&D by investing at the optimal levels consistent with their stabilization objective, either 450 ppm-eq or 500 ppm-eq.

Table 4.2 reports a brief description for all of the scenarios used in this study. The last row shows the ones which are additional to the LIMITS study protocol.

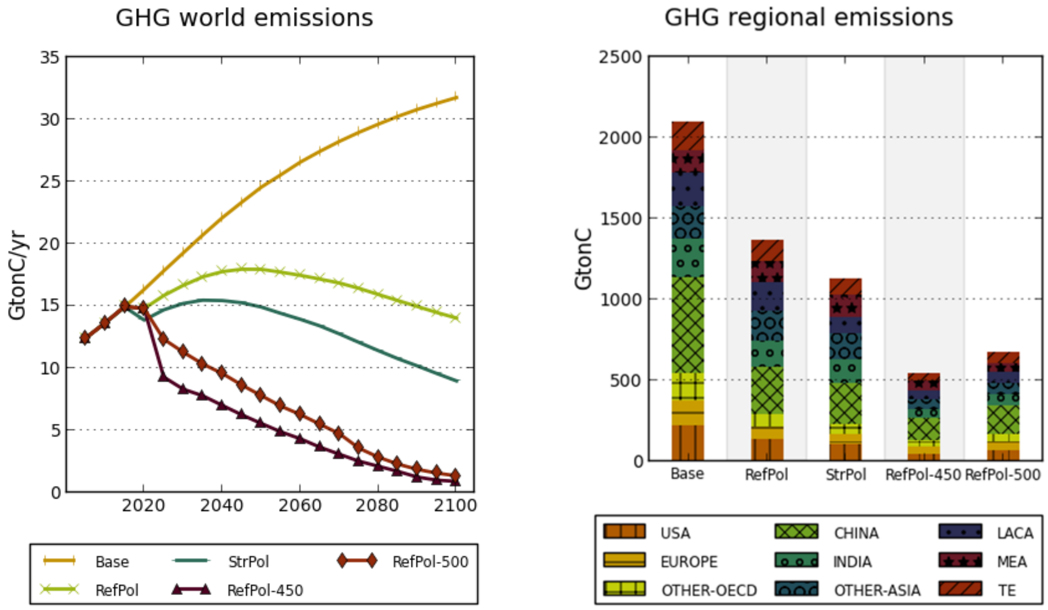
Table 4.2: *List of scenarios used in this study, along with their description.*

Scenario	Description
Base	No climate policy, either global or regional, is in place.
RefPol	Regions are subject to 2020 targets that represent the lower end (or lower if more plausible) of their (or of their neighboring regional leaders) Copenhagen pledges. The stringency level of 2020 regional targets is extended until the end of the century by using average GHG emissions intensity improvements per year as a proxy.
StrPol	Like RefPol, but the more stringent end of their (or of their neighboring regional leaders) Copenhagen pledges are taken into account, and extended until the end of the century.
RefPol-450	Regions apply the RefPol policy package up to 2020, then a globally-harmonized carbon tax is adopted so that the concentration of GHGs reaches 450ppm-eq in 2100, with overshoot allowed. This corresponds to a likely to very likely (>70%) chance of reaching the 2 °C target.
RefPol-500	Like RefPol-450, but with an as likely as not (~50%) chance of reaching the 2 °C target, and with the concentration of GHGs reaching 500ppm-eq in 2100.
RefPol2030-500	Like RefPol-500, but with global commitment delayed till 2030.
RD-deal-450 RD-deal2030-500	These scenarios correspond to those with the same names where RD-deal is replaced with RefPol. In the near-term, carbon emission mitigation pledges are removed from the corresponding RefPol policy packages, while energy R&D is fixed at the optimal level. Afterwards, a globally-harmonized carbon tax is adopted so that the concentration of GHGs reaches the levels of the corresponding scenarios.

In the next sections, after describing the challenge for the economy and the energy systems to stabilize the climate to non-dangerous levels, the R&D investment gap is quantified for what can be considered as first-best settings, where mitigation action, even if fragmented, starts immediately, and global cooperation starts in 2020 or in 2030. Then, R&D figures are analyzed in a class of second-best scenarios, in order to see if other sub-optimal policies, where the regional emission reduction efforts of the Copenhagen pledges are replaced by high energy R&D investments and global cooperation is delayed up to 2030, could constitute viable cost-effective alternatives.

4.4 Challenges of stabilization to 2° degrees

A world without any climate policy is expected by WITCH to be a world with a temperature in 2100 of 4° degrees above the pre-industrial levels, which is likely to imply serious ecological, social and economic consequences. More than 60% of yearly global GHG emissions are related to CO_2 emissions resulting from the burning of fossil fuels for energy related purposes, which are supposed to increase in the baseline on average by 1.3% per year. Population and global economy are also supposed to increase, at an average rate of 0.4% and 2.4% per year respectively, while global energy intensity levels are expected to decrease at an average rate of 1.4% per year. On one side, this implies an improvement of carbon intensity over the century, due to the expected diffusion of more efficient energy systems around the world. On the other side, countries are expected to show an increase in the average carbon emissions per capita, representing the worldwide claim for better living standards met by a fossil based energy system.



(a) *Emission profiles for a subset of LIMITS scenarios.*

(b) *Cumulative emissions over the century decomposed by regions.*

Figure 4.1: *Emissions, over time and cumulated, for a subset of LIMITS scenarios.*

Looking at the regional emission contributions, the largest emitter is expected to be with wide margin China, with almost 30% of the total cumulated GHG emissions of the century. Following with 10.4%, 9.8% and 9.3% we find India, USA and LACA, respectively. Europe (6.7%) places itself in the middle of the list, after TE (8%) and MENA (7.6%). When considering emissions growth rates, India distinguishes itself with its average rate of 2.1%, followed by China and MENA, both at 1.5%, concurrent with double growth rate figures for GDP.

If regional economies were able to respect a weak fragmented commitment to climate mitigation, as foresighted in the RefPol scenario, cumulated GHG emissions over the century could be reduced by about one third. A further 10% could be abated with a more stringent fragmented commitment (as in StrPol). The rate of carbon intensity reduction varies across regions, according to explicit targets set after 2020. Focusing on the RefPol case, for some regions like MEA, OTHER-ASIA and LACA, the baseline carbon intensity profile already meets the assumed pledge. For other regions, this target involves a binding constraint on emissions, pushing the transformation towards a less carbon intensive energy system. This transition is further elicited by explicit targets on the amount of renewable energy over the total final or electrical energy production after 2020, and of wind and nuclear capacity installed by

1. Again, China happens to be one of the most significant players,

with huge reductions in emissions and a significant slowdown of GDP. Of the 780 GTonC reduced from baseline in the RefPol, 322 (~41%) are to be attributed to China, more than what OECD countries together are supposed to mitigate (269 GTonC). This impacts its GDP with a yearly 2.9% loss with respect to the baseline, on average over the century, a rate which is above the average of 1% that is globally experienced. The countries with the highest losses are CAJAZ, TE and KOSAU, with yearly average GDP losses of 3.3%, 3.2% and 2.2% respectively. The carbon intensity rate improvements these regions are asked to provide on average are between 1 to 3 times those of the Base scenario.

A substantial decarbonization of the economy is required if more ambitious emissions targets are to be imposed, namely those where GHG concentrations reach 450ppm-eq and 500ppm-eq in 2100. This implies deep changes both in the electric and in the non-electric energy production sectors. Concerning the former, the reduction of carbon emissions is achieved in four ways: i) decreasing the power demand through efficiency improvements and economy contraction; ii) limiting the use of fossil fuels, partially switching to expensive technologies of carbon capture and storage (CCS); iii) increasing the diffusion of renewable energy sources; iv) enforcing the role of nuclear power, as a consequence of the reduction in the use of the base-load fossil technologies, and the limitations in the share of wind and solar power supply due to their intermittency issues[4].

Fossils cover around two thirds of the present world electric demand. In the Base scenario, this quota slightly increases over the century mostly at the expense of renewables, decreasing from 20% to 12%, while nuclear slightly decline from 14% to 12%. In the moderate Copenhagen scenarios, instead, fossil fuels are progressively substituted, especially in the second part of the century, mainly by nuclear and renewables: in 2100, nuclear settles around 20%, renewables take 25% of the power share, while fossils decrease accordingly. It is interesting to note that the role of CCS technologies grows considerably with the stringency of the climatic policy. Even if they only appear in the last decades of the century in the RefPol and StrPol cases, their share amounts to 13% and 22% in 2100. In the more stringent stabilization scenarios, finally, a complete decarbonization of the power sector takes place over the century: fossil fuel power supplies constantly decline, and need to be fully combined with CCS technologies. The diffusion of renewables is extensive: biomass plants reach 20% of the share, almost all of them with CCS, while wind and solar plants rise to 20%, capped by the aforementioned intermittency-related system integration constraints. In absolute terms, 2100 electricity consumption decreases by 23%, 32%, 49% and 50% in the considered scenarios (RefPol, StrPol, RefPol-500 and RefPol-450) with respect to the corresponding Base value. These reductions complement the transition to a less carbon intensive power system in meeting the emissions targets.

A strong decarbonization is recognizable also when looking at the overall energy sector. Again, energy efficiency improvements allow for equal levels of GDP given smaller final energy amounts. Jointly with a shrink of the economy forecasted by the model to meet the various targets, these effects determine a considerable decline in the absolute demand: in 2100, it is 12 $\div$ 25% lower than the Base case in the Copenhagen scenarios, while it is more than halved in the stabilization. Besides demand reduction, significant impacts of the policies under study can be seen in the share of fossil fuels and renewables in global primary energy supply, demonstrating a progressive transfer of production quotas from the former to the latter. Nonetheless, one of the most important factor in assisting the regional mitigation actions remains the diffusion of the carbon-

[4]The penetration of intermittent renewables in the electric system is limited by: penalty costs dependent on the share of intermittent renewables in the power mix; equations ensuring the presence of flexible generation options, like coal and gas plants, to adequately compensate for the intermittency of wind and solar supplies.

free backstop in the non-electric sector. While this technology does not enter in the baseline, it turns out to be very reactive to the stringency of the climatic policy when one is imposed. At the end of the century, the 25%-32% of the non-electric demand is satisfied by the backstop in the fragmented cases, whereas the share rises to 72% in the stabilization ones. In the latter scenarios, a complete switch from oil to advanced carbon-free biofuels is envisioned by the model by 2090.

The diffusion of the backstop, along with the energy efficiency improvements, is an essential part of the optimal model response to the ambitious targets under investigation. The huge reductions in energy demand would not be economically reasonable without adequate investments in energy efficiency improvements. Furthermore, if the transportation energy demand and the decarbonization requirements are to be jointly met, replacing oil with carbon-free alternatives becomes essential for the levels of stringency under consideration. The deployment of these two mitigation strategies would not be possible without specific investments in R&D, which will be explored in detail in the following sections.

4.5 The R&D gap for 2℃

In this section we quantify the R&D investments which are optimal for the set of 2°C compatible scenarios outlined in the previous sections. As described above, the WITCH model features two types of R&D investments that can improve the economic efficiency of the energy system. The first aims at compensating the need for final energy by increasing the energy efficiency of the whole energy sector. A second type involves the deployment of a non-electric carbon-free technology.

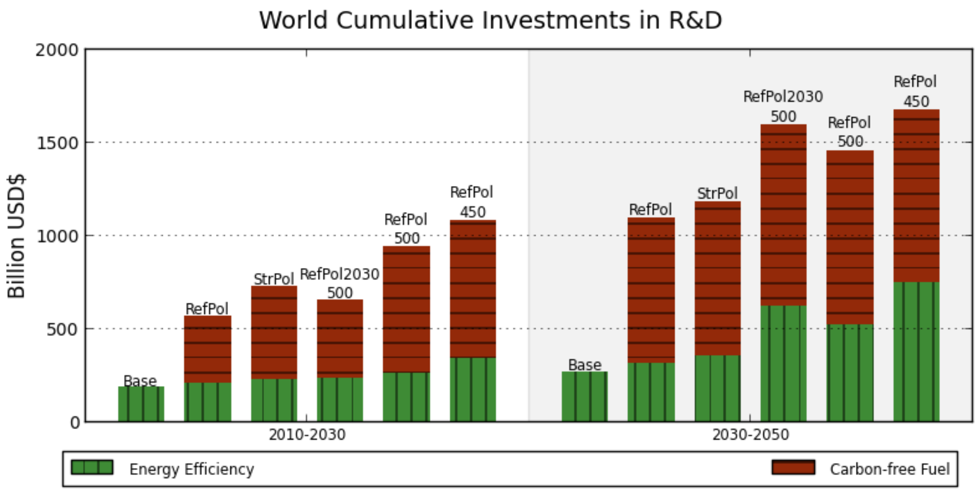


Figure 4.2: *Optimal innovation investments in response to different climate policy scenarios.*

It is interesting to note that the model promotes a certain level of innovation effort already in the baseline case, where no particular climate policy is in place. This is related to the economic benefit of reducing the cost of the energy production by saving energy, but does not involve investing in carbon-free fuels given that no price is attached to CO_2, and that fossil fuels are assumed to be relatively available throughout the century. Regarding the impact of climate policies on R&D, as shown by Figure 4.2, investment cumulative levels increase both over time and in the stringency of the climate policy. RefPol2030-500 shows a lower effort in the near term, similar to RefPol[5]. In the medium term, the avoided initial investments are fully recovered, bringing the overall cumulative amount to a level comparable with the RefPol-500 scenario.

The increase in investments due to the stringency of the climatic policy is not equal in the two sectors, as the non-electric carbon free R&D appears to be much more sensitive to the climate policy stringency. This is due to the fact that energy efficiency R&D is carried out already in significant quantity in the Base case, because of the rising cost of the energy production factor. Further investments provide smaller benefits, due to the assumption of decreasing returns. On the other hand, carbon-free R&D is particularly valuable in the presence of the climate policies, since it provides a carbon free alternative in a sector which is notoriously difficult to decarbonizes, namely the transportation sector.

Overall, Figure 4.2 indicates that the global R&D investment needs for attaining 2°C is approximately 1 USD Trillion in the period 2010-2030, and 1.6 USD Trillions in the period 2030-2050, if we consider RefPol-450 and RefPol-500 as our benchmark scenarios. Depending on the desired climatic target and on the near-term stringency of commitment, we can also quantify the gap between the optimal corresponding R&D investments efforts and the business-as-usual case. As no advancement is done in clean non-electric technologies, the global R&D gap to the no-policy baseline on average ranges from 30 (RefPol) to 58 (RefPol-450) USD Billions per year, up to 2050. These figures roughly double when considering the second half of the century in the same setting. The estimates reported above are consistent with previous studies with the same model (Bosetti et al., 2009), and more recent studies conducted by IEA (IEA, 2010), which establish the current annual public RD&D spending shortfall between 40 to 90 USD Billions. This projected additional effort asked to clean energy investors is 3 to 6 times the total annual amount of RD&D, averaged in the period 2005-2010, spent by IEA member states, which account for almost all of the OECD, and most of the global, R&D spending in that period (IEA, 2011). Cumulatively, between 1990 and 2010, the same countries invested about 220 USD Billions, less than half of the amount WITCH suggests to be optimally invested by OECD countries for the next 2 decades consistently with the 2°C target.

In relative terms, even if today R&D investments represent a small percentage of the world GDP (around 0.02%), it is clear from our results that most stringent scenarios will definitely benefit from increasing this share, and especially from doing so in the early near-term. This is what has been consistently found in the considered framework, where investments relative to GDP peak at around 2020 at 0.1%, and then gently decline to 0.05% towards the end of the century, as the return on investments decrease. For comparison, the level of investments in capital of wind and solar electric plants in 2020 is about 0.17%, and peaks before 2020 to 0.23% (RefPol) - 0.35% (StrPol) when imposing the constraints following from the Copenhagen pledges, and declines to 0.1%

[5]Even if one would expect that the 2010-2030 cumulative investments of RefPol2030-500 should be exactly the same of the RefPol, in period 2030 investments of the delayed scenario are let free to deviate from the RefPol, otherwise also the next period would be mostly fixed. This also applies to scenarios with a delay up to 2020, in which case investments are let free from period 2020.

at the end of the century. Further characterization of the R&D dynamics can be gained by inspecting the regional distribution of the R&D investments. This is illustrated first for the efficiency case in Figure 4.3. The chart highlights a rather constant allocation of regional contributions across time and scenarios. While China among non-OECD regions is the one that increases its share the most over time, the coverage of efficiency R&D investments by OECD countries remains dominant, fluctuating around 80%. The reason for this dynamics depends on the fact that the current energy intensity is considerably lower in industrialized countries, which use more efficient technologies and have a less energy intensive economic production[6]. As a result, further improvement in energy saving technologies must be fostered by inventive activities (in this model dependent on R&D investments), whereas - in emerging economies - there are more opportunities for reducing energy intensity by adopting more efficient technologies and shifting the production structure towards a more capital intensive one.

