UNIVERSITA' CATTOLICA DEL SACRO CUORE
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Ciclo XXI
S.S.D.: SECS-P/02, SECS-S/06

The economic analysis of climate policy: technology, innovation, forestry and uncertainty.

Tesi di dottorato di: Massimo Tavoni
Matricola: 3480077

Anno Accademico 2007/08

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Coordinatore. Ch.mo Prof. Luigi Campiglio

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Introduction

Climate change has emerged as one of the great global challenges that we are confronted with. During the writing of this thesis, a series of events have brought the issue to a new status in the way it is perceived by the society as a whole. Scientific contribution to the understanding of the natural processes governing climate change and of consequent socio-economic impacts has attracted an increasing attention from the public, culminating in the recognition of the Peace Nobel Prize in 2007[1]. In parallel to this growing consensus over the scientific basis for climate change, the climate challenge has become a public policy priority, and is now ranking high in the political agenda of many countries. No longer treated as an environmental issue alone, it is often directly dealt by head of states, who gave it top priority in G8 meetings such as the 2007 one[2], and commissioned and helped disseminating dedicated reports such as the Stern Review[3].

One might wonder what are the reasons behind this momentum, despite the many uncertainties and unresolved issues that characterize the global warming phenomenon. A likely candidate answer is the all-embracing nature of the problem. Climate change ranges widely into many directions: it involves different generations across time and space, with varied socio-economic and natural ecosystem impacts, most of which are unknown or hardly quantifiable. Its solution requires a coordinated effort of unprecedented scale, engaging many economic and natural activities and calling for a new role of the public sector. And it naturally raises distributional and legacy issues confronting developed and developing worlds.

From a research stand point, the diverse nature of the problem is a challenge as it is a motivation. Economists can offer important insights on the implications of both limiting and confronting the problem, thus offering fundamental guidance to the policy makers involved in the complex negotiation processes. But in order to do so, they need to draw from a series of traditional economic tools -e.g. public economics, economic growth, development economics, environmental economics, analysis under uncertainty- as well as from other fields, notably energy and natural systems analysis.

With all such stimulus, a growing numbers of scholars have contributed to climate change economics research in the past few years, ranging from theoretical to empirical work, aimed at different stakeholders. The work carried out in this Thesis aims at contributing to this young and

[1] The prize was assigned to Al Gore and the IPCC for "their efforts to build up and disseminate greater knowledge about man-made climate change, and to lay the foundations for the measures that are needed to counteract such change".

[2] http://www.g-8.de/nn_94646/Content/EN/Artikel/__g8-summit/2007-06-07-g8-klimaschutz__en.html

[3] http://www.hm-treasury.gov.uk/independent_reviews/stern_review_economics_climate_change/sternreview_index.cfm

thought-provoking literature by providing an extensive economic evaluation of the strategies needed to cope with climate protection.

Scope of the thesis

The work collected in this Thesis is an attempt at a better understanding of the economic implications of climate mitigation policies. The starting point assumed here is that global warming is dangerous and societies are committed to climate protection policies. The final objective is to inform on the socio-economic costs required to comply with the envisioned climate goals, and to provide with a set of strategies that would allow to achieve it in an economically efficient way.

This ambitious workplan requires a rigorous methodology that can deal with the complex nature of the problem. The main approach followed here is the one of numerical modelling of economy-energy-climate interactions, though some analytical insight is also provided. Models of this kind are particularly suited for applications in this research area, as they can reconcile aspects of economic analysis with energy and climate planning. Despite their recent development, integrated assessment models are now used widely in the analysis of climate change, so that for example they constitute an important part of IPCC reports.

The model WITCH developed and used in this work belongs to this strand of literature, but introduces a series of novelties that place it in the position to capture additional aspects of the problem at stake. It features a neo-classical optimal growth structure so that the very long term nature of climate change is accounted via inter-temporal optimization, and far-sighted economic agents can incorporate long term effects into current decisions. Strategies are thus time efficient, an important characteristic given that CO2 molecules stay in the atmosphere for hundreds of years, and investments in the energy sector can last for several decades[4], and thus todays decisions are important determinants of future responses. The energy sector, the largest responsible of greenhouse gas emissions, is accounted for in the model by a full integration into the economic production function, an “hard link” that ensures consistency of the economic output and the investments decisions in the main energy carriers. Technological change is portrayed via both diffusion and innovation processes, and policy induced innovation is thus accounted for. Last but not least, the model has one of its most important characteristics in the game theoretical set up that allows to mimic the free-riding incentives that the 12 regions that constitute the world are confronted with as a result of public goods or bads. Global externalities due to CO2, but also to extraction of exhaustible resources such as fossil fuels, and to limited appropriability of knowledge behind

[4] The half time of a molecule of CO2 is roughly 100 years. Power plants lifetimes can surpass half century.

innovation, are taken into account so that regions choose their investment paths strategically with respect to other regions choices.

The result is a hybrid model that can provide normative analysis about climate protection policies and that can be used to inform policymakers on the economic efficient set of policies needed to combat global warming but also to deal with additionally related environmental and economic inefficiencies.

Structure of the thesis

The thesis is structures around three papers and an Appendix. Each paper deals with a crucial aspect of climate mitigation policies, namely technologies and innovation, technology uncertainty and natural systems. The appendix provides a reference to the methodology employed. The analysis of investments in current and future energy technologies for climate change mitigation carried out in the first article is expanded in the second one by focusing on the role of uncertain innovation. The third paper adds the natural dimension by assessing the potential of forestry management in contributing to CO2 abatement.

The general setting is one of cost effective analysis of climate stabilization policies. To single out the role of the aforementioned mitigation options, we assume complete participation of countries in a global perfect carbon market that ensures the equalization of marginal abatement costs across countries.

Paper 1 "Optimal Investment and R&D Strategies to Stabilize Greenhouse Gas Atmospheric Concentrations"

The first paper deals with cost-effective strategies that stabilize CO_2 concentrations looking at the energy investment and R&D policies that optimally achieve GHG stabilization. Our results show that they are feasible, but require radical changes in the energy sector and large investments in R&D. Improvements in energy and carbon efficiency are shown to be essential, both via currently known technologies such as nuclear and renewables, but also via innovative ones for which large energy R&D programs are needed.

Paper 2 "Uncertain R&D, backstop technology and GHG stabilization"

The recognition of the role of knowledge as a way to decouple economic growth and climate protection is the motivation of this second paper, in which innovation strategies with uncertain effectiveness of R&D are evaluated. By means of both an analytical model and the numerical model

WITCH, we show the implications of innovation uncertainty on the productivity of the investments and the overall economic performance of the climate policy.

Paper 3 "Forestry and the carbon market response to stabilize climate"

Although the energy sector is the main responsible of green house gas emissions, natural systems are also important determinants of emissions. Forestry for example, both via avoided deforestation and afforestation, has the potential to be a convenient mitigation alternative. Its role in the climate mitigation context is analysed in the third paper, where the WITCH model is coupled with a global timber model to assess the global responses of the carbon market to the inclusion of forestry activities into climate policies.

Appendix. WITCH model description

The Appendix provides an explanation of the main modelling tool used throughout the thesis.

Acknowledgements

This work is the result of a three years collaboration that has meaningfully changed me professionally and personally. Thus, I'm trustfully grateful to the many people from whom I have benefited and learned, and without whose contribution this work would not have been possible.

I would like to thank FEEM for having given me the chance to do research in a fantastic environment. Many colleagues have contributed significantly, by reviewing, challenging, contributing, and giving precious advise. Among those many that directly influenced the work presented here, let me express gratitude to Marzio Galeotti, Alessandro Lanza, Anil Markandya, Bob van der Zwaan. A special thanks goes to Carlo Carraro, that has allowed me the opportunity to do this, and towards whom I am especially indebted. Emanuele Massetti, for starting it all on the very same desk.

I would also like to thank Università Cattolica del Sacro Cuore, for the opportunity of pursuing this doctoral research, rightly balancing independence and support. Thanks especially to Luigi Campiglio and Maurizio Baussola.

Finally, let me try to engrave my obligation to the person that has made possible this and all the rest. Valentina, for co-authoring papers and life, my thankfulness and esteem will never be enough.

OPTIMAL ENERGY INVESTMENT AND R&D STRATEGIES TO STABILIZE ATMOSPHERIC GREENHOUSE GAS CONCENTRATIONS

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Abstract

Stabilizing the atmospheric concentrations of greenhouse gases (GHG) at levels expected to prevent dangerous climate changes has become an important, long term global objective. It is therefore crucial to identify a cost-effective way to achieve this objective. In this paper, we use WITCH, a hybrid climate-energy-economy model, to obtain a quantitative assessment of equilibrium strategies that stabilize CO_2 concentrations at 550 or 450 ppm. Since technological change is endogenous and multifaceted in WITCH, and the energy sector is modeled in detail, we can provide a description of the ideal combination of technical progress and alternative energy investment paths in achieving the sought stabilization targets. Given that the model accounts for interdependencies and spillovers across 12 regions of the world, equilibrium strategies are the outcome of a dynamic game through which inefficiency costs induced by global strategic interactions can be assessed. Therefore, our results differ from previous analyses of GHG stabilization policies, where a central planner or a single global economy is usually assumed. Our results emphasize the drastic change in the energy mix that will be necessary to control climate change, the huge investments in existing and new technologies implied, and the crucial role of technological innovation.

JEL: H0, H2, H3.

KEYWORDS: Climate Policy, Energy R&D, Investments, Stabilization Costs.

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1. Introduction

Climate change may dramatically damage future generations. According to the latest IPCC report (IPCC, 2007), anthropogenic emissions of greenhouse gases (GHG) are among the main causes of climate change, even though uncertainty remains as to their exact relevance in the overall climatic process: thus it is necessary to identify when, where and how these emissions ought to be controlled in order to avoid dangerous climate changes.

The many uncertainties that still permeate the debate about the relationship between GHG concentrations and temperature change or the existence of temperature thresholds beyond which irreversible changes could occur, make it difficult to use the standard cost-benefit framework for jointly identifying the optimal stabilization target and related investment mix. Scientific uncertainties aside, the long-term stabilization target is clearly a political decision, and policymakers worldwide are indeed discussing how to tackle the climate change problem. At the 2008 G8 Summit in Japan, the leading industrialized nations agreed on the objective of at least halving global CO_2 emissions by 2050. Such an agreement follows earlier resolutions of other countries, such as the EU, Canada and Japan.[1] There is therefore increasing interest in, and a need for, research efforts providing information on the best strategy that different regions of the world should adopt in order to minimize the cost of achieving their own emission reduction target. In particular, it is crucial to identify the long-term investment mix in the energy sector in different world regions, taking into account the role of investments in energy R&D and the future evolution of different technologies.

For analytical purposes, this paper considers two long-term stabilization targets, both expressed in terms of atmospheric carbon concentrations. The first target is a 550 ppm (CO_2 only) concentration target. The second one stabilizes emissions at 450 ppm (CO_2 only). These two reference targets roughly coincide with IPCC Post-TAR stabilization scenarios C and B respectively. Although the IPCC considers even more stringent emissions pathways, our current analysis focuses on the two that we consider more politically realistic. The first target is often advocated for in the US (see for example Newell and Hall, 2007), whereas the second one is close to the EU objective of keeping future temperature changes within 2 degrees Celsius. We then compute the welfare maximizing path of energy R&D expenditures, investments in energy

[1] The European Union, for example, has identified both its long term target (a temperature increase of less than 2 degrees Celsius) and the short term target consistent with the former (i.e. a reduction of 2020 emissions by 20% with respect to 1990, which may become a 30% reduction if all countries jointly reduce their emissions in the same manner).

technologies and direct consumption of fossil fuels that is consistent with the proposed stabilization targets.

The equilibrium R&D and investment strategies in a given region of the world depend upon many factors, such as: the discount rate; the investment decisions taken in other regions or countries; and the effectiveness of R&D in increasing energy efficiency, or in providing new, low carbon, energy technologies. Equilibrium R&D and investment strategies also depend on the expected climate damages, on the pattern of economic growth in various regions of the world, and on other economic and demographic variables. In this paper, all these interdependent factors are taken into account.

To this purpose, we use WITCH (Bosetti, Carraro, Galeotti, Massetti and Tavoni, 2006), a climate-energy-economy model in which a representation of the energy sector is fully integrated into a top-down optimization model of the world economy. Thus, the model yields the equilibrium intertemporal allocation of investments in energy technologies and R&D that belong to the best economic and technological responses to different policy measures. The game theory set-up accounts for interdependencies and spillovers across 12 regions of the world. Therefore, equilibrium strategies are the outcome of a dynamic game through which inefficiencies induced by global strategic interactions can be assessed. In WITCH, technological progress in the energy sector is endogenous, thus enabling us to account for the effects of different stabilization scenarios on induced technical change, via both innovation and diffusion processes. Feedback from economic variables to climatic ones, and vice versa, is also accounted for in the dynamic system.

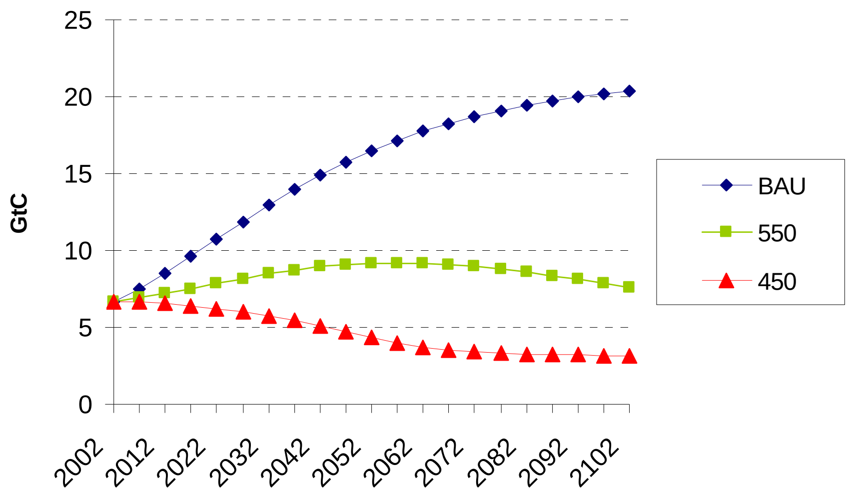
These features enable WITCH to address many questions that naturally arise when analyzing carbon mitigation policies. Among those that this paper aims to answer are the following: what are the implications of the proposed stabilization targets for investment strategies and consumption of traditional energy sources vis-a-vis low carbon options?; what is the role of public energy R&D expenditures for generating improvements in both energy efficiency and carbon intensity?; and how sensitive are the economic costs of climate policies to different technological scenarios, and in particular, to hypotheses on major technological breakthroughs?

The structure of the paper is as follows. Section 2 describes the framework of our analysis and explores the implications of stabilization targets for the energy sector. Section 3 informs readers about investment needs for known technologies, while Section 4 focuses on innovation strategies. Section 5 provides estimates of the economic costs of climate policy with a focus on technological choices, and Section 6 concludes the paper. The Appendix provides background information on the WITCH model.