More diversity in terms of regional R&D schedules is evident when focusing on the regional shares of backstop investments (Figure 4.4). The chart shows that the more stringent the climate target, the higher the share of investments in non-OECD countries. This is due to the fact that, for climate stabilization policies, the majority of the mitigation effort happens in the developing countries (see Tavoni et al., this issue). For the policy more compatible with 2°C (the 450ppm-eq case), R&D investments in low carbon fuels in the next 20 years are shown to be evenly balanced between industrialized and developing economies. This equal regional split consolidates in the medium term (2030 to 2050) for all scenarios.

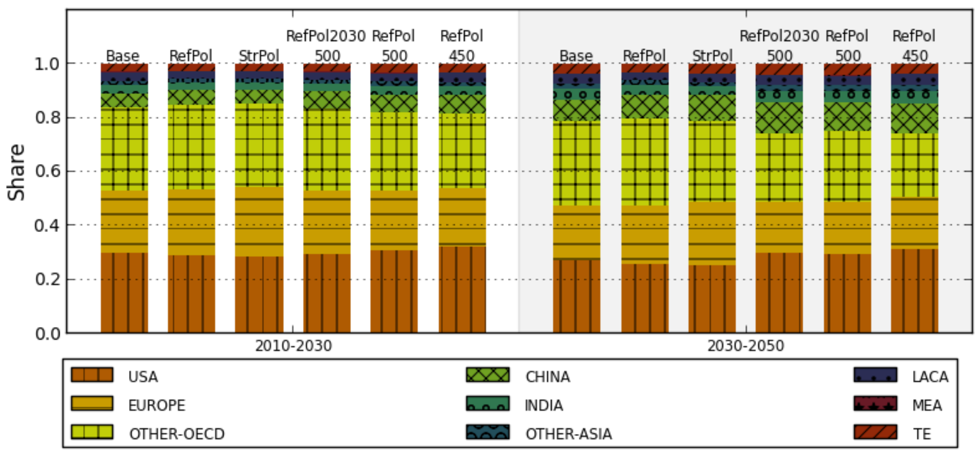


Figure 4.3: *Regional shares of cumulative R&D investments in energy efficiency for the near and medium terms.*

[6]In WITCH, GDP is measured in MER. Using the PPP metrics, instead, might weaken this effect, by reducing the energy intensity gap between industrialized and developing economies.

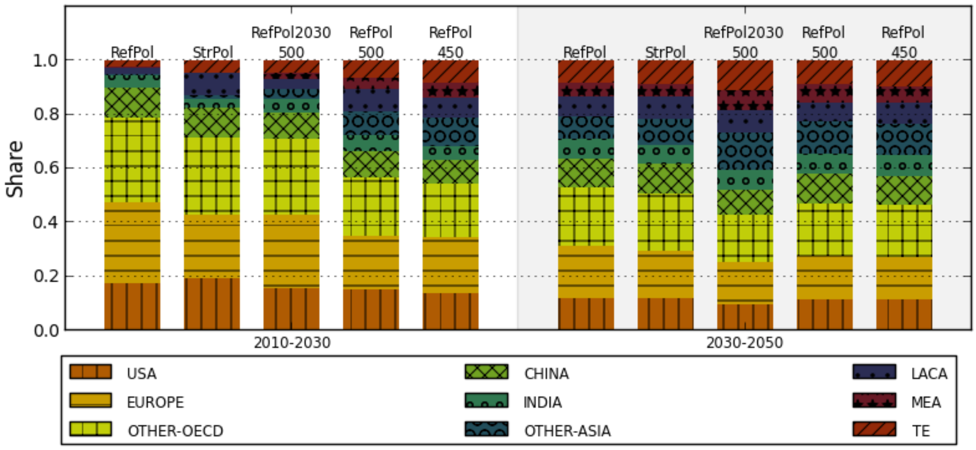


Figure 4.4: *Regional shares of cumulative R&D investments in carbon free fuel for the near and medium terms.*

Still focusing on the non-electric sector, it is useful to assess the consequences of the R&D investments by comparing the resulting backstop price with the price of oil, which is its main market competitor. In 2010, the carbon-free fuel is assumed to enter the energy scene with a price 13 times the price of oil. Thanks to the R&D efforts, its unit cost decreases at an average rate of 4-6%/yr to 2050, depending on the scenario and on the region. Simultaneously, oil price increases with its increasing cumulative extraction, in such a way that the two prices meet between 2025 and 2035, depending on the scenario. After that point, the backstop provides an alternative cheaper than oil for the rest of the century to the non-electric (mainly transport) energy needs.

4.6 Assessing the chances of an R&D deal to get us to 2° degrees

In the previous section, the optimal energy R&D response as proposed by the WITCH model was studied in the context of a set of idealized scenarios. These scenarios assume a policy commitment by all the regions, albeit fragmented and not particularly ambitious till 2025. However, the current state of international negotiations is dominated by huge uncertainties, and it is possible that a global consensus might not emerge under the Durban action platform negotiation round. The aim of this section is to analyze alternative policy designs which target innovation rather than emission reductions in the short term.

We thus consider two additional scenarios, based on an R&D based policy which might provide a trade-off between the inertia of regional political systems to seriously commit to climate change policies and the willingness to limit the GDP loss in view of a long-term acceptable climatic target. In these scenarios, called RD-Deal-450 and RD-deal2030-500, countries replace the fragmented commitment to reduce emissions till 2025 or 2035, respectively, with an agreement to cooperate on energy R&D. Specifically, investments in both energy efficiency and low carbon technologies R&D are set to the optimal levels. Optimal levels are computed from first best runs in which full cooperation starts already in 2015. Thus, these R&D policies are assumed to enter into force already in 2015. After this initial period, where no mitigation action happens and only accumulation of energy R&D knowledge is enforced[7], a globally harmonized carbon tax ensures that a carbon budget compatible with 450 or 500 ppm-eq respectively is met. The RD-deal-450 thus mimics a policy case in which, at the UNFCCC conference of parties in 2015 in Paris, countries decide to immediately adopt R&D investment objectives - maybe because of difficulties in agreeing upon short term emission reduction targets - for a transition period of 10 years, after which they decide to cooperate on the objective of achieving 2°C with high probability. The RD-deal2030-500 case mimics a case of prolonged difficulties in setting emission reduction objectives, and in which countries decide instead to focus on R&D cooperation for 20 years (e.g. from 2015 to 2035), and to cooperate afterwards. These two cases are direct counterparts of the RefPol-450 and RefPol-2030-500, against which they will be compared in what follows.

We also tried to run scenarios with a procrastinated agreement on R&D, but found that the 2°C could not be met[8]. Specifically, we have found that R&D deals to 2030 and 2040 are incompatible with attaining 2°C with likely (e.g. 450ppm-eq) and as likely as not (e.g. 500ppm-eq) probabilities respectively. This is an important result by itself, which shows a fundamental trade-off between investing for better future technologies and locking in currently dirty ones. The R&D agreement sets the right incentives for the first issue, but not for the second; as a result, carbon intensive capital is continued to be built while climate R&D investments are carried out. Due to the long term nature of energy investments, the RD deal - if carried out for too long - jeopardizes the chances of meeting the stringent carbon budget consistent with 2°C, even if it provides a more favorable technological future[9].

We begin our investigation of the R&D policy deals on the levels of investments in R&D. These are shown in Figure 4.5 for the two R&D deal scenario, and their respective Durban Action platform LIMITS scenarios. For energy efficiency (left panel), the chart shows that R&D investments are below the optimal levels (at which the RD deal scenario are set by design) till the time of inception of full cooperation on climate mitigation (2020 or 2030). For R&D aimed at making carbon free fuel competitive, investments are lower than optimal before full cooperation, but higher afterwards, in an effort to compensate the missed opportunity of starting to abate earlier. Investments eventually align between the RD deal and the Durban Action scenarios, as expected since in the long term the objective to collectively reduce emissions dominates the climate action strategy. The timing of investments is different between energy efficiency and decarbonization; for the former, investments continue to increase over time, since they represent continuous and gradual improvements in energy efficiency enhancing

[7]As detailed in Kriegler et al., this issue, beyond carbon emission constraints, the reference policy has explicit regional targets on the amount of renewable energy over the total final or electrical energy production after 2020, and of wind and nuclear capacity installed by 2020. These targets are retained in the RD deal scenarios, allowing for a more direct comparison with the corresponding RefPol ones. We also run the RD deal cases without these technology pledges, and we found negligible impacts on the results. Thus, in this framework it is appropriate to solely focus on the distinction between early mitigation and early innovation commitments.

[8]The model could not find a feasible solution to these programmes.

[9]It should be remarked that in this version of the model we don't feature R&D processes for innovative CO2 absorbing technologies such as Direct Air Capture (DAC). Allowing for such an option could potentially provide additional leverage to the R&D deal, as more negative emissions can be done later in the century, though it would also increase the chances of exceeding the temperature target. For a discussion about the impact of DAC for climate stabilization in the WITCH model, see Chen and Tavoni (2013).

technologies. For the latter, investments peak and then revert to a common optimal level of investments. The initial peak, which would be even more notable if measured in share of GDP, is needed to bring down the cost of the breakthrough technology, so as to make it competitive with fossil alternatives. Once this happens, investments are somewhat reduced, though only to a limited extent, since the stock of knowledge needs to be maintained to keep the low carbon alternative in the market.

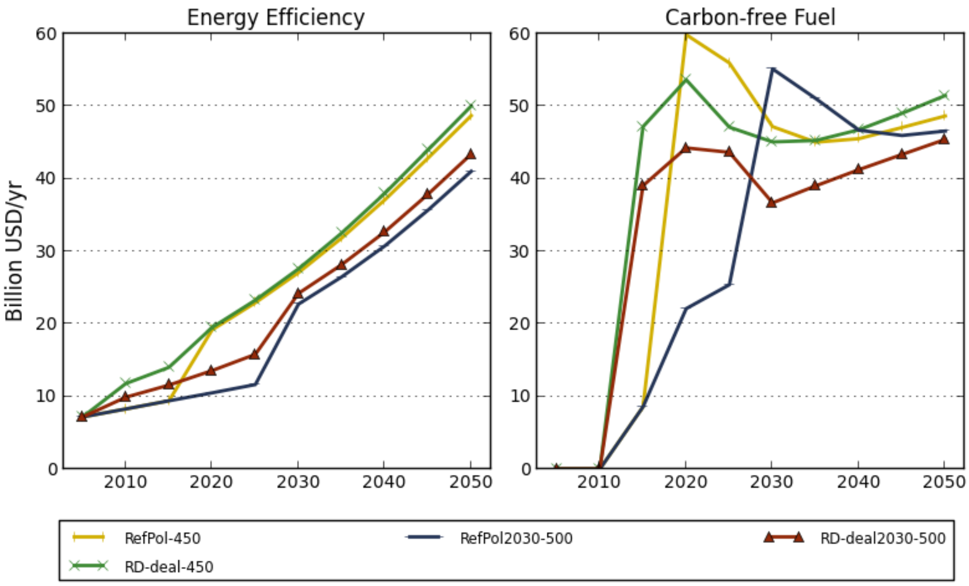
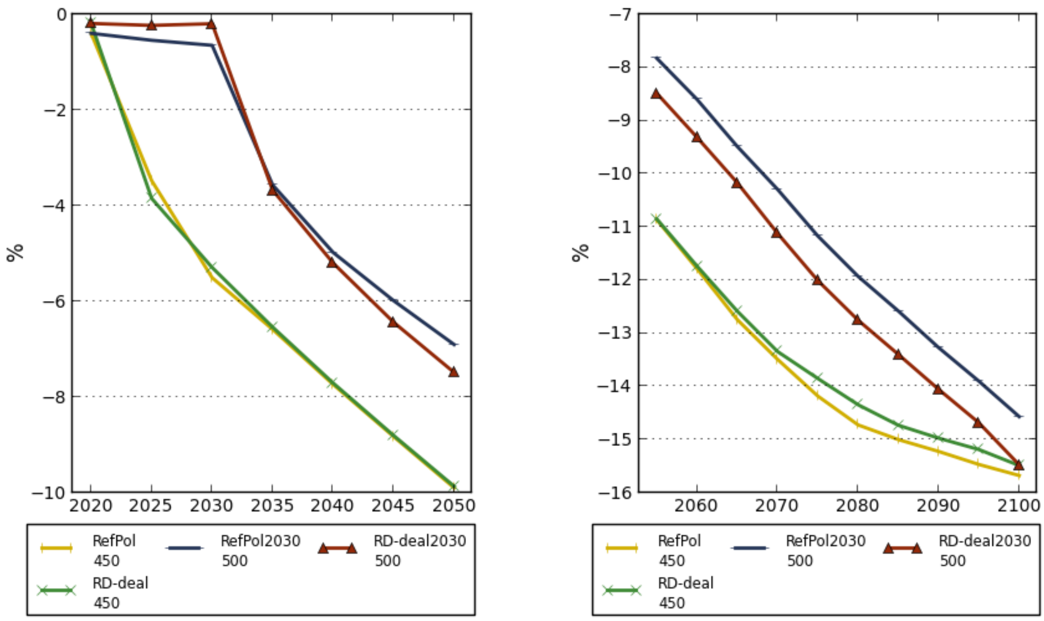


Figure 4.5: *Time profile of the annual global investments in energy R&D in second-best scenarios.*

Policy-efficiency considerations can be formulated by looking at Figure 4.6, which allows comparing the costs of the policies under discussion, assuming as a measure of cost the GDP loss with respect to the base case. The chart shows that till 2050 (left panel), policy costs are essentially identical for the 450 scenarios. This is reasonable since the two policies differ only in the strategies to 2020. For the 500 cases in which we assumed that full cooperation is enforced only after 2030 (precisely in 2035), the difference between the two scenarios is more clear. The R&D deal cases is as expected cheaper in the short term, since R&D investments are cheaper than actual mitigation measures, albeit at a reference policy levels[10]. The higher initial costs in the RefPol2030-500 are due to the partial cooperation on the Copenhagen commitments, which are assumed to be achieved independently for all regions with no opportunity to trade emission reductions. This leads to a diversity of regional carbon prices, with an associated efficiency loss. Over time, though, the RD-deal2030-500 policy turns out to be more expensive, due to the higher abatement needed to comply with the given concentration target (500ppm-eq) and the lower abatement carried out before 2030. Looking

[10]If measured in Consumption losses rather than GDP losses, policy costs for the R&D deal scenario would be higher in 2020 and 2035, due to the crowding out of consumption. On the other hand, in 2030 the opposite would hold, since by then R&D investments in the RefPol2030 case is higher than the ones in the RD-deal scenario, as shown in Figure 4.5.



(a) *Period 2020-2050.* **(b)** *Period 2050-2100.*

Figure 4.6: *Time profile of the world GDP loss in second-best scenarios expressed as a percentage with respect to the GDP of the Base case.*

beyond 2050 (right panel), the cost difference persists in the 500 cases, whereas it remains negligible –or even changes sign- for the 450 scenarios. If policy costs are looked in terms of net present values over the whole century, the RD-deal policy marginally underperforms the Copenhagen commitments for discount rates up to 8%.

While excessive emissions due to delayed mitigation makes the RD-Deal worse off, such a policy may still be beneficial on the long term with respect to a potential carbon lock-in of the energy system. By investing more in R&D, more advanced technologies are available, and the energy system is capable of faster and deeper rates of decarbonization than what would be possible in a less innovative future. This is confirmed both in terms of emissions per unit of GDP and emissions per unit of final energy. These indicators decrease in the second part of the century by at least 5% and 2% respectively in the RD-deal2030-500 scenario with respect to the RefPol2030-500 case. Also final energy per unit of GDP benefits from the RD-deal, with a relative decrease between 1% and 3% in the second half of the century with respect to its counterpart.

Thus, two main points emerge from our results. If there is willingness to commit to a stringent global climate policy rather quickly (e.g. after 2020), then the actions undertaken before than - be them either some mild fragmented mitigation or a collaborative international R&D programme - do not have a major economic impact once full cooperation is enacted. In the very long term (after 2060), the R&D deal strategy might be actually preferable, since it would allow for more deployment of advanced technologies. If on the other hand the international community opts for deferring global action to post 2030, then a strategy focusing on R&D would be preferable (in economic terms) till 2035, and worse after then. The ultimate choice between an agreement on innovation as opposed to a fragmented mitigation action would thus depend on the time preferences of the legislators, as well as on their aversion to a potential lock-in to a set of economically and environmentally suboptimal technologies. In both cases, however, delaying cooperation increases policy costs.

4.7 Conclusions

This paper has tried to provide some answers to two key questions related to the interplay between climate change mitigation and clean energy innovation policies. 1. What are the clean energy R&D investment needs to get to 2°C? 2. In the short term, is an international agreement on R&D better suited at preparing the ground for climate stabilization than continuing with fragmented and moderate emission reduction measures? Both questions are of high policy relevance for the Durban negotiation process which is assessed in the LIMITS special issue, to which this paper contributes. To our knowledge, both questions have not been yet addressed with the tools of integrated assessment modeling.

We have tackled these policy relevant questions by means of the WITCH integrated assessment model, which features endogenous technical change and multiple externalities. We have run a set of Durban Action Platform scenarios, integrating them with two additional ones based on a clean energy R&D climate deal, meant to replace early emission reduction Copenhagen commitments with early high R&D investments efforts. A series of key findings emerge.

1. We find that in order to attain 2°C with sufficiently high probability, a strong decarbonization of the energy system is required, and mitigation actions call for an increased financing in climate R&D. We quantify the global climate mitigation R&D investment needs for attaining 2°C is approximately 1 USD Trillion cumulatively over the period 2010-2030, and 1.6 USD Trillions in the period 2030-2050.

2. The investments would be initially concentrated in the industrialized countries, but would balance off with those of developing economies after 2030. The largest share of investments would be concentrated for the development of low carbon alternative fuels, though energy efficiency investments would also play an important (and growing) role.

3. We find that focusing on an international clean energy R&D effort slightly underperforms a continuation of the fragmented mitigation effort outlined by the Copenhagen pledges for the sake of climate stabilization. Nonetheless, the actual ranking between fragmented mitigation or R&D investments in the short term depends on the time preference of the legislators, and on their aversion to a potential carbon lock-in.

4. An exclusive focus on R&D at the expenses of mitigation is however incompatible with climate stabilization if maintained for too long. Specifically, R&D deals to 2030 and 2040 do not attain 2°C with likely (e.g. 450ppm-eq) and as likely as not (e.g. 500ppm-eq) probabilities respectively.

These considerations lead to some direct policy implications. If the chances of getting to a global climate agreement before 2030 remain slim (as they appear to be today), then one could consider shifting the focus of short term policy from emission reduction targets towards an R&D investment objective, if the latter has better chances of being legislated. This policy shift would not significantly affect the ultimate objective of climate stabilization, which in any case requires full cooperation on emission reductions no later than 2030. An agreement on R&D and innovation might have more political capital given the current debate on competitiveness, and has been proposed in the past as way out of the backlog of climate negotiations (De Coninck et al., 2008b; Newell, 2008b). Actual experiences in the field of climate, such as the 'Asia-Pacific Partnership on Clean Development and Climate (APP)', have not yielded significant results, but the same can be claimed for some emissions reductions programs. A refocus towards innovation could generate a risk of 'policy lock-in', which for the case of R&D we showed would eventually jeopardize the chances of meeting climate stabilization. However, the study has clearly highlighted the importance of dedicating significant investments - either by means of specific R&D policies or indirectly by the incentives induced by carbon pricing - to innovating for energy efficiency and decarbonization. These investments - of the order of 50 USD Billions per year - are an essential pre-requisite for meeting the huge transformation of energy and land use required by climate stabilization. The effectiveness of these investments remains conditional to the need of achieving a comprehensive agreement on GHGs mitigation by 2030, if the 2°C target is to be met.

This analysis is limited by the assumptions embedded in the specific model which we have used. The multi model ensembles carried out by the modeling community over the past few years, of which LIMITS represents an important contribution, has invariably shown that models differ widely in terms of results, for many key variables. Thus, single model assessments should be taken with care. Moreover, the difficulty of understanding and representing the process of technical change poses considerable challenges for the modelers involved in the type of analysis presented in this paper. More work, both on empirical and modeling sides, is needed to improve our grasp of climate innovation, and our ability to represent it as a result. Hopefully, more modeling papers and more multi model ensembles will address the fundamental issue of innovation and climate in the future.

4.8 Acknowledgements

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4.A Appendix

$$ES_{n,t} = \left[\alpha_{HE} HE^{\rho}_{n,t} + \alpha_{EN} EN^{\rho}_{n,t}\right]^{1/\rho} \tag{1}$$
$$Z_{n,t} = a_n IRD^{b}_{n,t} HE^{c}_{n,t} SPILL^{d}_{n,t} \tag{2}$$
$$HE_{n,t+1} = HE_{n,t}(1-\delta) + Z_{n,t} \tag{3}$$

ES energy services (input to gross domestic production)

EN energy supply (input to energy services production)

HE stock of energy efficiency knowledge (input to energy services production)

IRD investments in energy efficiency knowledge

Z flow of new ideas that adds to the previously cumulated stock

$\alpha_{HE}, \alpha_{EN}, \rho$ parameters of the energy services CES

a, b, c, δ parameters of the energy efficiency knowledge stock update equations

n region

t time period

$$SPILL_{n,t} = \frac{HE_{n,t}}{\sum\limits_{n' \in nHI} HE_{n',t}} \left(\sum_{n' \in nHI} HE_{n',t} - HE_{n,t} \right) \tag{4}$$

where nHI is the set of OECD countries, representing the technology frontier.

$$\frac{P_{n,t}}{P_{n,0}} = \left(\frac{KRD_{n,t-2}}{KRD_{w,0}}\right)^{-r} \left(\frac{\sum_{t' \in [0,t)} K_{w,t'}}{K_{w,0}}\right)^{-s} \quad (5)$$

$$Z_{n,t} = a_n IRD^{b}_{n,t} SPILL^{d}_{n,t} \quad (6)$$

$$KRD_{n,t+1} = KRD_{n,t}(1-\delta) + Z_{n,t} \quad (7)$$

P average cost of backstop

KRD stock of backstop knowledge

IRD investments in backstop knowledge

K stock of backstop used

Z flow of new ideas

r learning-by-researching index

s learning-by-doing index

w world

0 first time period

Table 4.3: *Parameter values for the R&D equations.*

	Energy Efficiency	Carbon-free Advanced Biofuels (Backstop)
r (Learning-by-researching index)	0.20	0.20
s (Learning-by-doing index)	n.a.	0.15
a	(average) 0.04	1.00
b	0.18	0.85
c	(average) 0.39	n.a.
d	0.15	0.15
δ (Depreciation of knowledge capital)	5%	5%
Regional initial stock of knowledge (OECD) [USD Billions]	(average) 20	0.5
Regional initial stock of knowledge (Non-OECD) [USD Billions]	(average) 1	0.5
World initial stock of experience [TWh]	n.a.	278

CHAPTER 5

Sensitivity to Energy Technology Costs: A Multi-model comparison analysis[1]

5.1 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

[1]This chapter is based on the paper "Sensitivity to Energy Technology Costs: A Multi-model comparison analysis" by V. Bosetti, G. Marangoni, E. Borgonovo, L. D. Anadon, R. Barron, H. C. McJeon, S. Politis and P. Friley, published in *Energy Policy*, 80 (May 2015): 244-263, http://dx.doi.org/10.1016/j.enpol.2014.12.012. R. Barron and Haewon C. McJeon provided the results for the GCAM model. S. Politis and P. Friley provided the results for the MARKAL US model.

models. The findings that emerged from these and other studies, as summarized in the IPCC latest assessment report 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, Harvard, and FEEM . Each of these groups collected the opinions of 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.

5.2 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 macroeconomic 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.

5.2.1 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 5.1). 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 5.1: *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

5.2.2 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[2].

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[3] 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, \$$\beta$,\$ following the asymptotic rule below:

$$x_{i,t} = x_{i,2005} + \frac{x_{i,t'} - x_{i,2005}}{1-\beta} + \left(1 - \beta^{\frac{t-2005}{t'-t}}\right) \tag{5.1}$$

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

[2]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 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).

[3]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.

capped by a floor (ceiling) value for cost (efficiency) which is the minimum (maximum) provided with the sampling statistics.

5.2.3 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 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 on how costs and efficiency parameters were implemented are also provided at the end of each model description in the Appendix.

5.2.4 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 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 (**x**) to the model output (y) is regarded as a generic mapping of the form

$$y = g(x), \qquad g : \Omega_X \to R \tag{5.2}$$

with and $\Omega_k \subseteq R^k$ denoting the number of model inputs. To illustrate, in our case, we have k=8, Ω_X is Cartesian product of the eight ranges displayed in Table 5.1, 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 5.2 [for a more detailed overviews the reader is referred to (Anderson et al., 2014; A Saltelli, Ratto, Tarantola, & Campolongo, 2005)].

Table 5.2: *Sensitivity measures used in this work for the identification of key-drivers.*

Sensitivity Measure	Equation
Variance-Based	$\eta_i = \frac{\mathbb{V}[\mathbb{E}[Y\|x_i]]}{\mathbb{V}[Y]} = \frac{\mathbb{V}[Y]-\mathbb{E}[\mathbb{V}[Y\|x_i]]}{\mathbb{V}[Y]}$
Density-Based	$\delta_i = \frac{1}{2}\,\mathbb{E}[\int_{\Omega_Y} \mid f_Y(y) - f_{Y\|X_i}(y) \mid dy]$
CDF-based	$\beta_i^{KU} = \mathbb{E}\left\{\sup_y \mid F_Y(y) - F_{(Y\|X_i=x_i)}(y) \mid + \sup_y \mid F_{(Y\|X_i=x_i)}(y) - F_Y(y) \mid\right\}$

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

$$\xi_i = \mathbb{E}\left[s\left\{F_Y(y), F_{Y|X_i}(y)\right\}\right] \tag{5.3}$$

where $s\left\{F_Y(y), F_{Y|X_i}(y)\right\}$ is some form of separation measurement between the unconditional $F_Y(y)$ and conditional model output distribution $F_{Y|X_i}(y)$ [we refer to (Glick, 1975) on the concept of separation measurement].

Variance-based sensitivity measures (second row in Table 5.2) quantify the separation as expected variance reduction. In particular, the sensitivity measure 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 5.2), 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 5.2 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 5.2]. 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, 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. is integrable, we can expand it in the form

$$g(x) = g_0 + \sum_{i=1}^{n} g_i(x_i) + \sum_{i<j}^{n} g_{i,j}(x_i, x_j) + \ldots + g_{1,2,\ldots,n}(x_1, x_2, \ldots, x_n) \tag{5.4}$$

where the terms in eq. 5.4 have the following meaning. g_0 is the mean value of y. $g_i(x_i)$ is the individual effect of x_i, namely, the expected behavior of g as a function of x_i alone. In formulae,

$$g(x_i) = \mathbb{E}[g(x)|X_i = x_i] - g_0 = \int \ldots \int g(x) \prod_{s=1,s\neq i}^{n} dF_s - g_0 \tag{5.5}$$

that is, is the conditional expectation of g given x_i, from which the mean value of g is subtracted. Note that in eq. 5.5 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 subroutine[4]. 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.

5.3 Discussion of Results

5.3.1 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 5.1 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.

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

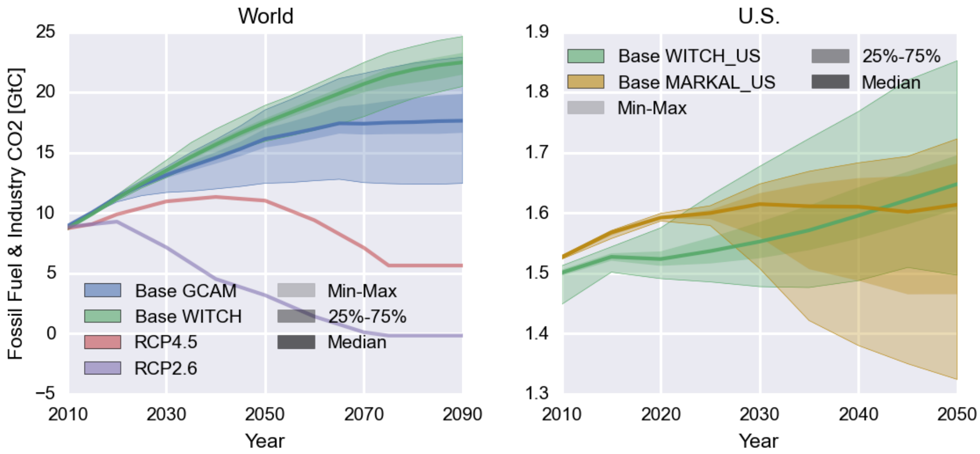


Figure 5.1: *Global (left panel) and US (right panel) carbon dioxide emissions from Fossil Fuel combustion and Industrial processes (FFI). Different colors correspond to different policies, where the light color encompasses the minimum-maximum range, and the darker one encompasses the 25%-75% quantiles 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 25^{th}-75^{th} 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 5.1 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.

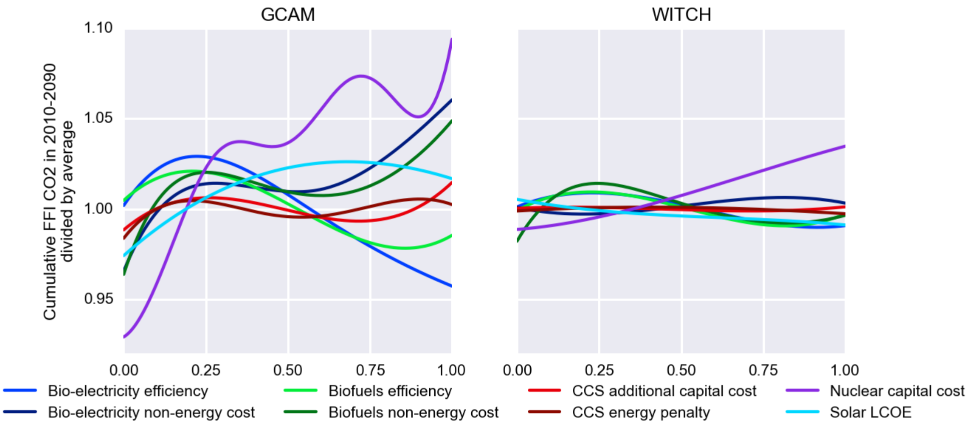
Figure 5.2 portrays the extent changes in baseline emissions, both in sign and magnitude, are attributable, in a first order approximation, to the individual variations of each input. This type of analysis casts light on the sign of change setting discussed in the methods section. The lines in Figure 5.2 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 5.2 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 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[5].

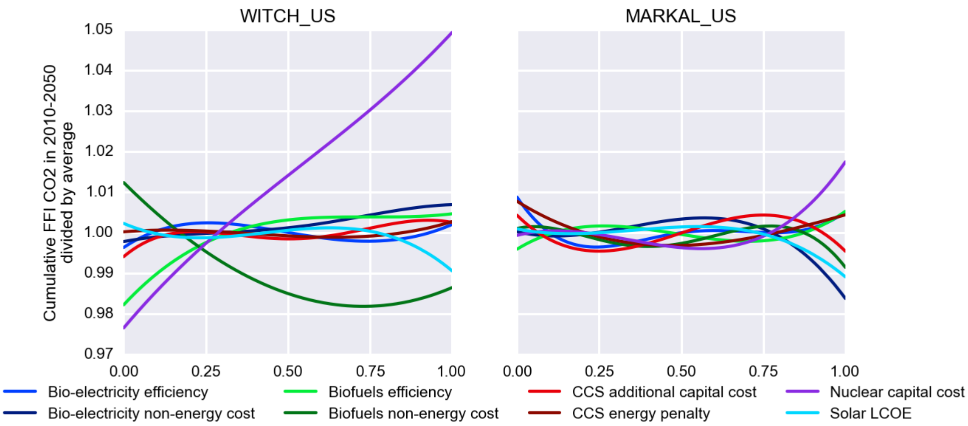
In addition, in the GCAM model, bioelectricity efficiency and non-energy costs (and biofuels, to a lesser extent) do play a role in shaping emissions, in particular for high cost (low efficiency) realizations.