2. The Challenge of Stabilizing Atmospheric GHG Concentrations.

As previously indicated, we investigate best response strategies, particularly in the energy sector, to achieve two stabilization targets. According to the first one, atmospheric concentrations must be stabilized at 550 ppm (CO_2 only) by the end of the century. This is roughly equivalent to a 650 ppm target if all GHGs are included. The second target is more stringent and requires that CO_2 concentrations be stabilized at 450 ppm (550 ppm all gases included) at the end of the century. Figure 1 shows Business as Usual (BaU) emissions together with emission time profiles for the two stabilization targets. These are optimal time profiles because they were obtained by computing the fully cooperative equilibrium of the game given the GHG concentration constraints, i.e. by solving aglobal joint welfare maximization problem where all externalities are internalized. Note that feedbacks from climate damage to the production of economic goods[2] are taken into account when computing the optimal emission profiles.

Figure 1. World fossil fuel emissions in the three scenarios (2002-2102).



Current annual fossil fuel CO_2 emissions are roughly 7 GtC/yr. According to the model projections, without any stabilization policy (the BaU or "baseline" scenario), CO_2 emissions are expected to reach about 21 GtC by the end of the century, a value in line with the IPCC B2 SRES scenario. In the case of the 550 ppm stabilization target, annual emissions slowly increase until 2060 (when they reach 10 GtC per year) and then decrease to 8 GtC by the end of the century. If the target is 450 ppm, CO_2 emissions start decreasing immediately and reach 3GtC by the end of the century. That is, the optimal emission profile does not allow for overshooting emissions which

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[2] We adopt the same damage function as in Nordhaus and Boyer (2000). Future damages are discounted at a declining discount rate (starting from 3% and declining to 2%).

would trade off current and future abatement. The emission reductions required to meet the more stringent stabilization target are particularly challenging, given the expected growth rate of world population and GDP: per capita emissions in the second part of this century would have to decline from about 2 to 0.3 tC/cap per year[3].

To achieve the two stabilization targets and the related optimal emission profile, it is assumed that all regions of the world agree on implementing a cap and trade policy. This is an obvious simplification which is useful in this paper to focus on differences in the technological make-up of the economy under the two stabilization scenarios, and on the difference in R&D portfolios. In two companion papers (Bosetti*, et al.*, 2008a,b), we analysed the implications of partial agreements, delayed action in developing countries, and uncertain stabilization targets. In this paper, the global cap and trade policy is implemented by assuming an equal per capita allocation of initial allowances.

Given the adopted climate policy, countries use the permit market to trade emissions (banking is also allowed) and determine their investments and R&D strategies, as well as their demand for permits, by maximizing their own welfare function (see the Appendix) given the strategy adopted in the other regions of the world. The intertemporal Nash equilibrium of the dynamic game defines the equilibrium investment strategies in each world region.

To assess the implications of the equilibrium of the game under the two concentration constraints, let us compare the impact of imposing the two stabilization targets on the dynamics of the main economic variables. Table 1 shows the changes in the variables belonging to the well-known Kaya's identity (emissions, per capita GDP, energy intensity, carbon intensity of energy and population) for two periods: 1972-2002 (historical values) and 2002-2032 (WITCH scenarios).

In the BaU, future changes of all economic variables are close to those observed in the past thirty years. Baseline emissions almost double in 30 years time, due to increasing population and improving lifestyles. This increase is partially compensated by looser economy-energy interdependence, but not by an energy-carbon decoupling. The characteristics of the baseline have important implications in terms of efforts required to stabilize the climate (and therefore in terms of stabilization costs). In this respect, the reproduction of history – at least over short time horizons – provides a useful benchmark.

[3] Note that 0.3 tC $yr^{-1}cap^{-1}$ is the amount of carbon emitted on a *one way* flight from the EU to the US East Coast.

Table 1. Ratio of future over past values of Kaya' s variables in the three scenarios (BAU, 450 ppm and 550 ppm).

WORLD

2032 vs 2002	∆ EMI	∆ GDP/POP	∆ EN/GDP	∆ EMI/EN	∆ POP
BAU	1.94	1.92	0.74	1.04	1.31
550	1.28	1.91	0.61	0.84	1.31
450	0.86	1.89	0.49	0.70	1.31

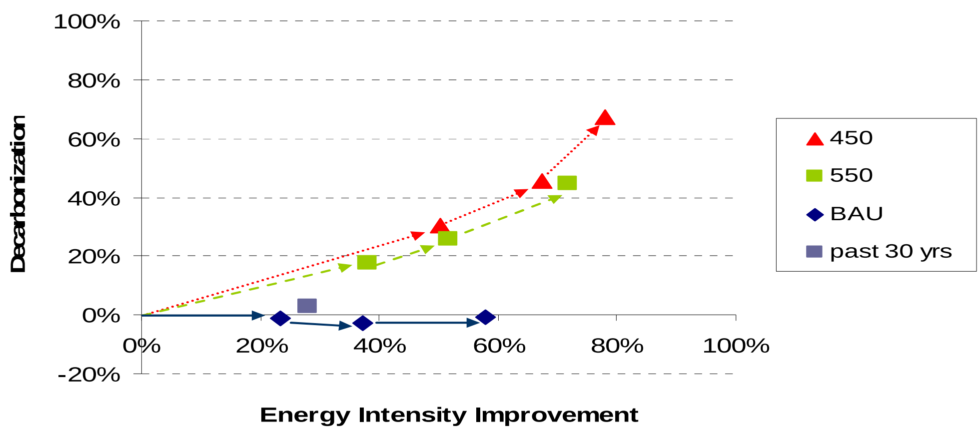
2002 vs 1972	∆ EMI	∆ GDP/POP	∆ EN/GDP	∆ EMI/EN	∆ POP
Historical	1.96	1.64	0.76	0.97	1.63

In the 550 ppm scenario, lesser growth in emissions stems mainly from energy efficiency improvements as testified by the decrease of energy intensity (∆ EN/GDP column), although some de-carbonization of energy is also needed. A more fundamental change is required in the 450 ppm scenario. Keeping carbon concentrations below this target can be achieved only if both energy intensity and carbon content of energy are significantly decreased.

Figure 2 provides some additional interesting information on the modifications required in the energy sector, as it plots the evolution of energy intensity and carbon intensity of energy in 2030, 2050 and 2100. The BaU scenario is characterized by an improvement of energy intensity, even though slightly less pronounced than the historical one. It also shows a slight carbonization of energy over the century: although small, this effect reflects the increasing share of coal in the energy mix in the absence of climate policy (this is also consistent with the Energy Information Agency's medium term projections; see EIA, 2007). This increase is mostly driven by the growing energy consumption of developing countries. Coming to the stabilization scenarios, they both show energy efficiency measures to be the most relevant in the short-term, but both call for the development of low carbon options in the long-term, especially for the more stringent 450 stabilization target.

The dynamic paths of energy intensity and carbon intensity of energy implied by the two stabilization scenarios require drastic changes in the energy sector. The next section will analyze the equilibrium investment paths in different energy technologies over the next century. This will allow us to identify the welfare maximizing investment strategies that different regions of the world ought to implement to achieve the two stabilization targets.