The lower panel of Figure 5.2 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 5.1, right hand side panel), 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 5.2. 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

[5]The slightly oscillatory behavior is mainly due to the smoothing method adopted and the finite sample size.



(a) *Global.*



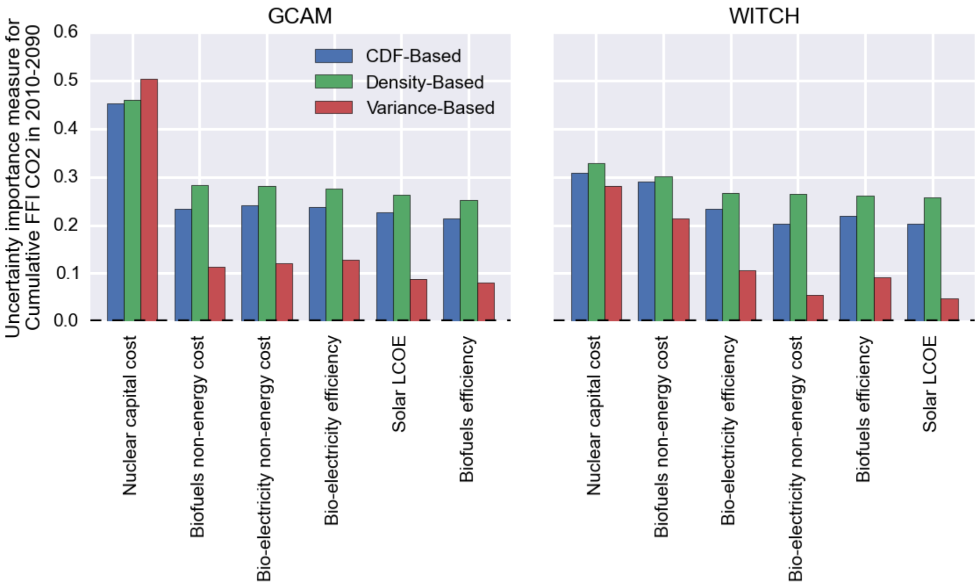
(b) *US.*

Figure 5.2: *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).*

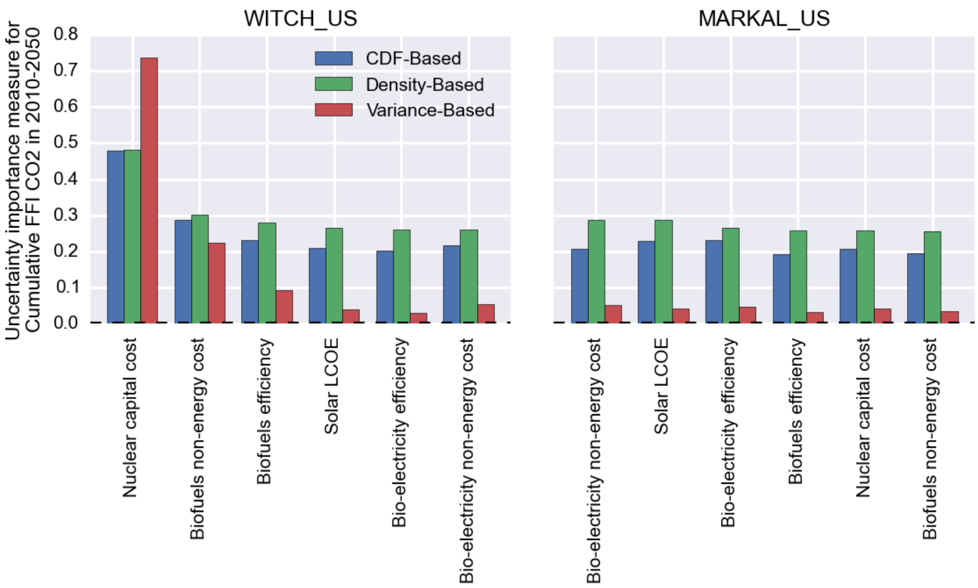
(RFS), as legislated by the Energy Independence and Security act of 2007, requires 36 billion U.S. gallons of biofuels by 2022. Hence, while biomass-based fuels gain market share versus petroleum-based fuels in MARKAL_US, biomass-based power generation is relatively disadvantaged by other fuels in the electric generation market in MARKAL_US.

Figure 5.3 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.

In the lower inset of Figure 5.3 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 a non-null value. This combination indicates that individual effects are negligible



(a) *Global.*



(b) *US.*

Figure 5.3: *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 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.

5.3.2 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 CO2 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 5.4).

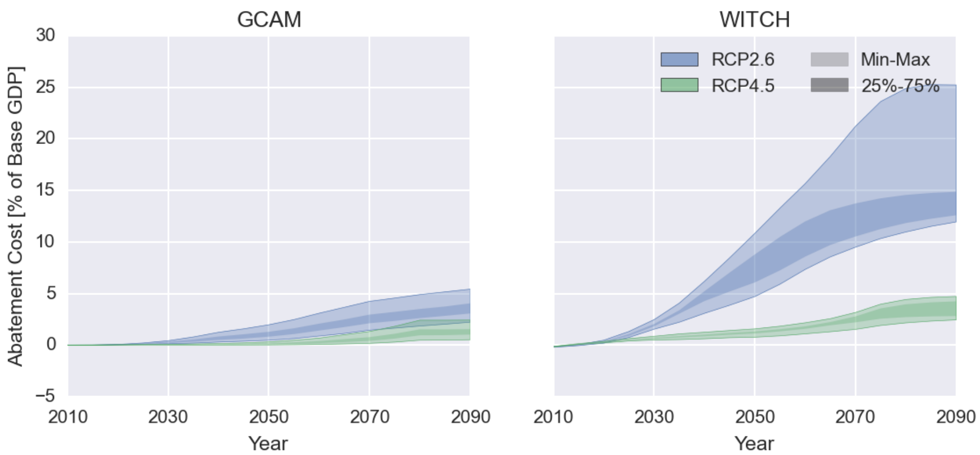
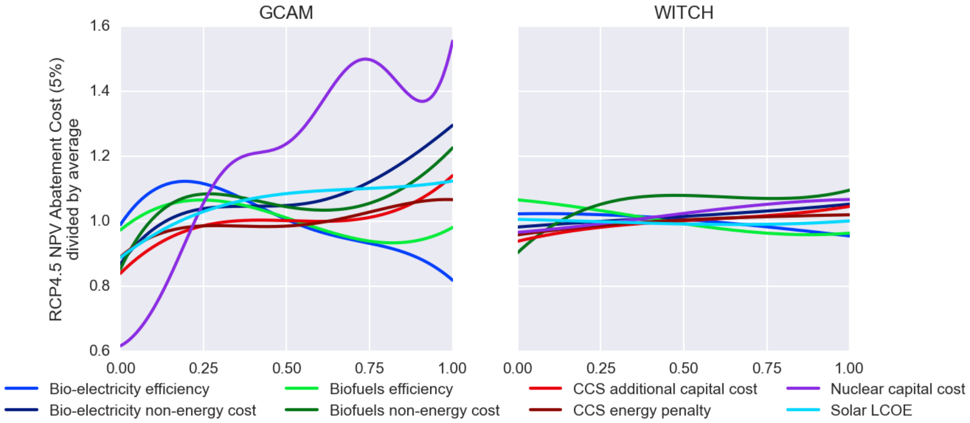


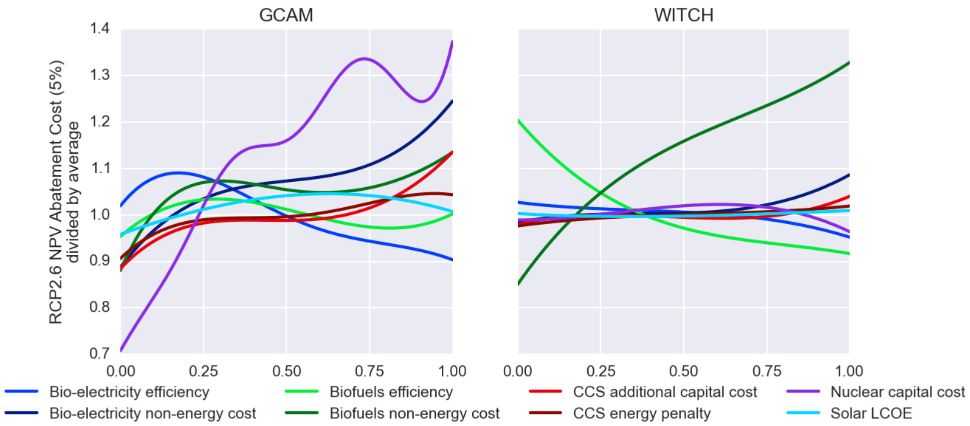
Figure 5.4: *Abatement costs of the two implemented climate policies as percentage of Base GDP. For GCAM, absolute costs are expressed as the area under the MAC curve. In WITCH they correspond to consumption losses.*

Notably, WITCH reports much higher costs and a much larger variation in cost realizations associated with the range of technology performance. Figure 5.5 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.

The dominant technology, though different across the two models, tends to be robust across mitigation targets (upper and lower insets in Figure 5.5). 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 including



(a) *Global.*



(b) *US.*

Figure 5.5: *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%.*

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 5.6 for the 2.6 RCP scenario, where we can also include the results for the MARKAL_US model.

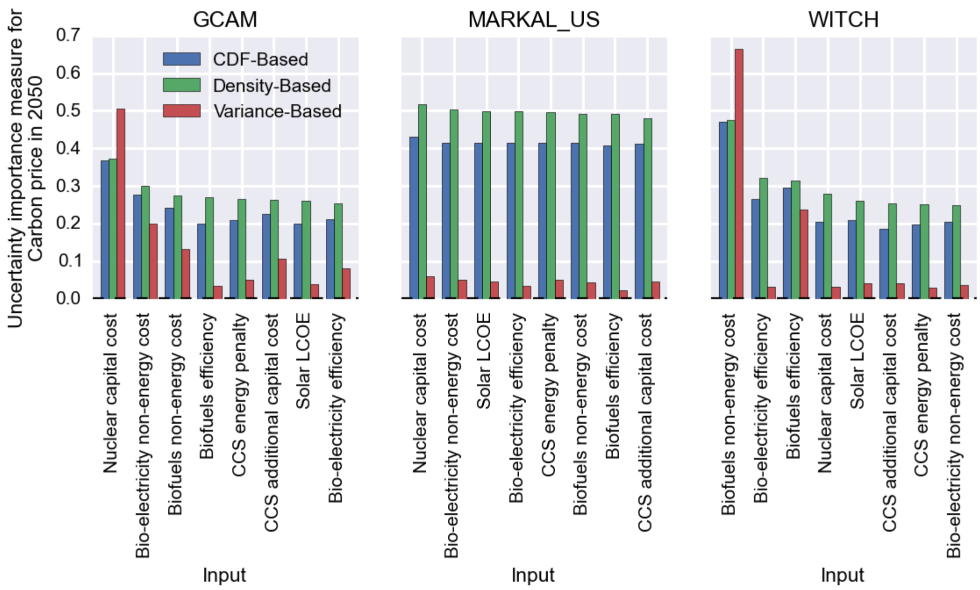


Figure 5.6: *Ranking of uncertainty drivers of Carbon Prices for the RCP 2.6 policy.*

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 5.7. 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.

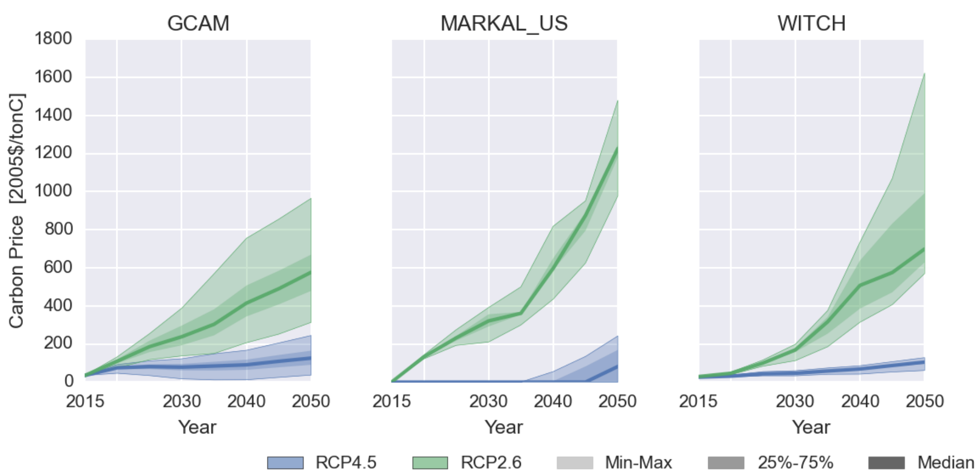


Figure 5.7: *Price of carbon up to 2050 for each of the models in the climate constrained scenarios.*

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. 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 5.8 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-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.

5.4 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

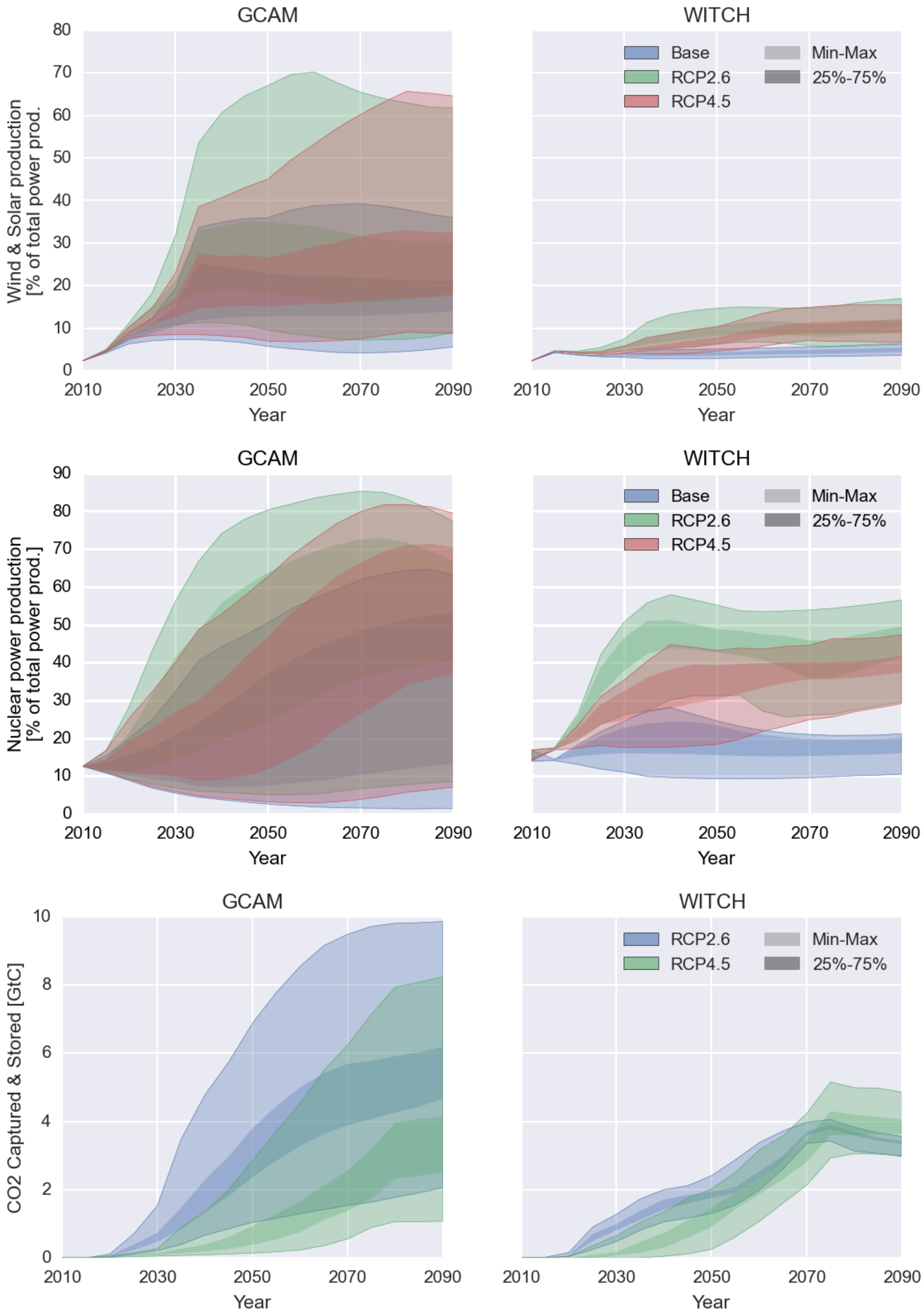


Figure 5.8: *Distributions of three key technology penetrations under the two climate policies and the baseline scenarios considered. Upper panels: Carbon dioxide captured & stored from fossil fuels and biomass plants with CCS Middle Panels: Wind and solar electricity production over total power production. Bottom panels: Nuclear power production as a share of total power production.*

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 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.

5.5 Acknowledgements

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5.A Appendix

5.A.1 IAMs Description

GCAM 2.1 Model

1. 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[6] 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.

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

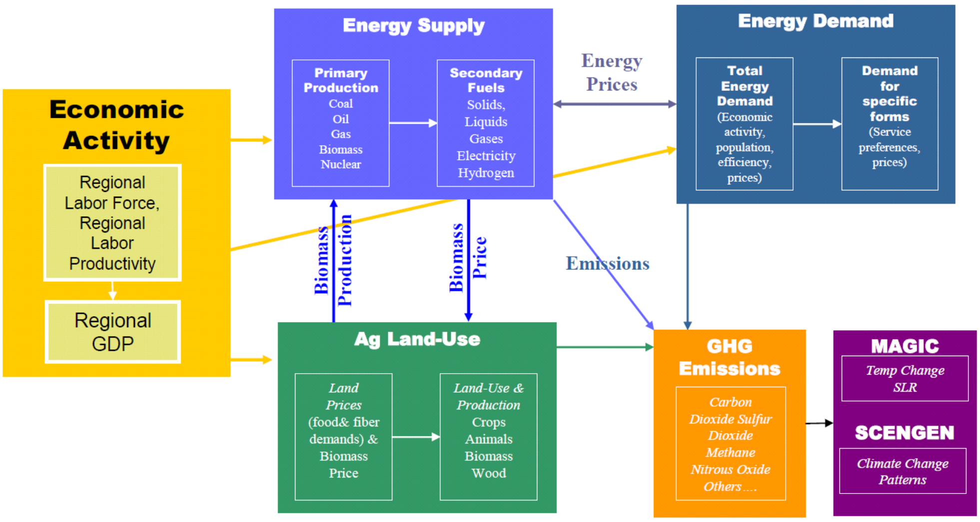

Figure 5.9: *Overview of the GCAM model.*

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.

2. 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 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.

3. 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:

   (a) The total emission in the base year is calibrated to the Carbon Dioxide Information Analysis Center (CDIAC) database (Boden et al,

      i. The fossil fuel consumption in the base year is calibrated to

      the International Energy Agency (IEA) Energy Balances Database 2007.

   (b) 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).

   (c) These emission coefficients are applied to each sector in the base year.

   (d) 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.

4. 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`).

   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 5.3: *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

1. 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 to describe 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 5.10 provides an overview of the key features of WITCH.

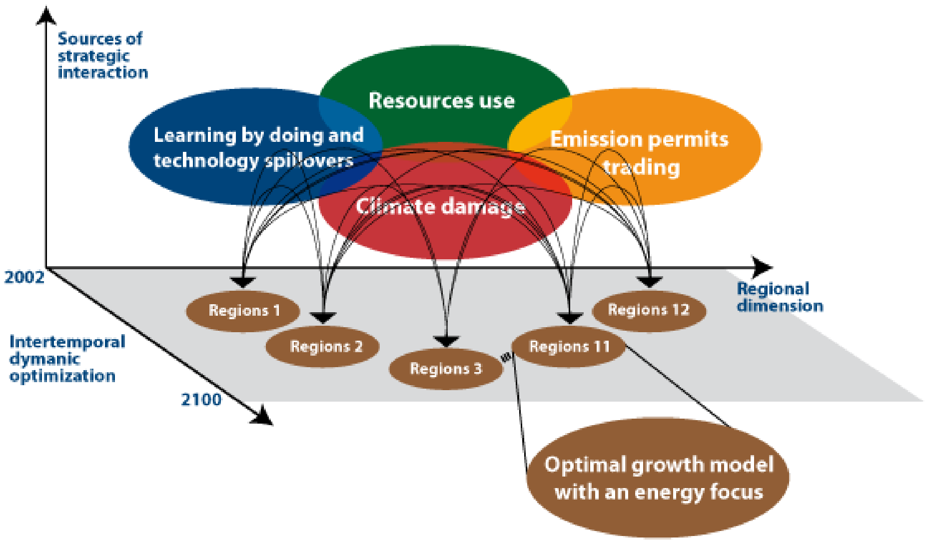

Figure 5.10: *Overview of the WITCH model.*

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.

2. 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).

3. Modeling Greenhouse gas emissions

   The model represents greenhouse gases emissions either directly (for CO_2) or via exogenous assumptions (for the other gases). 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.

4. 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 5.4 below.

Table 5.4: *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	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

Regarding biofuels, 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

1. 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).

2. 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 Figure 5.11, which shows an aggregated energy system representative of most MARKAL models.

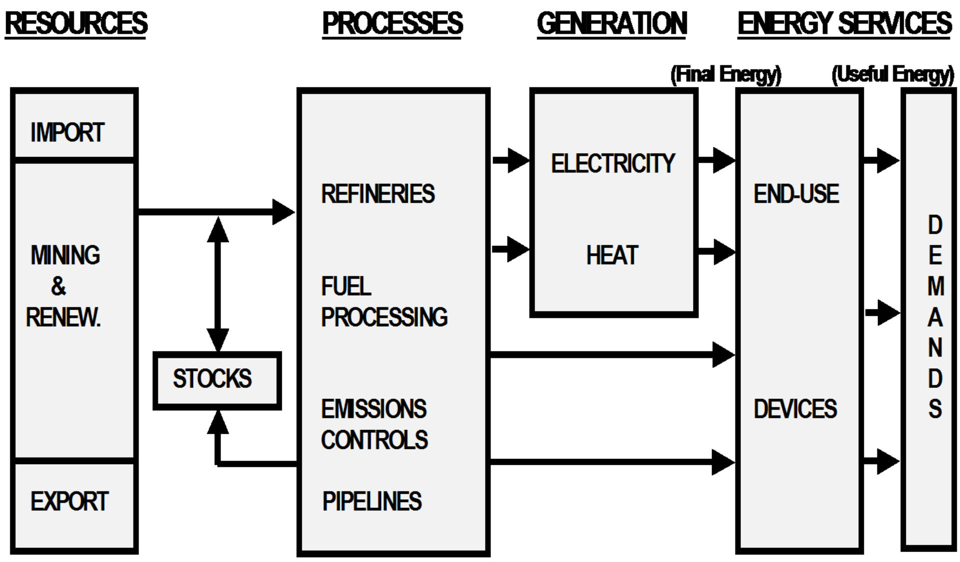

Figure 5.11: *Overview of the MARKAL_US Energy System.*

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.

3. 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.

4. 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.

5. 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 5.5: *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

CHAPTER 6

Optimal Clean Energy R&D Investments Under Uncertainty[1]

6.1 Introduction

A successful climate change mitigation strategy will require significant improvements of existing technologies, and the introduction in the market of alternatives currently available only in the lab, to reduce energy consumption and energy carbon intensity at acceptable costs. Applying deterministic approaches, researchers have been developing complex Integrated Assessment Models (IAMs) to inform this type of decisions, and identify ideal decarbonization pathways (Clarke et al., 2014; Marangoni and Tavoni, 2014). Experience with these models has shown that technology availability plays a major role on the feasibility and costs of facing the challenge of stringent climatic targets (Kriegler, Weyant, et al., 2014). Nonetheless, technological change is highly uncertain and capital intensive, requiring risky efforts in research and development (R&D), thus a more appropriate approach should account for this source of uncertainty. The fact that these efforts may or may not lead to a technological breakthroughs has important implications when considering energy R&D investment strategies for a low-carbon future.

Previous literature has already highlighted how the joint modelling of endogenous technical change and uncertainty has important quantitative and qualitative impacts on optimal technological climate change policies (Baker and Shittu, 2008). When accounting for the uncertain effectiveness of R&D investments results can drastically differ from their deterministic counterparts, both in terms of magnitude as well as in terms of composition. In addition to this, a large literature on energy technologies expert

[1]This chapter is drawn from the paper "Optimal Clean Energy R&D Investments Under Uncertainty" by G. Marangoni, G. De Maere and V. Bosetti, to be submitted.

elicitation (Anadón et al., 2012; Baker, Bosetti, et al., 2015; Chan et al., 2011; Nemet, Anadon, and Verdolini, 2016) emphasizes the significant uncertainty that experts attach to R&D investments, as well as the huge disagreement across experts. This uncertainty cannot be neglected, especially considering the significant impact of future technological costs on the implementation of stringent climate policies (Bosetti, Marangoni, et al., 2015).

So far, the most common approach has been that of including uncertainty within a simple analytical framework, with inputs derived from the output of IAMs. G. J. Blanford, 2009 captures the essential elements underlying the relationship between R&D investment and research outcomes, where the latter are assessed by running an IAM (MERGE, Manne, Mendelsohn, and Richels, 1995) in a variety of technology scenarios, representing outcomes of alternative R&D programs. Optimal portfolios are then calculated by linking R&D investments to a probability distribution over alternative outcomes. In a similar way, Bosetti and Tavoni, 2009 develop a simple analytical model, with two time periods and two technologies, which mimicks a social planner who minimizes costs by choosing optimal abatement and innovation efforts consistently with a given environmental target. Uncertainty is introduced by modeling the R&D outcome on the abatement cost of a carbon-free breakthrough technology (backstop) as uncertain. A stochastic version of WITCH is devised to account for such uncertainty, but only two states of nature for the effectiveness of R&D in a single technology can be introduced mantaining the model computationally tractable.

The need to consider problems with multiple technologies, coupled with more complex IAMs, has spurred researchers to find new ways to overcome the resulting "curse of dimensionality". In a recent study, Baker, Olaleye, and Reis, 2015 consider four sets of probabilistic distributions, related to different elicitation teams of experts, conditional to three funding levels per set, and five technologies. Furthermore, the economic interactions of technologies are estimated through a large IAM. To alleviate the computational burden, the authors use importance sampling. A single sampling distribution is derived from all the available ones, and the resulting set of samples is run through the IAM. The sampled output is then used to evaluate alternative portfolios.

In a different context of climate change economics research, Cai, Judd, and Lontzek, 2013 show an application of an alternative approach, Approximate Dynamic Programming, to account for uncertainty in a IAM. The authors jointly model the uncertain elements of catastrophic climate change damages and annual economic productivity within a dynamic stochastic general equilibrium version of a widely accepted IAM. The problem is solved within the framework of dynamic programming, where the value function given by the solution of the original model is approximated with a finitely parameterized collection of functions.

In this paper, we employ the approximate dynamic programming algorithm proposed by ibid. that allows us to keep the complexity of the IAM results intact and, at the same time, to account for the uncertain effectiveness of R&D efforts in four low-carbon innovative technologies. To compute the value function we use a fairly complex IAM (WITCH). In order to quantify the intrinsic uncertainty concerning learning rates, costs and efficiency parameters, we resort to recent expert elicitations (Bosetti, Catenacci, et al., 2011). To provide novel and robust insights on the optimal portfolio of clean energy R&D investments, we perform a set of experiments.

First, we define the optimal level and composition of a public R&D portfolio of investments in four key clean energy technologies, given experts' judgments on their future probabilistic costs, the potential economical and technological implications of such costs (as modelled by a complex IAM), and the uncertain effect of R&D investments on costs.

Second, we study how the portfolio composition changes when considering different limits on the RD&D budget, different risk-aversion preferences, and different assumptions about the characteristics of the R&D program.

While providing policy relevant results, the main goal of the paper is that of introducing a fairly general method that can be easily adapted to use alternative IAMs, or a collection of them, to approximate the value function, as well as different expert elicitations or historical based data to inform the probabilistic relationship between R&D and the future evolution of technological costs.

6.2 Optimal R&D Portfolio Problem

The problem of finding near-term R&D investments $\boldsymbol{I}_{T_1} = \boldsymbol{I} = [I_1, \dots, I_n]$ in n technologies that maximize social welfare π under uncertain effectiveness of R&D can be formulated as a two-stage stochastic program. This can be schematically described as:

$$\max \pi = U_{T_1}(\boldsymbol{I}_{T_1}) + \mathbb{E}\left[U_{T_2}(\boldsymbol{I}_{T_1}, \boldsymbol{\lambda})\right]. \tag{6.1}$$

The first part of the objective function $U_{T_1}(\boldsymbol{I}_{T_1})$ is the welfare over the first period T_1. This term decreases deterministically with the expenditure in R&D $\boldsymbol{I}$, as the resulting benefits are assumed to materialize only after the first stage. The second part of the objective function $U_{T_2}(\boldsymbol{I}_{T_1}, \boldsymbol{\lambda})$ models the welfare associated with the stream of consumption in the second period, given the realization of future technological costs. This term increases with the expenditures in R&D $\boldsymbol{I}$ done in the first period, as costs are reduced with the cumulated level of knowledge, and more wealth can be generated. Nonetheless, benefits depend on the realization of the effectiveness of the R&D investments. This uncertain effectiveness can be conceptualized by introducing stochastic learning rates $\boldsymbol{\lambda} = [\lambda_1, \dots, \lambda_n]$ affecting how knowledge turns into cost reductions (Gritsevskyi and Nakićenovi, 2000). Optimal R&D investments then should be chosen by the policy maker trading off the benefits of shifting the distributions of future costs towards the lower end, with the burden of sustaining today those investments.

In order to approach the problem of Eq. (6.1), two elements are necessary (Baker, Olaleye, and Reis, 2015). The first is the quantification of the stochastic relationship between R&D investments and their effect on future technological performance (i.e. the distribution of learning rate, $\boldsymbol{\lambda}$); the second relates to the calculation of the stream of benefits associated to the various realizations of technological costs and efficiency parameters.

This paper shows how the framework just described can be implemented to support today public R&D investment decisions in clean energy technologies for a low-carbon. Both empirical analyses of past R&D program effectiveness (Wiesenthal et al., 2012) and expert elicitations (Morgan, Henrion, and Small, 1992) can be used to quantify the probabilistic relationship between R&D investments and their effectiveness. Here, we use data coming from an expert elicitation regarding the future cost and efficiency of key energy technologies and how these parameters might be affected by changes in the R&D efforts (Bosetti, Catenacci, et al., 2011). We focus on the impact of R&D investments on future costs of four technologies related to low-carbon energy supply:

- the cost of electricity produced with solar technologies;
- the production cost of liquid biofuels;
- the module cost of batteries for light-duty vehicles;
- the cost of electricity produced with biomass.

To quantify future welfare implications of different techno-economic-climatic scenarios, the scientific community typically resorts to integrated assessment models (IAMs). Here, we employ WITCH (World Induced Technical Change Hybrid Model), a general equilibrium IAM that can project forward the societal implications of energy technology costs (Bosetti, Carraro, et al., 2006; Bosetti, Tavoni, et al., 2009; Emmerling et al., 2016). The space of possible future cost realizations is sampled to provide a discrete set of input configurations for WITCH. The simulations yield a set of economic outcomes which are then used to approximate a continuous value function.

The choice of WITCH among the many existing IAMs was mainly driven by its fairly rich technological and economical description, and by its numerous previous applications to the study of endogenous innovation in the energy system (Bosetti and Tavoni, 2009; Marangoni and Tavoni, 2014). The model divides the worldwide economy into 13 regions, whose main macroeconomic variables are represented through a top-down inter-temporal optimal growth structure, while the energy sector is detailed in a bottom-up fashion. The different regions behave as forward-looking agents optimizing their welfare in a non-cooperative game-theoretic set-up. Actions of each agent interrelate through several externalities, like dependence on exhaustible natural resources and trade of oil. While the focus of this paper is on the EU15+EFTA region, economic scenarios involve assumptions and optimization for all the other regions. For our application to be policy relevant, we assume that countries represented in the model optimize welfare whilst obeying to a lenient climate change policy, in line to recent UNFCCC negotiated targets[2].