Figure 2. Reductions of energy and carbon intensity in the next 30, 50 and 100 years, and over the past 30 years (changes w.r.t 2002)



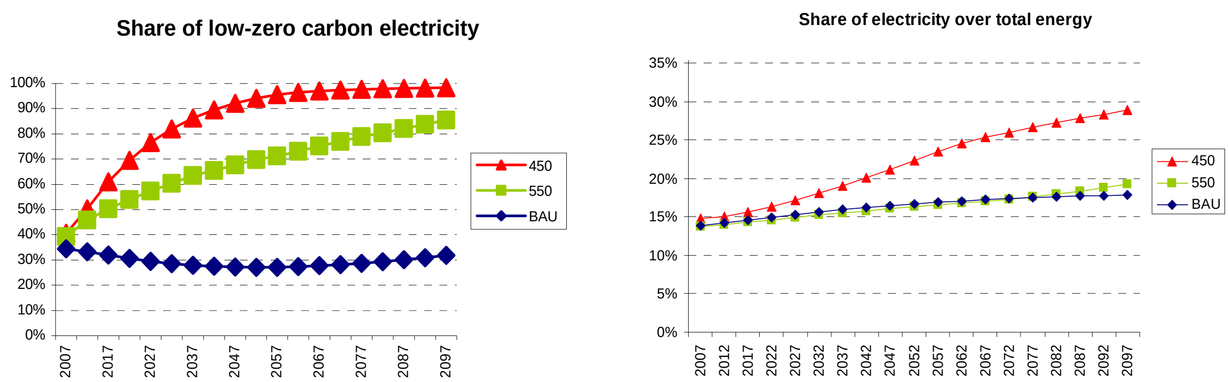
4. Equilibrium Mitigation Strategies with Known Energy Technologies.

The energy sector is characterized by long-lived capital. Therefore the investment strategies pursued in the next two/three decades will be crucial in determining the emissions pathways that will eventually emerge in the second half of the century. The previous section highlighted the urgent need for a new strategy in the energy sector, targeted to de-carbonize energy production. This can be done through the extensive deployment of currently known abatement technologies (Pacala and Socolow, 2004) and/or through the development of new energy technologies. Let us analyze the equilibrium investment mix and the related shares of existing and innovative technologies in the stabilization investment portfolio.

Emission reductions can be achieved by increasing energy efficiency and by reducing carbon intensity. As shown in Figure 2, energy efficiency improvements beyond the baseline scenario are the first essential option to endorse. Many economic sectors are characterized by the potential for large savings at relatively low costs. Yet, especially for ambitious emission reductions, energy efficiency improvements are not enough and energy de-carbonization is essential. Supply cost curves of abatement vary widely across sectors; for example they are believed to be especially steep in the transport sector. Power generation is comparatively more promising: it is a heavy weight sector in terms of emissions and one of the few for which alternative production technologies are available.

Not surprisingly, our scenarios show a significant contribution of electricity in mitigation, as illustrated by Figure 3. To optimally achieve a 450 ppm concentration target, almost all electricity (around 90%) will have to be generated at low, almost zero, carbon rates by 2050 (left panel). The milder 550 target allows a more gradual transition away from fossil fuel based electricity, but nonetheless shows a noticeable departure from the no climate policy BAU scenario. The role of electricity is strengthened by its growing share with respect to primary energy supply. The substitution towards electricity is especially important for the more stringent 450 scenario (Figure 3, right panel), since it makes it possible to meet the strong emissions cuts needed in the traditional non-electric sector. Such a radical change is achieved through three already operational technologies[4]: nuclear energy, renewable sources (wind & solar) and carbon capture and sequestration (CCS) (see Figure 4 that shows the power generation shares for the 550 (left) and 450 (right) scenarios.).

Figure 3. The role of electricity in mitigation

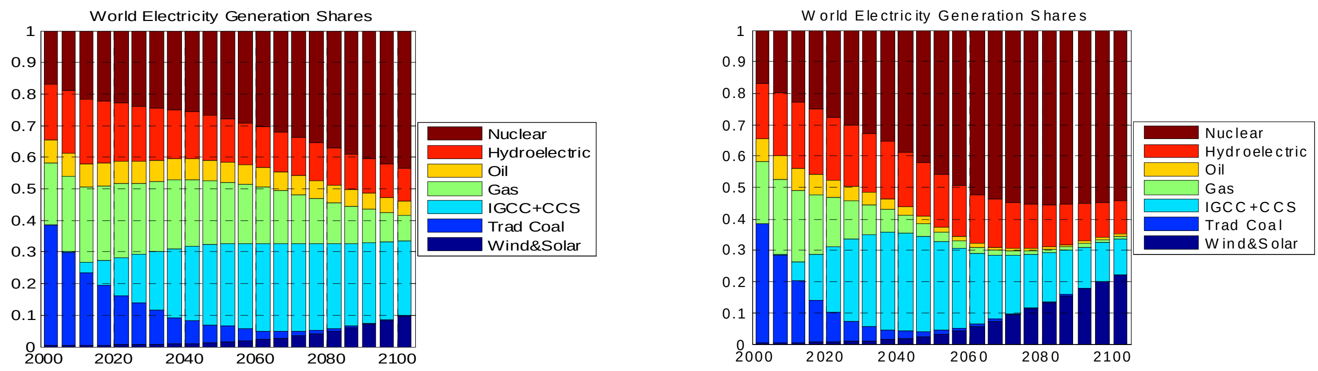


Nuclear power becomes extremely competitive given the range of carbon prices implicit in the adoption of climate policy, especially for the 450 case, where it eventually guarantees about 50% of total electricity generation. This remarkable expansion requires a 10-fold increase in present generation capacity. Twenty or more 1GigaWatt (GW) nuclear plants would need to be built each year in the next half century, bringing the nuclear industry back to the construction rates of the 1980s. Clearly, this gigantic capacity deployment for such a contentious technology would raise significant social and environmental concerns, to the point that the feasibility of a nuclear-based scenario would ultimately rest on the capacity to radically innovate the technology itself, as well as on the institutions controlling its global use.

[4] Although for carbon capture and sequestration only pilot projects are in place at the present moment, the technology has been operating on a smaller scale for enhanced oil recovery for a long time now.

Renewable energies, especially wind power, have developed at an impressive rate in recent years (up to 10GW per year), but the limited annual operating hours and costs bind their potential electricity contribution, at least in the short run. Only later in time would capacity additions reach 30 GW per year - especially via solar power - and be able to significantly contribute to the de-carbonization of the power sector.

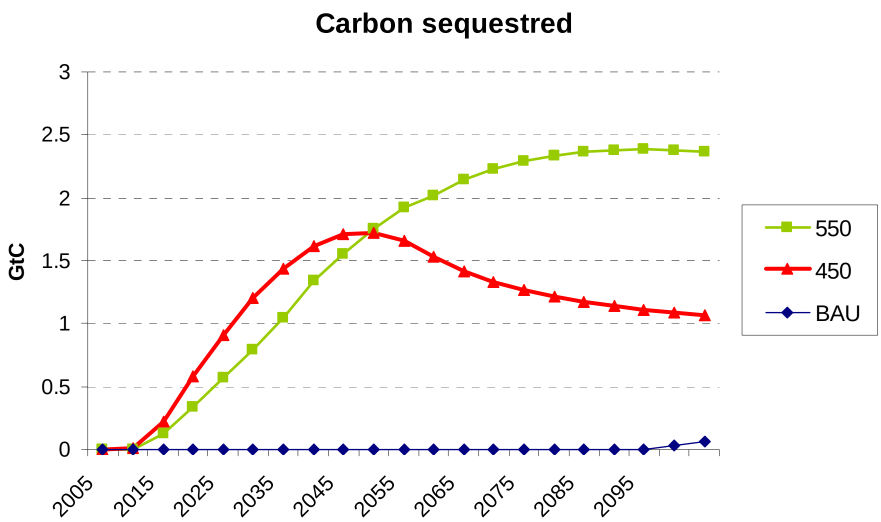
Figure 4. Power generation shares for the 550 (left) and 450 (right) scenarios.