6.3 Two-stage stochastic program

The first stage decision concerns which technologies to promote by investing a dedicated amount in R&D during the period 2010-2030. This is before the realization of the effectiveness of this R&D investment in 2030. In this first stage, the decision maker allocates a time-invariant R&D budget I_j, yearly between 2010 and 2030, for each of the J modelled technology $j \in \mathcal{J} = \{j_1, ..., j_J\}$. R&D expenditures reduce available consumption of final good Q_t in period $t \in T_1 = \{2010, 2015, 2020, 2025\}$ by subtraction from a counterfactual consumption level $\bar{Q}_t$ without R&D:

[2]We assume that countries will pursue similar levels of climate mitigation strigency for the rest of the century. This target entails an expected increase in global average temperature of around 2.8°C above pre-industrial levels by the end of the century. The probability of the temperature increase to exceed 2°C, the threshold commonly considered as safe by the scientific community to avoid irreversible climate changes, is very high (88%-97%, Kriegler, Tavoni, et al., 2013). While climate policy makers will hopefully commit to stronger and more coordinated actions in the future, the stringent pledges we consider here reflect realistic national near-term efforts, also in line with the commitment shown by the latest Intended Nationally Determined Contributions (INDCs) circulated in the COP21 in Paris.

$$Q_t = \bar{Q}_t - r \sum_j I_j \qquad t \in T_1 \tag{6.2}$$

Public investments in energy R&D crowd out investments in other R&D, which have a social rate of return r times higher than that of private investments. It is assumed that 1 dollar of I_j costs $r = 4$ dollars otherwise usable for direct consumption or private investments (Popp, 2004). Reference consumption $\bar{Q}_t$ is a baseline counterfactual calculated by the integrated assessment model WITCH, assuming no explicit R&D expenditures and median cost realizations after 2030 for the technologies in $\mathcal{J}$. Any repercussion of I on the economy other than the one in Eq. (6.2) is assumed to be negligible. This is reasonable as R&D investments constitute a tiny fraction of overall GDP, and benefits from R&D may take some time to materialize, in this case a couple of decades. t is defined on a discretized time horizon of periods of $T_\Delta = 5$ years. Over this time horizon, knowledge in each technology j builds up according to the usual capital law of motion. Starting from an initial value $K_{0,j}$, the R&D stock in period t is given by a fraction $(1 - \delta_R)^{T_\Delta}$ of the stock in the previous period, plus the flow of new ideas due to T_Δ years of investments:

$$K_{j,t+T_\Delta} = K_{j,t}(1 - \delta_R)^{T_\Delta} + T_\Delta I_j. \tag{6.3}$$

The initial R&D stock $K_{0,j}$ in 2010 is estimated from IEA, 2015, applying the same cumulation dynamics to historical R&D budgets, separately for each region. Yearly obsolescence of R&D δ_R is assumed to be 5% for all technologies.

The link between knowledge accumulated in the first stage $\boldsymbol{K} = [K_1, ..., K_J]$ by 2030, and the cost $\boldsymbol{C} = [C_1, ..., C_J]$ in 2030, follows a one-factor learning curve. In particular, the cost $\boldsymbol{C}$ can be thought as the sum of a floor cost $\boldsymbol{C_f}$ with the initial cost $\boldsymbol{C_0}$ scaled according to the upscaling in stock of knowledge $\boldsymbol{K}$ over time, and to a learning rate $\boldsymbol{\lambda} = [\lambda_1, ..., \lambda_J]$:

$$\boldsymbol{C}(\boldsymbol{\omega}) = \boldsymbol{C_f} + \boldsymbol{C_0}\left(\frac{\boldsymbol{K}}{\boldsymbol{K_0}}\right)^{-\boldsymbol{\lambda}(\boldsymbol{\omega})}. \tag{6.4}$$

$\boldsymbol{\lambda}$ is assumed to be revealed in 2030 according to the realization $\boldsymbol{\omega} = [\omega_1, ..., \omega_J]$. This parameter drives the uncertainty of the problem of choosing investments today. Omitting the dependency of $\boldsymbol{\lambda}$ on $\boldsymbol{\omega}$ for brevity, optimal investments $\boldsymbol{I}$ maximize the following utility function:

$$\begin{aligned} U(\boldsymbol{I}, \boldsymbol{\lambda}) &:= U_{T_1}(\boldsymbol{I}) + \mathbb{E}\left[U_{T_2}(\boldsymbol{I}, \boldsymbol{\lambda})\right] \\ U_{T_1}(\boldsymbol{I}) &:= \sum_{t \in T_1} F_t(Q_t(\boldsymbol{I})) \\ U_{T_2}(\boldsymbol{I}, \boldsymbol{\lambda}) &:= V(\boldsymbol{C}(\boldsymbol{I}, \boldsymbol{\lambda})) \end{aligned} \tag{6.5}$$

In the first part of the objective function $U_{T_1}(\boldsymbol{I})$, utility at time t is a concave function F_t increasing with consumption Q_t, and decreasing with $|\boldsymbol{I}|$. A constant relative risk aversion equal to the inverse of the elasticity of intertemporal substitution η is implied. The dependency of F_t on time is due to changing levels of population L_t and discount factor β_t[3].

[3] In period t, utility is multiplied by a standard geometric discount factor $\beta_t = 1/(1 + \rho)^{t-2005}$, with pure rate of time preference ρ equal to 1%. The specific expression we consider for U_{T_1} is $\sum_{t \in T_1} L_t \beta_t/(1 - \eta)((Q_t(\sum_j I_j)/L_t)^{1-\eta} - 1)$

The second part of the objective function $U_{T_2}(\boldsymbol{I}, \boldsymbol{\lambda}(\boldsymbol{\omega}))$, represents future welfare from 2030 till the end of the time horizon (2150 in WITCH). It depends on future cost $\boldsymbol{C}$, which in turn depends on the knowledge accumulated till then and on the actual sample outcomes $\boldsymbol{\omega}$ of the stochastic learning parameter $\boldsymbol{\lambda} = [\lambda_1, ..., \lambda_J]$. This function is implemented via the WITCH model by observing the economic and energy-related consequences of changing cost assumptions $\boldsymbol{C}$.

Multiple technologies and continuous distributions for $\boldsymbol{\lambda}$ lead to an intractable problem if any change in $\boldsymbol{I}$ or $\boldsymbol{\lambda}$ (hence in $\boldsymbol{C}$) needs to be propagated into the solution of a new instance of a complex integrated assessment model like WITCH. We adopt an Approximate Dynamic Programming (ADP) approach (Cai, Judd, and Lontzek, 2013) by substituting $V(\cdot)$ with an approximating function much easier to calculate. This replacement, along with the assumption that uncertainty on technological change in the second stage does not impact the first stage objective function $U_{T_1}(\boldsymbol{I})$, makes the R&D portfolio problem numerically solvable in reasonable times. Finally, the expectation in Eq. (6.5) is translated into an average over 1000 scenarios for $\boldsymbol{\lambda}$, obtained via latin hypercube sampling of its distribution.

To show that the problem is well formulated and has a unique solution, we would need to prove that the utility is strictly concave. In section 6.A.1 in the appendix we study and provide proof of concavity in the case of one technology. The case for multiple technologies is treated only numerically, as the intuition behind the well-posedness of the problem would be obscured by the required cumbersome analytical derivation.

The optimization problem slightly changes to accomodate for different risk-aversion preferences. As section 6.A.2 in the appendix illustrates, the problem turns into the following minimization:

$$\min \sum_{t \in T_1} G_t(Q_t(\boldsymbol{I})) + \mathbb{E}\left[\left(H(\boldsymbol{C}(\boldsymbol{I}, \boldsymbol{\lambda}))\right)^{\frac{1-\alpha}{1-\eta}} \right]^{\frac{1-\eta}{1-\alpha}} \tag{6.6}$$

for some appropriate functions G_t and H (related to utility in T_1 and T_2 respectively). This formulation allows the risk-aversion parameter α to be made explicit and independent from the the inverse of the elasticity of intertemporal substitution η.

6.3.1 Learning rate estimation

Since we are considering relatively novel technologies, with scarce historical data and high potential for improvement, extrapolating historical trends may be inadequate to represent their future behaviors. We rely instead on expert elicitation to assess probabilistic distributions of future costs. Distributions are estimated from the data collected by the ICARUS project (Bosetti, Catenacci, et al., 2011). For this project, leading experts from the academic world, the private sector, and international institutions took part in a survey designed to collect probabilistic information on the role of R&D investments in lowering costs and increasing penetration of 8 carbon-free technologies. The survey could focus only on a limited amount of R&D budgets for each technology. In our framework we want to be able to search for the optimal budget allocation in a continuum of possibilities. This is possible by introducing and calibrating a particular model for technical change, like the single-factor learning model considered here (Eq. (6.4)). Then, uncertainty is assumed to lie exclusively in the learning rate λ.

The goal is to translate cost distributions, given by the experts, into distributions of learning rates. Let the random variable C_s be the cost in 2030 of one technology under an R&D scenario s, chosen among 3 future R&D budget scenarios (representing an increase of 0%, 50% and 100% with respect to baseline levels). The ensemble of experts predictions is summarized into N samples of $C_{j,s}$ cumulative distribution function (CDF). By inverting Eq. (6.4), N samples for λ_s CDF are obtained. If the one-factor model with uncertain learning perfectly represented reality, these CDF would overlap, as learning rate (hence its CDF) does not depend on the scenario: while investments do affect costs, they should be independent from the learning rates according to Eq. (6.4). Taking the mean across s of λ_s empirical distributions and fitting a Weibull distribution, we identify a parametric description of the uncertain learning rates. Using Eq. (6.4) again, a parametric description of the uncertain costs as a function of investments can be derived. The details of these calculations are reported in Algorithm 1, while a graphical representation of both empirical and fitted CDFs can be found in Figure 6.1.

6.3.2 Value function interpolation

In order to apply the Approximate Dynamic Programming paradigm, we need to construct the value function, i.e. a continuous function approximating the WITCH regional welfare response to technological cost $\boldsymbol{C}$ in the space of interest. We start by evaluating WITCH on a representitive discrete subset of costs combinations. The extreme of the ranges of this space are reported in Table 6.1 under the min and max cost columns. Current cost $C_{0,j}$, used until 2030, is just below the maximum value. Costs are assumed to reveal themselves in 2030, and are obtaining by sampling a value in the ranges. Afterwards, they decay autonomously a further 20% by 2060, and then they remain constant. Floor cost $C_{f,j}$, appearing in the learning equation (6.4), is slightly above the minimum value of the range. The margins from extreme values, especially on the lower end, keep the R&D portfolio program away from extreme boundary behaviors.

Table 6.1: *Table summarizing minimum, maximum, current and floor costs of the four considered technologies.*

Technology j	Unit	Min cost ($C_{m,j}$)	Floor cost ($C_{f,j}$)	Current cost ($C_{0,j}$)	Max cost ($C_{M,j}$)
Solar	cUSD/kWh	2	3	27.8	28
Biofuels	USD/lge	0.05	0.08	2.98	3
Batteries	USD/kWh	50	75	1019	1025
Bioelectricity	cUSD/kWh	3	4.5	24.9	25

We follow the methodology presented by Cai, Judd, and Lontzek, 2013 and construct the value function based on Hermite approximation, including both the Lagrange data and the slope information. To do so, ten samples are picked along each of the cost dimension according to a Chebysev nodal formula[4], which is known to provide greater

[4] The i-th sample cost for technology j is chosen as: $C_j^{(i)} = \frac{C_{m,j}+C_{M,j}}{2} + \frac{C_{M,j}-C_{m,j}}{2} \cos\left(\pi \frac{i-0.5}{10}\right)$.

Algorithm 1

procedure $\textsc{Fit}(\mathrm{k}_0, \delta, \mathrm{I}, \mathrm{c}_F, \mathrm{C}_{i,s}, \mathrm{EMPCDF}(\mathrm{C}_{i,s}), \mathrm{FITCDF}_x)$

$\mathrm{k}_0 \leftarrow$ R&D capital in start year

$\delta \leftarrow$ Yearly depreciation rate of R&D capital

$\mathrm{I} \leftarrow$ Yearly baseline R&D investment

$\mathrm{c}_F \leftarrow$ Floor cost

$\mathrm{C}_{i,s} \leftarrow$ Cost sample i under R&D scenario s

$\mathrm{EMPCDF}(\mathrm{C}_{i,s}) \leftarrow$ Empirical CDF of $\mathrm{C}_{i,s}$ according to experts

$\mathrm{FITCDF}_x \leftarrow$ CDF w/ parameters x for LbR rates, to be fit to EMPCDF

    for $s \leftarrow \{1, 1.5, 2\}$ **do** ▷ 3 R&D baseline investment multiplier scenarios

        $\mathrm{K}_{2010,s} \leftarrow \mathrm{k}_0$

        for $t \leftarrow \{2011, ..., 2030\}$ **do**

            $\mathrm{K}_{t,s} \leftarrow \mathrm{K}_{t-1,s}^{1-\delta} + s\mathrm{I}$ ▷ Capital accumulation

        end for

        $\mathrm{R}_s \leftarrow \mathrm{K}_{2030,s}/\mathrm{K}_{2010,s}$ ▷ Ratio over intial capital

        for $i \leftarrow$ index sample in empirical CDF from experts **do**

            $\mathrm{L}_{i,s} \leftarrow -\dfrac{\log\left(\left(\mathrm{C}_{i,s} - \mathrm{c}_F\right)/\mathrm{c}_0\right)}{\log \mathrm{R}_s}$ ▷ Invert 1-factor learning curve to obtain sample LbR rates

        end for

        $\mathrm{EMPCDF}(\mathrm{L}_{i,s}) \leftarrow 1 - \mathrm{EMPCDF}(\mathrm{C}_{i,s})$ ▷ $\mathrm{EMPCDF}(\mathrm{L}_{i,s}) =$ Prob(LbR rate $\leq$ given LbR rate)= = Prob(Cost $\geq$ given Cost)= = 1 - Prob(Cost $\leq$ given Cost) = = 1 - $\mathrm{EMPCDF}(\mathrm{C}_{i,s})$

    end for

    $x \leftarrow \arg\min_x \sum_{i,s} \left(\mathrm{FITCDF}_x(\mathrm{L}_{i,s}) - \mathrm{EMPCDF}(\mathrm{L}_{i,s})\right)^2$

    return x

end procedure

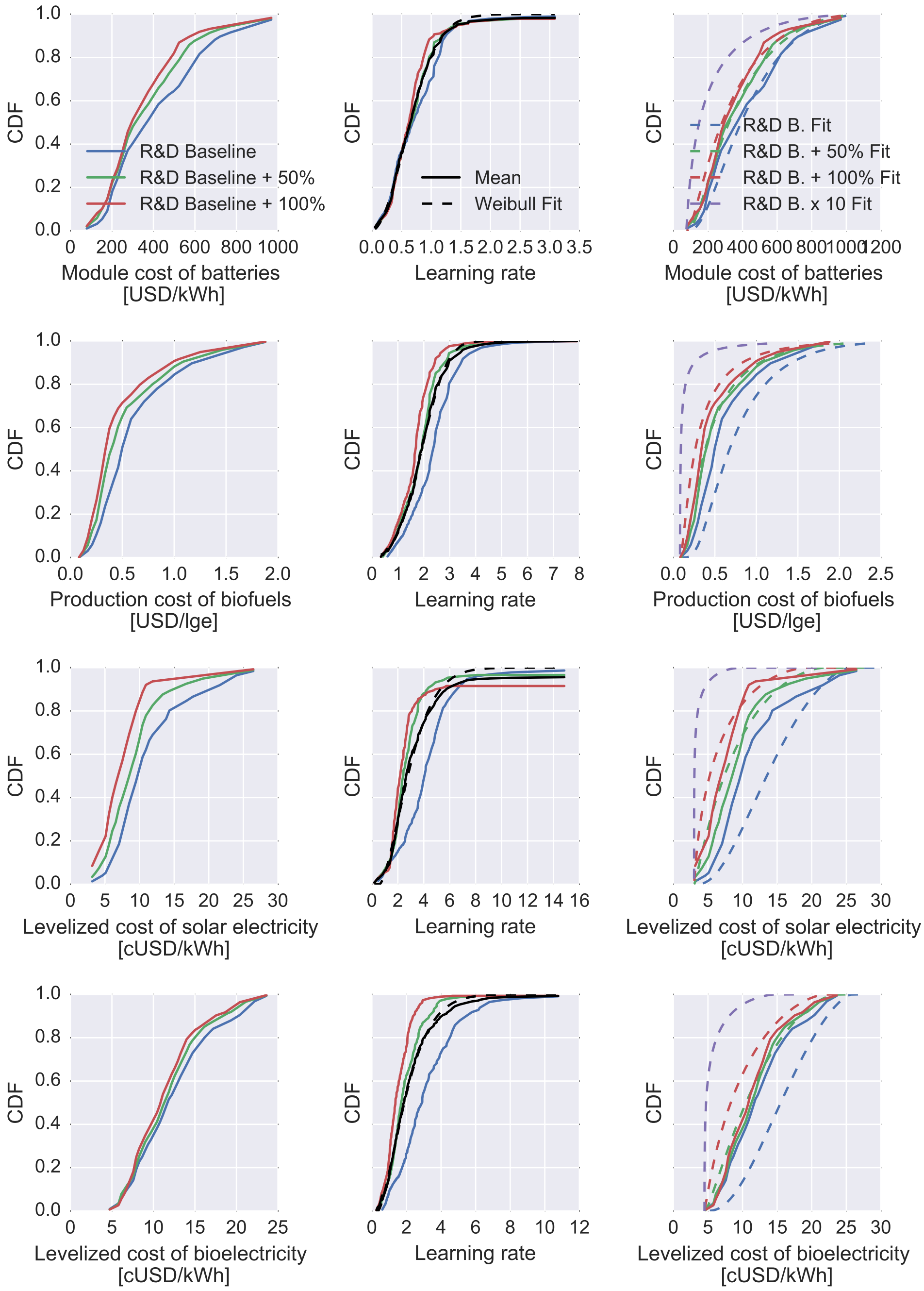

Figure 6.1: *Left column: empirical CDFs of 2030 costs as elicited from experts, one technology for each row and one R&D budget for each color. Middle column: corresponding learning rate distributions, according to the one-factor learning curve model, plus a Weibull fit of the mean empirical CDF. Right column: empirical CDFs of costs along with their fitted versions, for the 3 original R&D budgets plus an extra one.*

accuracy for polynomial interpolation.

As we study in this paper the impact on four different technology, a total of ten thousands runs of WITCH is required to performed the approximation. The exact procedure is described in section 6.A.3 in the appendix.

6.4 Results

With our model we run two scenarios: "Stochastic", where the optimal portfolio program is solved assuming that the learning rate λ is sampled from its fitted Weibull distribution, and "Certainty equivalent", where λ is set to the mean value of its distribution. The "Stochastic" scenario is also run for different values of the crowding out factor r, the risk-aversion parameter α, and the total allowable budget ($\max \sum_i \boldsymbol{I}_i$).

Figure 6.2 compares yearly public R&D investments per technology under the two simulated scenario with actual historical data on energy R&D (labelled "Historical"). The latter come from averaging 2010 to 2014 R&D investment flows reported by IEA in the relevant technological categories (IEA, 2015). Also for the estimation of the initial R&D capital, values in the period 2010-2014 were averaged, as a way to incorporate in the model the most recent available information. Results from both optimization runs imply a stark break with past trends, both in terms of total R&D expenditures (left hand side panel) and in terms of composition of the portfolio (right hand side panel). The "Certainty equivalent" case implies an optimal future budget 24 times higher than the historical 2010-2014 average of 485 million USD. Uncertainty seems to duplicate optimal R&D efforts, for a total of 22.7 billion USD. In increasing order, the three budgets constitute the 0.3%, 8% and 16% of the GDP in 2010 for the EU15+EFTA region. While GDP is estimated to grow in the first-stage, the fixed yearly "Stochastic" budget would remain above 10% of the overall economic output.

A clear break with history happens also in terms of shares. The biggest part of recent European R&D investments was devoted to solar technologies, with biofuels in the second place, followed by bioelectricity and eventually batteries for personal transport. Our stochastic solution suggests a quite different scenario, where batteries dominate the portfolio with a share greater than 80% in the stochastic case, and similar in the deterministic. This is equivalent to an upscaling of two orders of magnitude in batteries R&D investments, with respect to current efforts. A minor role is played by other technologies, with different rankings depending on whether the full distribution is taken into account or not. In particular, shares in the "Certainty equivalent" case are 75%, 13%, 9% and 3% for battery, solar, biofuels and bioelectricity respectively. In the "Stochastic" case, biofuels are cut out of the budget, with their share mostly redistributed in favor of battery (85%). Among power technologies, a minor shift occurs in favor of bioelectricity (4%) to the detriment of solar (11%).

Several reasons may justify these results. First, the expected net present value of future welfare is much more sensitive to changes in future costs of batteries than in all the other costs (see Figure 6.6). The non-electric sector, and in particular the personal transport sector, is traditionally considered one of the most difficult and expensive to decarbonize (Bosetti, Marangoni, et al., 2015; Luderer et al., 2011). Through electrification of vehicles, Europe can spread the benefit from the efforts already diffused in

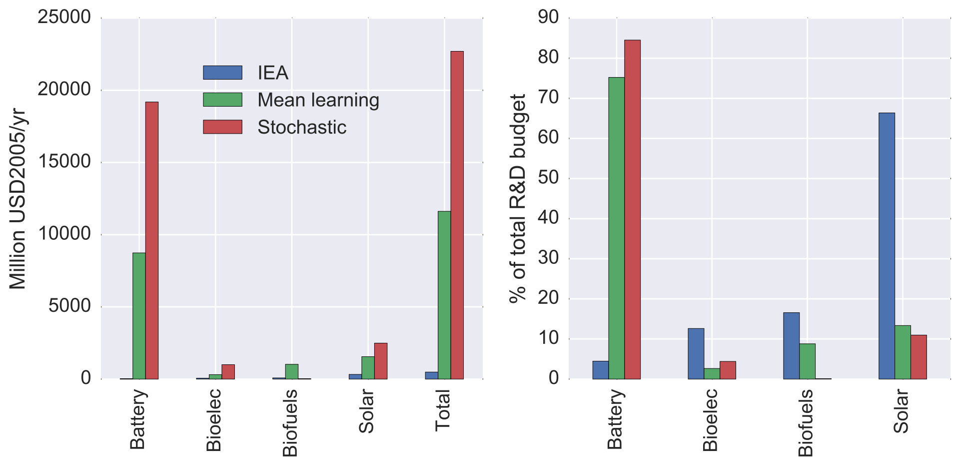

Figure 6.2: *R&D portfolio composition. Left-hand side reports yearly R&D investments per technology for the two scenarios and the historical 2010-2014 average as reported in the IEA RD&D Database. Right-hand side shows the percentage of total R&D investments in each of the four technologies.*

supporting clean power generation also to transport emissions. Europe's determined contribution can then be achieved at contained costs. Such an electrification is possible only with an adequate battery technology in place, which requires a considerable increase in the R&D from the status quo. Second, according to the experts' judgment, the probabilistic distribution of future battery costs seems to be less sensitive to an upscaling in investments when compared to other technologies. As reported in the last column of Figure 6.1, a ten-fold increase in battery investments gives the smallest change in the cumulative distribution function of 2030 costs. Finally, batteries has received a marginal attention in terms of European R&D funds in the recent past, making the initial cost quite high. It is important to remark that the scope of our analysis is limited to public R&D expenditures in Europe. By doing so, we are potentially neglecting spillovers of innovation from the private sectors, and from the R&D efforts in other counties. This might lead to an over-estimation of optimal regional public R&D needs, which could partially justify the deviation from historical trends.

Comparing the "Stochastic" and "Certainty equivalent" solutions we can grasp the effect of accounting for uncertainty in the optimal response. While uncertainty seems to have a minor effect on the shares of the portfolio, its role is clear in the upscaling of battery investment levels. A precautionary mechanism emerges from the optimization, where the risks of low learning in batteries are strongly hedged against by increased investments. This is done to the detriment of the biofuel sector, which would receive almost no investments. Biofuels and batteries are potentially substitutes in decarbonizing the transport sector, and having greater expected learning rates with a lower impact on utility function makes biofuels fall behind in the R&D competition for budget.

Next, we report results for different sensitivity tests aimed at understanding the robustness of the optimal stochastic solution to reasonable changes in key components of the model. As discussed in Section 6.3, we employ the assumption that 1 USD of public investments in energy R&D crowds out r dollars of investments in other R&D, with a nominal value of 4 (Popp, 2004). Figure 6.3 shows how results change in response to different crowding out factor assumptions. As r decreases, opportunity costs of energy R&D investments are lower, hence greater energy R&D budgets can be optimally allocated, and more so again in the battery sector. Increasing r, on the other side, increases the social cost of energy R&D investments, which become less attractive. Going from $r = 2$ to $r = 6$ means to cut more than half of the investments. A slight convexity makes this behavior marginally decreasing towards greater r values. We remark that the concern about energy R&D crowding out other forms of R&D might be minimal according to some empirical evidence (Popp and Newell, 2009), so that r is more likely gravitating towards 2 rather than 6.

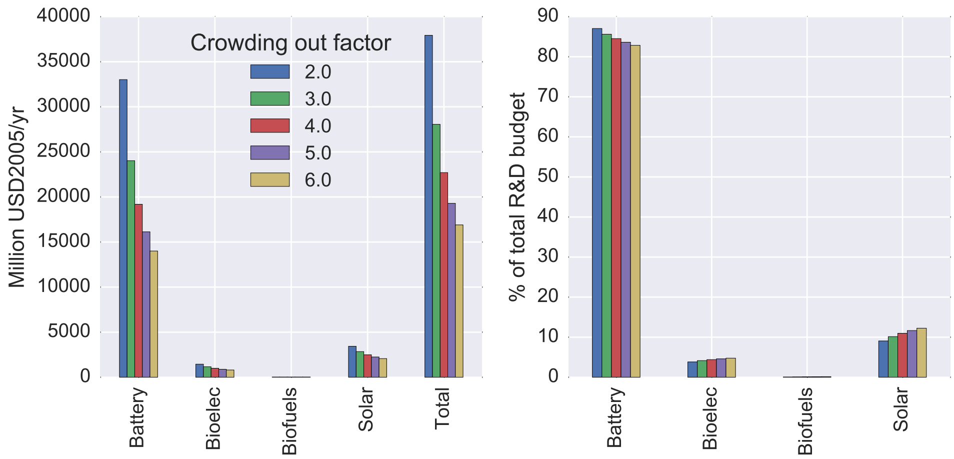

Figure 6.3: *Sensitivity to different crowding-out assumptions of the optimal R&D portfolio under uncertainty. Results are presented both in terms of yearly absolute investments levels (left-hand side) and corresponding shares (right-hand side).*

Another important parameter is the one affecting the decision maker propensity to avoid risk. In the nominal solution we assumed the relative risk aversion parameter α to be equal to the inverse of the elasticity of intertemporal substitution $\eta = 1.5$. Empirical estimates of α from observed trade behavior can be in the 10-20 range. Figure 6.4 shows the impact of increasing α on the optimal solution of the stochastic problem, using the modified utility derived in Section 6.A.2. Greater risk aversion justifies greater R&D investments, and the additional budget is directed towards battery. As discussed previously, the model is particularly sensitive to the uncertain learning rate of batteries, and reducing the uncertainty of the problem involves mostly reducing the uncertainty in batteries future cost realizations. Total and battery investments increase linearly in α, with an average 0.3% gained per added unit of α.

Finally, it may be the case that the actual budget for energy R&D will be limited by other constraints, not explicitly modelled in this work. Current budget deficits and other financial constraints might impose a total energy R&D budget way smaller than

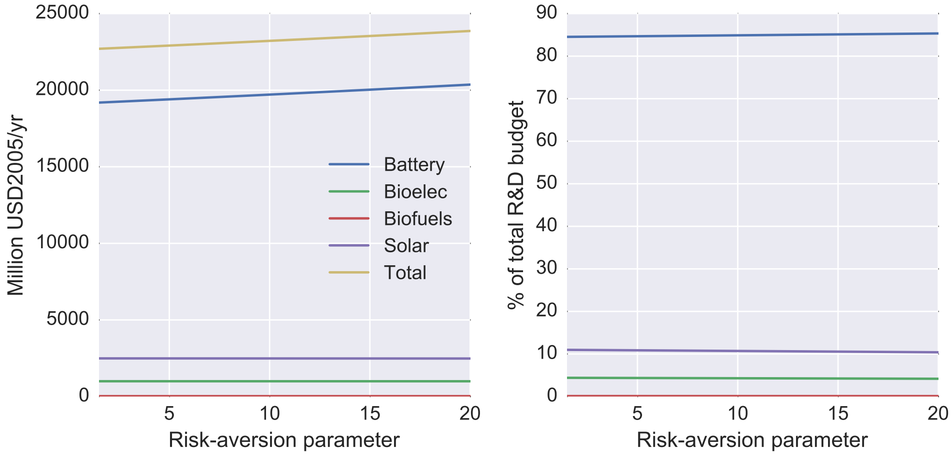

Figure 6.4: *Sensitivity to different risk aversion assumptions of the optimal R&D portfolio under uncertainty. Results are presented both in terms of yearly absolute investments levels (left-hand side) and corresponding shares (right-hand side).*

the optimal one. Figure 6.5 illustrates the change in R&D allocation when the total R&D budget is constrained. The constraint is expressed as a fraction of the total R&D budget that would be otherwise optimal. Along with total investments, also the levels of the individual technology budgets scale proportionally, excepted for the smallest fractions. As the available total R&D funds shrink, and eventually get to 10% of the unconstrained ones, battery R&D becomes less predominant in the portfolio. Given constrained total budget, the model tends to reallocate efforts more equally across technology. Lower investments in other technologies make lower realizations of the learning rates more likely, and the model starts to hedge against these. This is true for solar and bioelectricity, while biofuels would need further to emerge in the portfolio.

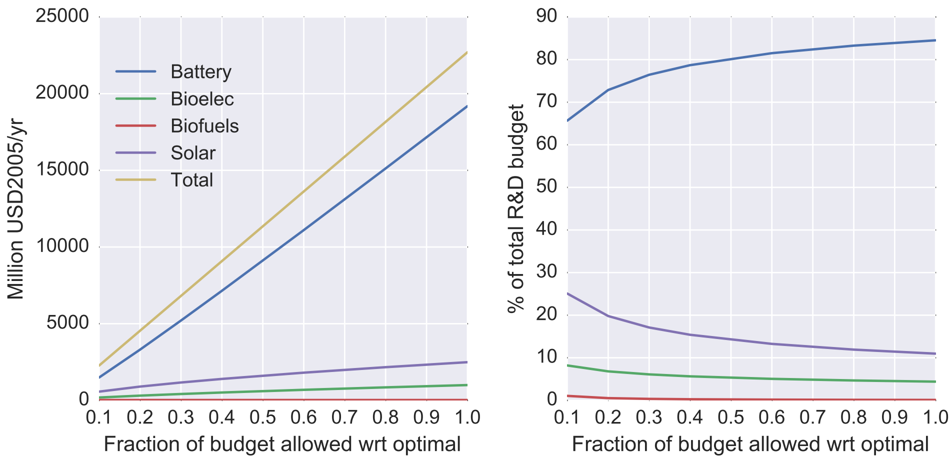

Figure 6.5: *Sensitivity to different total budget limitations of the optimal R&D portfolio under uncertainty. Results are presented both in terms of yearly absolute investments levels (left-hand side) and corresponding shares (right-hand side).*

6.5 Conclusions

This paper copes with the problem of including uncertainty endogenously in the optimization problem of a complex Integrated Assessment Model used for climate policy assessment. In our case, the decision variables of interest are energy R&D public investments to be allocated across 4 key low-carbon technologies in the near-term. Uncertainty affects the learning rate that will make these investments more or less effective in decreasing 2030 costs of these technologies. The problem is framed as a two-stage stochastic program: in the first stage (before 2030), a stock of knowledge is built through yearly R&D investments, decided for each technology; in the second stage (after 2030), learning rates will reveal themselves, and so will costs in 2030 and beyond, depending on the realization of the learning rates and on the cumulated stock of knowledge. The utility resulting from these costs is evaluated through the WITCH model. To make the problem computationally tractable, we successfully applied the Approximate Dynamic Programming paradigm by replacing WITCH value function with a surrogate function interpolated from 10000 instance of the model, evaluated at different points in the cost space.