Carbon capture and sequestration (CCS) makes it possible to burn coal in power plants while massively reducing carbon emissions. The decoupling of coal use and carbon emissions is particularly important for regions with a large endowment of coal reserves and because coal-fired power plants are very attractive for energy security reasons. However, the necessary investments are very large. To achieve the 550 ppm target, between 30 and 40 1GW coal-with-CCS power plants would need to be built each year from 2015 onwards, a value in line with the historical capacity building of traditional coal plants (roughly 50% of electricity generated in the world). A number of large-scale pilot plants should thus be put into place in the next ten years to ensure the feasibility of such a massive deployment.

Figure 5 further elaborates on the role of CCS. The optimal amount of injected carbon is shown to be significant: about 2 GtC/yr (about 1/4 of today's emissions) are stored underground by mid century. Over the whole century, about 150GtC are injected in underground deposits (a figure in line also with the IPCC 4AR WGIII). However, in the 450 scenario, the use of this technology decreases after 2050. The reason is that a more stringent target calls for a relatively greater deployment of very low carbon technologies; renewable energies and nuclear power are thus progressively preferred to CCS, because they have lower emission factors[5]. Advances in the capacity to capture CO_2 at the plant (assumed at 90%) would increase CCS competitiveness; though this could be counterbalanced by potential leakage from reservoirs (our simulations show that leakage rates of 0.5% per year would jeopardize the deployment of this technology).

Figure 5. CCS



Summing up, an equilibrium investment strategy in the energy sector that can achieve the two stabilization targets at reasonable economic costs (about 2.1% of global GDP in the 450 ppm case, see Section 5) exists. This energy investment strategy is based on the massive deployment of existing technologies (nuclear, solar and coal+CCS). It requires huge investments and urgent decisions. In the next section, we will explore how the potential availability of new energy technologies, developed through adequate R&D expenditures, can modify the investment scenario in the energy sector.

4. Innovation Strategies for Energy Efficiency and Technology Breakthrough.

The previous section has outlined the need for a profound transformation of the energy sector, particularly if an ambitious climate target is to be achieved. Massive deployment of technologies that are controversial, such as nuclear power, or whose reliability and affordability is still to be

[5] A coal+CCS power plant emits roughly 1/3 of a natural gas one. Constraining the potential deployment of nuclear and renewables would offset this effect, since the power sector would have fewer options. A similar effect would result from the deployment of very low carbon options in the non-electric sector, since it would alleviate the mitigation effort required from the power sector, as shown in Section 4.

proved, such as CCS, indicate that currently known technologies alone might not suffice, especially in the mid- to long- term, and that the simultaneous achievement of global economic and environmental wellbeing is likely to ultimately rest on our ability to produce innovation. This is especially important for sectors that, at present, have a restricted portfolio of abatement options, such as transport. It is also important in case some of the mitigation alternatives described in the previous section do not deliver their expected abatement potential.

The technology and innovation features of the WITCH model allow us to devise the optimal combination of investments in currently available technologies and in R&D to bring about the technology advancement needed for both energy efficiency improvements and de-carbonization. WITCH features separate R&D investments for energy efficiency enhancements and for the development of breakthrough technologies in both the electric and non-electric sector. We can therefore compute the equilibrium R&D investments that countries need to implement to achieve the required improvements in energy efficiency and timely market penetration for new carbon free energy technologies. We refer to these technologies as “backstops”. They substitute nuclear power for power generation and oil in the non-electric sector. For a complete description, see the Appendix.

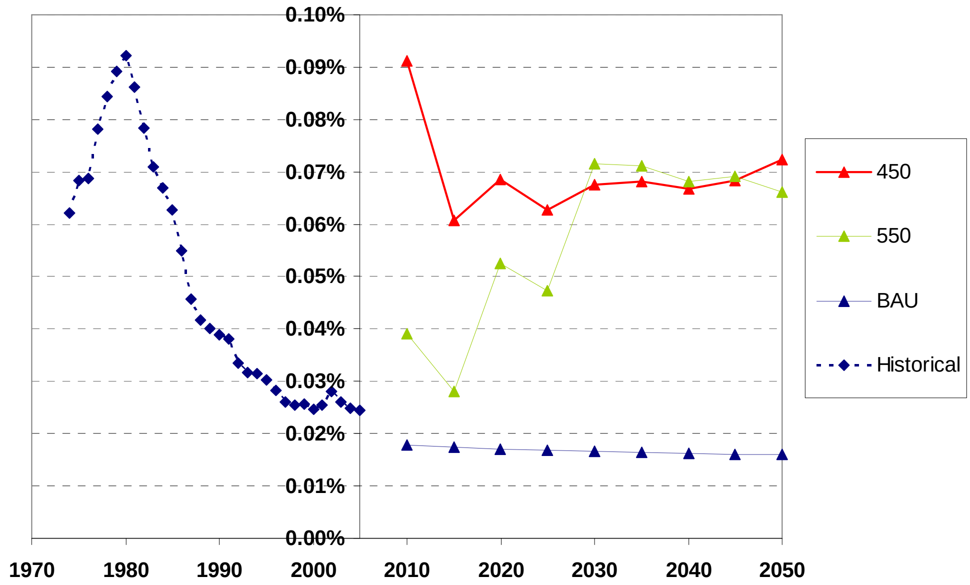
Figure 6 shows global public energy R&D expenditures. In the left-hand panel, we plot historical investment in R&D as share of Gross World Product (GWP); in the right-hand panel we plot optimal R&D investment in the three scenarios being examined. Historic data shows the well known decline in public expenditure for energy related R&D after the 1980 peak caused by the oil crises. Very low oil prices in the 1990s led to cuts in public expenditure, which have yet to regain momentum despite the oil price surge of the past few years. A very different picture of future R&D investments emerges from the two scenarios considered here. While the baseline scenario foresees low and stable investments in R&D, both climate policy scenarios require a significant innovation effort.

For the 450 ppm case, energy expenditures ramp up to roughly 0.07% of GDP, the same share that prevailed in the 1980s. The public sector would thus be required to invest roughly 40-50 billion USD per year, globally, in the years to come; given the long time lags that separate research from commercialization, the innovation effort must be carried out immediately to allow for innovative technologies to become competitive in the medium term[6]. It should be pointed out that such investment inflow, although sizeable, is two to three orders of magnitude smaller than the investments needed to de-carbonize the energy sector using already existing technologies. The strategy based on R&D investments can thus be thought of as a hedging policy.

[6] We assume that a ten-year lag time is necessary for R&D investments to bring cost reductions in backstops. See the Appendix for more details.

The less stringent 550 ppm scenario shows a more gradual innovation pathway, with expenditure rising over time to eventually reach figures similar to those in the 450 ppm scenario, only with a 20-year delay.

Figure 6. Public Energy R&D Investments across scenarios to 2050



A key policy question is where such public R&D investments should be directed to. Table 2 shows the optimal allocation of R&D investment between energy efficiency and de-carbonization programs, in both the electric and non-electric sectors, for the 450 scenario.

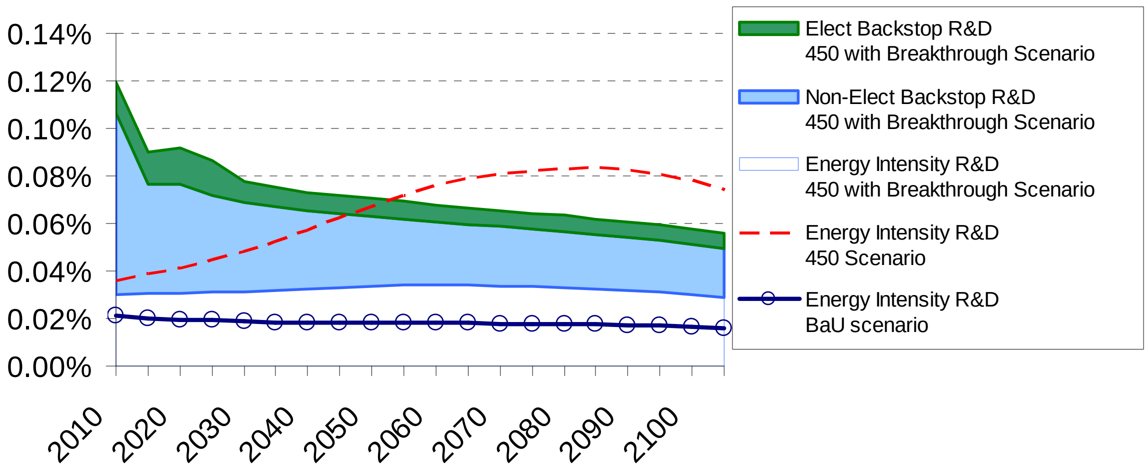
Table 2. Destination of R&D expenditure in a 450 scenario

	2010	**2030**	**2050**
Energy Efficiency	25%	40%	48%
Low carbon innovation in non-electric sector	64%	48%	42%
Low carbon innovation in power generation	11%	12%	12%

It shows that the non-electric sector, particularly to substitute the transport-led non-electric oil demand, should receive most of the innovation funding initially, though over time energy efficiency innovation expenditure increases its relevance and eventually takes the lead (in 2050).

The power sector is allocated a smaller but constant share. This shift in the timing is due to the very nature of investment in breakthrough technologies: a flow of investments in specific R&D is needed to continue improving energy efficiency, which exhibits decreasing marginal returns. On the other hand, investing in backstop R&D builds a stock which decreases the costs of the technology with very high returns at the beginning. Once the technology becomes available and economically competitive, then investing in backstop R&D becomes less important as a channel to decrease the price of the backstop technology. In other words, R&D in energy efficiency does not have a permanent effect, while R&D in backstop does. Note also that R&D investment in backstops substitute part of the energy efficiency R&D when the 450ppm stabilization target is to be achieved without the aid of the backstop technologies, though investments in the backstop technologies remain higher than in the BaU (see Figure 7).

Figure 7. Energy R&D Investments/GDP for BaU and 450 scenarios with and without the possibility of breakthrough innovation.



The possibility of technology breakthroughs in the electricity sector also has an effect on the optimal investments in already known technologies. For example, investments in CCS are crucially affected by the presence of backstop technologies. In the 450 scenario, CCS investment no longer displays the peak effect observed in Figure 5. The reason for this is the presence of a carbon free backstop in the non-electric sector: it relieves the electricity sector from an excessive mitigation burden, which jeopardized CCS in the long run due to the non-perfect capture rate of carbon.

5. Economic Impacts of Different Technological Scenarios

The previous sections have illustrated the need for drastic changes in the way we consume and produce energy. They highlighted the need to mobilize substantial investment resources towards carbon free technologies. This is likely to have important implications for the economic system. In this section, we summarize the economic impact of both 550 ppm and 450 ppm stabilization scenarios, with a particular focus on the role played by energy technologies.

Table 3 shows net present value losses of GWP for both climate policy scenarios and different technology settings[7]. The reference case shows how, in the 550 ppm scenario, costs are almost negligible, whereas they are significant in the 450 ppm case. The cost difference between the two mitigation policies is a direct consequence of the different magnitudes of energy sector modifications required. It also stems from the non-linearity of endogenous marginal abatement curves in the model. The 450 ppm policy requires drastic cuts in emissions, especially in the second half of the century, when emissions are stabilized at around 3GtC/yr. With growing economies and population, this entails a significant increase in energy costs, particularly as mitigation gets more and more stringent. The effect of temporal discounting is partially compensated by the growing dimension of economic activity.

Table 3. Total costs of stabilization (Net present value, percent of GWP losses at 5% constant discount rate).

	550 ppm	450ppm
Reference case	0.27%	2.1%
Limited power technologies	1.08%	3.6%
Breakthrough innovation	0.22%	1.1%

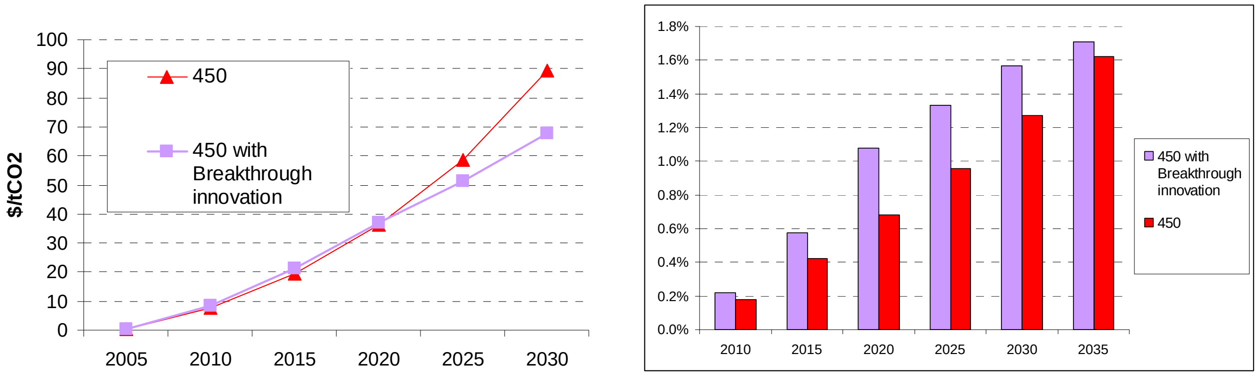
[7] The numbers shown include the avoided climate damages induced by the policies. However, the NPV calculations at 5% put most of the weight on early periods for which almost no temperature decrease is achieved, so that gross economic losses are only 10-20% above the ones indicated here.

The economic effect of limiting the power sector technologies described in Section 3 is shown in the second row. Indeed, if we assume a world in which the expansion of wind and solar technologies is bound by limits to large scale deployment, the options to expand nuclear energy are limited (possibly because of political or environmental reasons) and IGCC+CCS technologies do not become competitive[8], then achieving a stabilization target is much more costly, with an increase in the order of 1.5 to 3 times. On the other hand, allowing for R&D investments in new low carbon technologies, that would enable breakthrough innovation, is shown to be able to substantially reduce the economic policy costs. These differences are particularly important for the stringent 450 ppm target, which requires a fundamental restructuring of the energy sector.

However different these scenarios may be, it should be noted that, in the short term, a strong carbon price signal would be needed to bring about what could be called a technology revolution. As shown in Figure 8, left panel[9], the carbon signal of a reference 450 scenario is very similar to that of the most optimistic case of breakthrough inventions.

Higher GWP losses will be experienced initially in the breakthrough technologies case (right panel) in order to make R&D resources available, but this would pay off in the future allowing for the substantial cost reductions shown in Table 3.

Figure 8. Carbon price (left) and GWP loss (right) for a 450 scenario with and without the possibility of breakthrough innovation.