The scope of this analysis is limited to Europe, as the estimation of learning rates distributions is limited to the expectations of European experts on future costs conditional to different R&D scenarios. Nonetheless, WITCH solves the economy and determines the operation of the energy sector at a global scale, so that the European value function in the stochastic program accounts for world-wide strategic interactions and climate policy commitments. We decided to portrait a realistic future scenario, where countries adhere to a stringent interpretation of their Copenhagen pledges, given the recent progress in climate negotiations obtained in Paris.

In this framework, we find the optimal R&D portfolio to be dominated by the sector of batteries for personal electric vehicles. Batteries seem to have a great potential in supporting the required decarbonisation, and low learning rates that need to be hedged against. Compared to the past, a significant upscaling of investments is suggested: 10-fold for the total budget and 100-fold concerning batteries. The share of batteries is robust to different assumptions of risk-aversion, R&D budget limitation and crowding-out effects.

Several further improvements could follow this study. As a first application of the methodology introduced in this paper, the number of technologies is limited to four, and only one climate policy is considered. In the future, these dimensions could be augmented. Investment decisions could be extended to all WITCH regions in the form of a Nash game. Other models beyond WITCH could be involved in a similar exercise to provide a further layer of robustness check to the analysis. Nonetheless, the main merit of this paper remains to prove that the suggested methodology can be successfully applied to a fairly complex IAM for informing robust optimal clean energy innovation policies, and could similarly applied in many other contexts.

6.6 Acknowledgements

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6.A Appendix

6.A.1 Solution existence and uniqueness for one technology

The problem of maximizing Eq. (6.5) has a unique solution if utility is strictly concave. For simplicity, we consider analytically only the case with one technology, i.e. $J = 1$. Let consider $U_{T_1}(\boldsymbol{I})$. Its first and second derivatives are:

$$\frac{\partial U_{T_1}(I)}{\partial I} = \frac{\partial}{\partial I}\sum_{t\in T_1} L_t\beta_t/(1-\eta)((Q_{0t}-rI)/L_t)^{1-\eta}-1) \tag{6.7}$$

$$= \sum_{t\in T_1} -r\beta_t((Q_{0t}-rI)/L_t)^{-\eta} \tag{6.8}$$

$$\frac{\partial^2 U_{T_1}(I)}{\partial I^2} = \frac{\partial}{\partial I}\sum_{t\in T_1} -r\beta_t((Q_{0t}-rI)/L_t)^{-\eta} \tag{6.9}$$

$$= \sum_{t\in T_1} -\frac{r^2\eta\beta_t}{L_t}((Q_{0t}-rI)/L_t)^{-\eta-1} \tag{6.10}$$

All parameters have positive values, so that $U_{T_1}(I)$ is decreasing ($U'_{T_1} < 0$) with a strictly concave behavior ($U''_{T_1} < 0$).

Let consider $U_{T_2}(\boldsymbol{I})$, assuming λ fixed.

$$\frac{\partial U_{T_2}(I)}{\partial I} = \frac{\partial V(C(I))}{\partial I} = \frac{\partial V(C)}{\partial C}\frac{\partial C(I)}{\partial I} \tag{6.11}$$

The cost C depends on investments in R&D I via one-factor learning and cumulation of R&D capital euqations:

$$C(I) = C_f + C_0\left(\frac{K(I)}{K_0}\right)^{-\lambda} \tag{6.12}$$

$$K(I) = K_0(1-\delta_R)^{2030-2005} + \Delta_T I \sum_{t=2010,\ldots,2030}(1-\delta_R)^{t-2010}. \tag{6.13}$$

Renaming positive constants to yield a form as compact as possible, Eq. (6.11) becomes:

$$\frac{\partial U_{T_2}(I)}{\partial I} = V'(C)\frac{\partial}{\partial I}[c_f + c_0(\Delta_a + \Delta_b I)^{-\lambda}] \tag{6.14}$$

$$= V'(C)[-\Delta_c(\Delta_d + I)^{-\lambda-1}] \tag{6.15}$$

$V(C)$ is decreasing ($V'(C) < 0$), so that $U_{T_2}(I)$ results increasing in I ($U'_{T_2} > 0$). Regarding the second derivative:

$$\frac{\partial^2 U_{T_2}(I)}{\partial I^2} = \frac{\partial}{\partial I}V'(C)[-\Delta_c(\Delta_d + I)^{-\lambda-1}] \tag{6.16}$$

$$= V''(C)[-\Delta_c(\Delta_d + I)^{-\lambda-1}] + V'(C)[\Delta_c(\lambda+1)(\Delta_d + I)^{-\lambda-2}] \tag{6.17}$$

This is the sum of two negative terms, as $V(C)$ is convex ($V''(C) > 0$), and decreasing with C ($V'(C) < 0$). U_{T_2} is thus strictly concave in I. and the maximization problem is well posed.

6.A.2 Risk aversion derivation

So far, we made implicit assumptions on the risk aversion of the decision maker. We introduce an explicit parameterization of risk preferences following Epstein and Zin, 1989. Let consider first a recursive utility V_t at time t, defined as a constant elasticity of substitution (CES) production function of Q_t/l_t and of utility at time $t+1$:

$$V_t = \left((1-\gamma_t) \left(\frac{Q_t}{l_t} \right)^{1-\eta} + \gamma_t V_{t+1}^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{6.18}$$

If we raise V_t to the power $(1-\eta)$ and unfold the recursion starting from the first period, replacing for brevity years {2005, 2010, 2015, ...} with their integer indices {1, 2, 3, ...}, we obtain:

$$\bar{W}_1 = V_1^{1-\eta} = (1-\gamma_1) \left(\frac{Q_1}{l_1} \right)^{1-\eta} + \gamma_1 (1-\gamma_2) \left(\frac{Q_2}{l_2} \right)^{1-\eta} \tag{6.19}$$

$$+ \gamma_1 \gamma_2 (1-\gamma_3) \left(\frac{Q_3}{l_3} \right)^{1-\eta} + ... \tag{6.20}$$

$$= (1-\gamma_1) \left(\frac{Q_1}{l_1} \right)^{1-\eta} + \Gamma_1 (1-\gamma_2) \left(\frac{Q_2}{l_2} \right)^{1-\eta} + \Gamma_2 (1-\gamma_3) \left(\frac{Q_3}{l_3} \right)^{1-\eta} + ... \tag{6.21}$$

$$= \theta_1 \left(\frac{Q_1}{l_1} \right)^{1-\eta} + \theta_2 \left(\frac{Q_2}{l_2} \right)^{1-\eta} + \theta_3 \left(\frac{Q_3}{l_3} \right)^{1-\eta} + ... \tag{6.22}$$

which is related by an affine transformation to a scaled version $\widetilde{W}_1$ of WITCH utility W_1, obtained dividing by the sum of population levels over the finite time horizon of the model $L := \sum_t l_t$:

$$\widetilde{W}_1 = \frac{1}{L} W_1 = \frac{\bar{W}_1 - \sum_t \theta_t}{1-\eta} \tag{6.23}$$

The need to introduce a scaled version of W_1 comes from the CES requirements on γ_t to be less than one. New coefficients are related to each other and to WITCH ones by:

$$\theta_t = \frac{\beta_t l_t}{L} \tag{6.24}$$

$$\gamma_t = \frac{1 - \sum_{t' \le t} \theta_{t'}}{1 - \sum_{t'' \le t-1} \theta_{t''}} \tag{6.25}$$

$$\Gamma_t = \prod_{t' \le t} \gamma_{t'} = 1 - \sum_{t' \le t} \theta_{t'} \tag{6.26}$$

with the last equation due to the telescoping nature of the product of γ_t. In particular, the following For $\eta = 1.5$, maximizing W_1 (i.e. solving WITCH) is equivalent to maximizing $\widetilde{W}_1$, or minimizing $\bar{W}_1$, or maximizing $V_1 = \bar{W}_1^{1/(1-\eta)}$. The advantage of thinking in terms of V_t is that a simple transform can be applied to future utility in

Eq. (6.18) to make the Epstein-Zin risk preference parameter α explicit:

$$V_t = \left((1-\gamma_t)\left(\frac{Q_t}{l_t}\right)^{1-\eta} + \gamma_t \mathbb{E}\left[V_{t+1}^{1-\alpha}\right]^{\frac{1-\eta}{1-\alpha}}\right)^{\frac{1}{1-\eta}} \tag{6.27}$$

$$= \left((1-\gamma_t)\left(\frac{Q_t}{l_t}\right)^{1-\eta} + \gamma_t \mathbb{E}\left[\left(V_{t+1}^{1-\eta}\right)^{\frac{1-\alpha}{1-\eta}}\right]^{\frac{1-\eta}{1-\alpha}}\right)^{\frac{1}{1-\eta}} \tag{6.28}$$

$$= \left((1-\gamma_t)\left(\frac{Q_t}{l_t}\right)^{1-\eta} + \gamma_t \mathbb{E}\left[\left(\bar{W}_{t+1}\right)^{\frac{1-\alpha}{1-\eta}}\right]^{\frac{1-\eta}{1-\alpha}}\right)^{\frac{1}{1-\eta}} \tag{6.29}$$

Unfolding the recursion above for our stochastic program, the expectation operator only appears only after the first 5 periods, when utility starts to be affected by uncertainty:

$$V_1^{1-\eta} = \sum_{t\in\{1,\ldots,5\}} \theta_t \left(\frac{Q_t}{l_t}\right)^{1-\eta} + \Gamma_5 \mathbb{E}\left[\left(\bar{W}_6\right)^{\frac{1-\alpha}{1-\eta}}\right]^{\frac{1-\eta}{1-\alpha}} \tag{6.30}$$

We want to link $\bar{W}_6$ with WITCH utility after-2030 W_6:

$$\frac{W_6}{L} = \frac{1}{1-\eta}\left[\left(\theta_6\left(\frac{Q_6}{l_6}\right)^{1-\eta} + \theta_7\left(\frac{Q_7}{l_7}\right)^{1-\eta} + \ldots\right) - \sum_{t\geq 6}\theta_t\right] \tag{6.31}$$

$$\bar{W}_6 = (1-\gamma_6)\left(\frac{Q_6}{l_6}\right)^{1-\eta} + \gamma_6(1-\gamma_7)\left(\frac{Q_7}{l_7}\right)^{1-\eta} + \ldots \tag{6.32}$$

$$= \frac{1}{\Gamma_5}\left(\theta_6\left(\frac{Q_6}{l_6}\right)^{1-\eta} + \theta_7\left(\frac{Q_7}{l_7}\right)^{1-\eta} + \ldots\right) \tag{6.33}$$

$$= \frac{1}{\Gamma_5}\left((1-\eta)\frac{W_6}{L} + \sum_{t\geq 6}\theta_t\right) \tag{6.34}$$

Maximizing W_1 in the risk aversion formulation is thus equivalent to the problem of:

$$\min \sum_{t\in\{1,\ldots,5\}} \theta_t \left(\frac{Q_t}{l_t}\right)^{1-\eta} + \Gamma_5 \mathbb{E}\left[\left(\frac{1}{\Gamma_5}\left((1-\eta)\frac{W_6}{L} + \sum_{t\geq 6}\theta_t\right)\right)^{\frac{1-\alpha}{1-\eta}}\right]^{\frac{1-\eta}{1-\alpha}} \tag{6.35}$$

6.A.3 Hermite interpolation of the value function

Let $\boldsymbol{i} = [i_1, \ldots, i_J]$ be the index of a single cost/welfare sample. After running the model, we collect all welfare samples $W^{(\boldsymbol{i})}$:

$$W^{(\boldsymbol{i})} := V(\boldsymbol{C}^{\boldsymbol{i}}) = \sum_{t\in\{2030,2035,\ldots\}} L_t\beta_t/(1-\eta)((Q_t(\boldsymbol{C}^{(\boldsymbol{i})})/L_t)^{1-\eta} - 1) \tag{6.36}$$

along with first derivatives $\partial W/\partial C_j|_{\boldsymbol{C}^{(i)}}$, obtained from the marginals of the equations that input 2030 costs into the model. Next, we choose a polynomial of degree m defined in the normalized cost space $\mathcal{U} = [-1, 1]^J$ to fit the welfare data points. Let $\boldsymbol{l} = [l_1, \ldots, l_J]$ be a vector of integers such that $\sum_j l_j = m$, and $\tilde{V}(\boldsymbol{X}) = a_{\boldsymbol{l}} \prod_j (X_j)^{l_j}$, $\boldsymbol{X} =$

$[X_1, ..., X_J] \in \mathcal{U}$ our polynomial function. The interpolation problem is casted in the form:

$$\min_{a_l} \sum_i \left(\tilde{V}(\boldsymbol{X}^{(i)}) - W^{(i)}\right)^2 + \sum_j \gamma_j \left(\frac{\partial \tilde{V}(\boldsymbol{X})}{\partial X_j}\bigg|_{\boldsymbol{X}^{(i)}} - \frac{\partial W}{\partial C_j}\frac{\partial C_j}{\partial X_j}\bigg|_{\boldsymbol{X}^{(i)},\boldsymbol{C}^{(i)}} \right)^2 \tag{6.37}$$

$$\text{s.t.} \qquad X_j^{(i)} = -1 + 2\frac{C_j^{(i)} - C_{m,j}}{C_{M,j} - C_{m,j}} \qquad j \in \mathcal{J} \tag{6.38}$$

The function to be minimized is a weighted sum of the error both in absolute and derivative terms, the latter being done with respect to all technologies. An affine transformation maps $\boldsymbol{X}$ into $\boldsymbol{C}$, while the γ_j balances differences in units.

Both absolute levels and curvatures of the actual WITCH value function can be well replicated with a polynomial of degree 4 (Figure 6.6). Looking at bidimensional slices of the function, it turns out that the greatest impact is given by changing the cost of battery, followed by biofuels. Changing the cost of solar and bioelectricity seems to yield minor effects. These results are consistent with the expected challanges of decarbonizing the non-electrical sector, and underline the crucial impact of technical change supporting this decarbonization.

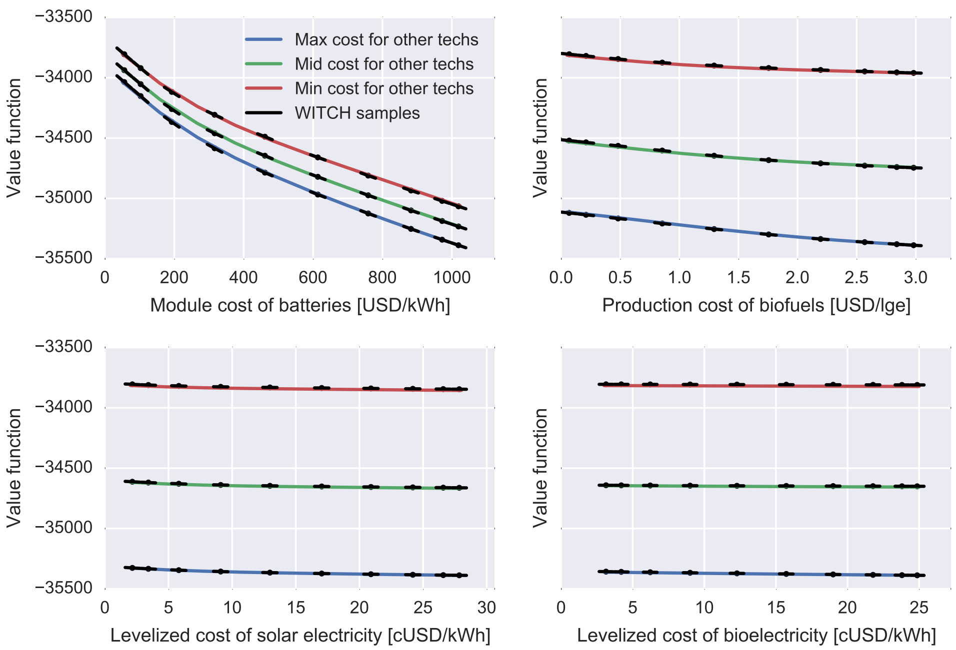

Figure 6.6: *Bidimensional slices of WITCH 2030-onwards utility as a function of the 4 costs considered. A fitted polynomial of degree 4 is evaluated and plotted in color along each cost dimension, with the other costs either at maximum, minimum, or middle level. Actual values from WITCH are plotted in black. The segment around each sample brings information about actual partial derivatives.*

List of Figures

List of Tables