6. Conclusions

This paper has investigated optimal investment strategies in the energy sector for two climate policy scenarios. Our results show that the stabilization of CO_2 concentrations at 550 and 450 ppm

[8] The specific constraints used are: nuclear energy cannot expand above current generation levels, CCS is not allowed; W&S can provide at most 35% of total electricity.
[9] The carbon prices displayed assume full country participation to an international carbon market; in case of fragmented agreements, they would rise very significantly.

(650 and 550 CO_2 equivalent) is feasible at reasonable economic costs, but that it requires radical changes in the energy sector and large investments in R&D.

Both energy efficiency and the de-carbonization of energy should be pursued. Currently known technologies in the power sector such as nuclear, renewables and CCS will be essential, but very large investments – greater than the energy sector has ever experienced – will be needed. At the same time, R&D investments for the development of new technologies, especially in the transport sector, will be required. Public R&D expenditures should increase considerably, over the peak levels of the 1980s for at least 3 decades. Given the long time lags inherent to the innovation process, such investments should be made starting today.

Our results thus support the call for R&D policies that complement climate stabilization policies and reduce the costs of limiting dangerous climate change. They also indicate that a strong price signal will nonetheless be needed if the climate change challenge is to be met, regardless of whether we expect low carbon breakthrough technologies to be available in the future, because of the inertia in the accumulation of GHGs in the atmosphere and low decay rates.

Substantial economic resources should be mobilized to attain the climate protection goal. This will impose economic costs on societies around the world, the magnitude of which will depend on the stringency of the target, and on the availability of commercial and non-commercial technologies.

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Uncertain R&D, backstop technology and GHGs stabilization☆

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ABSTRACT

This paper analyses optimal investments in innovation when dealing with a stringent climate target and with the uncertain effectiveness of R&D. The innovation needed to achieve the deep cut in emissions is modeled by a backstop carbon-free technology whose cost depends on R&D investments. To better represent the process of technological progress, we assume that R&D effectiveness is uncertain. By means of a simple analytical model, we show how accounting for the uncertainty that characterizes technological advancement yields higher investments in innovation and lower policy costs. We then confirm the results via a numerical analysis performed with a stochastic version of WITCH, an energy–economy–climate model. The results stress the importance of a correct specification of the technological change process in economy–climate models.

1. Introduction

Technological change is an uncertain phenomenon. In its most thriving form, ground-breaking innovation is so unpredictable that any attempt to model the uncertain processes that govern it is close to impossible. Despite the complexities, research dealing with long-term processes, such as climate change, would largely benefit from incorporating the uncertainty of technological advance. Yet, bringing uncertainty into models has proved particularly difficult, especially with regards to technological change, see Clarke and Weyant (2002).

On a more general level, the challenge of modelling endogenous technological change in all its features, including randomness, becomes increasingly important when dealing with the analysis of stringent climate targets. Many energy–economy models have been used to perform cost effectiveness of climate policies. Not surprisingly, the related literature has produced a dispersed range of costs estimates for these policies, resting on the different formulations and assumptions that stand behind each model. Nonetheless, one core fact upon which everyone seems to agree is the role of technological change in shaping those costs, see for example the summary of an updated modeling comparison exercise on innovation in Grubb et al. (2006).

The recognition of the relevance of this issue has led researchers to model technological change as an endogenous process, although typically in a deterministic fashion. The existing literature accounting for uncertainty has mostly concentrated on the uncertainty affecting climate damages and abatement costs, as well as other parameters, such as the discount factor. Within this framework, few studies have looked at the consequences of *uncertainty on innovation*. In particular, Baker et al. (2006a) investigate the effects of climate uncertainty on R&D investments, to verify whether innovation serves as a hedge against uncertainty, but find no unambiguous answer: optimal R&D might increase or decrease with uncertainty depending on a variety of factors regarding the specification of technological change and uncertainty.

However, as noted above, little focus has been devoted to the analysis of the intrinsic *uncertainty of innovation*, and how uncertainty might change results and policy recommendations. Baker and Adu-Bonnah (2008) is the only case to our knowledge that tackles this issue in the context of climate change.[1] They analyze how optimal R&D investments change with the risk-profile of the R&D program and with climate uncertainty. They differentiate between two types of technologies, and find that technological specification and climate damages are key in the role played by uncertainty.

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[1] 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.

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The current paper delves into the issue of uncertain technological progress when a climate obligation is in place. In particular, we seek to analyze different optimal responses in terms of investments and climate policy costs when we model innovation as a backstop technology characterized by either a deterministic or an uncertain process. To this scope, we first develop a simple analytical model. Then, we augment the hybrid integrated assessment model WITCH, introduced in Bosetti et al. (2006), to incorporate a carbon-free backstop technology whose cost is currently not competitive but can be lowered by investing in innovation in the form of R&D. The R&D outcome is modeled as uncertain, and we thus devise a stochastic version of the model to account for this effect. We restrict our analysis to a climate policy of 450 ppmv CO_2 only (i.e. roughly 550 CO_2e) stabilization.

Both our analytical and numerical results show how accounting for the uncertainty of technological advancement yields higher investments in innovation aimed to decrease the abatement costs via a backstop technology. The analytical set-up provides an unequivocal relation between the uncertainty and innovation effort, and the richness of the numerical model a thorough representation of the impacts in terms of technological change. The findings of this paper stress the importance of a correct specification of technological change in economy–climate models when assessing the optimal level of R&D investments as well as the cost of a climate policy. Our results are in line with Baker and Adu-Bonnah (2008), although in our case the results are independent of the climate target.

The paper is structured as follows: in the next section we devise a simple toy model, and present the first analytical insights. Section 3 deals with the implementation of uncertain technological change in the WITCH model, and shows the numerical results. Section 4 concludes.

2. A simple model of uncertain innovation

To analyze the issue of uncertain innovation we introduce a simple analytical model. We use a two-period, two-technology model where the social planner minimizes costs but needs to achieve a given environmental target. We resort to such a standard framework to ensure an analogy with the climate change policies costs effectiveness studies of numerical models, such as those presented in the second part of the paper. Although less realistic than the numerical counterpart, such a framework mimics the most essential features of the numerical analysis and can thus provide a useful generalization of the problem.

Given a target level of abatement to be undertaken during the second period, the planner can choose a combination of two carbon-free technologies: a traditional technology (say nuclear fission) and an advanced, backstop technology (say nuclear fusion). Abatement costs with the backstop technology are initially higher than with the traditional one, but can be reduced by investing in R&D during the first period. We introduce uncertainty by modeling the R&D outcome on the abatement cost of the backstop technology as uncertain: the innovation effort leads to a central value reduction in abatement costs with a given probability p, and to lower and higher abatement costs states with probability $\frac{(1-p)}{2}$, respectively. The high cost state represents the failure of the R&D program: abatement costs are not reduced by the innovation effort, and remain higher than the traditional carbon-free technology costs for any level of abatement. In this case, the planner chooses not to operate the backstop technology, because it is too costly, and resorts to the, cheaper, traditional technology. The low cost state represents a greater than expected success of the R&D program: backstop technology costs are always lower than in the central case, the lower the costs the higher the abatement pursued with the advanced technology.

The objective of the social planner is to choose the optimal level of investment in innovation, together with abatement shares in both traditional and backstop technologies, such that expected total costs are minimized subject to a given level of abatement. Formally:

$$\min_{I} C(I) + E_w\left[\min_{\mu_T,\mu_B}(C_T(\mu_T)) + C(\mu_B, I, w)\right] \text{ s.t. } \mu_T + \mu_B = \bar{\mu} \quad \mu_T, \mu_B, I \geq 0 \tag{1}$$

where I, μ_T, μ_B are respectively the innovation effort (i.e. investment in R&D) and the abatement in the traditional and backstop technologies. C, C_T, C_B are the respective cost functions. w represents the uncertain effectiveness of R&D. $\bar{\mu}$ is the exogenously set abatement target.

This formulation requires that the abatement cost functions using the two technologies are separable. That is, we assume that an amount of abatement undertaken using one technology doesn't affect the costs of abatement using the other technology. Although this assumption is often violated in real world application, where technologies develop around common technological clusters, we retain it here as we model the two abatement technologies as belonging to very different classes, e.g. concentrated base load providers such nuclear or CCS on one side, and smaller scale intermittent renewables on the other.

To simplify the problem, let's assume the backstop technology takes value $C_B(\mu_B, I)$ with probability p, while with probability $\frac{1-p}{2}$ R&D is more effective and backstop costs are lower than expected (and equal to $C_B^L(\mu_B^L, I)$). In the remaining $\frac{1-p}{2}$ cases, R&D fails, and the costs of backstop technology are not modified by innovation (and are equal to $C_B^H(\mu_B^H)$). As stated earlier, the main scope of our analysis is to compare the certain formulation (case where $p=1$) vis à vis the most uncertain one (case where $p=0$). In order to make these two cases equivalent, we equate the central case cost function to the mean between the high and low case, i.e. we set:

$$C_B(\mu_B, I) = \frac{1}{2}C_B^H(\mu_B) + \frac{1}{2}C_B^L(\mu_B, I) \tag{2}$$

The problem can thus be restated as follows:

$$\min_{I}\left\{\begin{aligned} & C(I) + p\min_{\mu_T^C,\mu_B^C}\left[C_T(\mu_T) + C_B^C(\mu_B^C, I)\right] \\ & + \frac{1-p}{2}\min_{\mu_T^L,\mu_B^L}\left[C_T(\mu_T^L) + C_B^L(\mu_B^L, I)\right] \\ & + \frac{1-p}{2}\min_{\mu_T^H,\mu_B^H}\left[C_T(\mu_T^H) + C_B^H(\mu_B^H)\right] \end{aligned}\right\} \tag{3}$$

$$\text{s.t. } \mu_T^i + \mu_B^i = \bar{\mu} \quad \mu_T^i, \mu_B^i, I \geq 0 \quad i = C, L, H$$

Solving the problem backward and labeling with * the optimal values for the abatement shares in the two technologies, we can simplify our expression in the following way:

$$\min_{I}\left\{\begin{aligned} & C(I) + p\left[C_T(\mu_T^{C*}) + C_B(\mu_B^{C*}, I)\right] \\ & + \frac{1-p}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I\right)\right] \\ & + \frac{1-p}{2}C_T(\bar{\mu}) \end{aligned}\right\} \tag{4}$$

$$\text{s.t. } \mu_T^i + \mu_B^i = \bar{\mu} \quad \mu_T^i, \mu_B^i, I \geq 0 \quad i = C, L$$

where the third term in brackets, the optimal cost in the case the R&D program fails, is the cost of traditional technology only, i.e. $C_T(\mu_T^H) + C_B^H(\mu_B^H) = C_T(\bar{\mu})$.

One of the questions we are interested in tackling with this set-up is the effect of uncertainty on the costs of meeting the environmental obligation. For example, we might wonder whether knowing that R&D will make the backstop technology either extremely competitive or totally ineffective affects the costs of reducing carbon emissions with respect to the case of certain average innovation effectiveness. The following result clarifies this issue.

Result 1. *We find that while the abatement costs using the backstop technology in the central case are equal to the average of the low and high R&D effectiveness cases (Eq.* (2)*), the total costs of meeting the environmental target are higher for the central certain case*. For the algebra underlying this result, we refer the reader to Appendix A. This result suggests that R&D programmes with high/low payoffs are preferable whenever an alternative, less advanced, abating technology is available to limit the downside of R&D failure.

A second issue we seek to investigate is the effect of uncertainty on the behavior of investments in R&D, i.e. we ask ourselves what is the sign of $\frac{dI^*}{dp}$. If $\frac{dI^*}{dp}<0$ then we have that R&D investments increase with uncertainty. This would imply that modeling R&D as having an uncertain outcome, a fact often believed to be the case, would yield a share of innovation higher than if uncertainty were neglected. In Appendix B we prove that investigating the sign of $\frac{dI^*}{dp}$ coincides with comparing marginal benefits of innovation for different levels of abatement:

$$\mathrm{MB}^C\left(\mu_B^{C*}\right)-MB^C\left(\mu_B^{L*}\right)\lesseqgtr 0?$$

where MB stands for the reduction in abatement cost using the backstop technology as a result of a marginal dollar spent on innovation.[2]

The equation compares the marginal benefit of innovation in the central case computed for levels of abatement resulting from the central and low cost cases, μ_B^* and μ_B^{L*}; its sign depends on how the marginal benefit of R&D changes with the level of abatement. In this paper we restrict our attention to the case of innovation lowering the marginal abatement costs for every level of abatement.[3] Thus, marginal benefits weakly increase with abatement. Therefore, since abatement in the low case is always higher than (or at least equal to) the abatement in the central case ($\mu_B^{L*} \geq \mu_B^{C*}$), we find that $\frac{dI^*}{dp} \leq 0$, which leads us to the second result.

Result 2. *We assume that marginal benefits of innovation increase with abatement using the backstop technology. Then, for interior solutions for the abatement variables, investments in innovation increase with uncertainty*. Conversely, innovation is uninfluenced by uncertainty for the case $\mu_B^{L*}=\mu_B^{C*}=\overline{\mu}$, the corner solution implying that the traditional technology is never employed when innovation is productive. In addition, this latter result also holds when marginal benefits of innovation are constant with abatement, for example when innovation shifts down the abatement curve by a constant.

Ruling out the last two special cases, the intuition for the result is the following. Let us concentrate on the two extreme cases of zero uncertainty, i.e. the central case is always achieved ($p=1$), and full uncertainty, i.e. R&D has either full success or full failure with 50% chance each ($p=0$). Choosing the optimal level of R&D investments implies equating the marginal costs of generating innovation with the marginal benefits of decreasing the abatement costs. When confronting the two cases, we should compare the marginal benefits of innovation for the central value (zero uncertainty) and low value (full uncertainty). The latter has half the chances of occurring, but marginal benefits are by construction twice those of the central case, so that the fraction due to the probability cancels out. However, since the share of abatement using the backstop technology is higher in the low cost case and assuming that marginal benefits increase with the level of abatement, marginal benefits of innovation are higher with full uncertainty than with no uncertainty. That is, innovation is more productive when its outcome is explicitly modelled as uncertain.

How does this finding translate into real life considerations? First, one has to bear in mind that the social planner can pick from a variety of technologies to achieve an environmental target, say, to reduce CO_2 emissions. Investing in R&D is a risky procedure. However, if it fails existing technologies would be able to limit the costs of abatement, whereas if it is successful, the benefits would be higher than would have been in the central case. This payoff asymmetry is such that the upside of super productive innovation outweighs the downside of failure. Hence, in the presence of innovative technologies, a risk-neutral planner would choose to invest more when R&D outcome is uncertain.

Our set-up and results are similar to those in Baker and Adu-Bonnah (2008). They too find that the relation between uncertainty and innovation depends on whether marginal benefits of R&D increase or decrease with the level of abatement. Even though the sign of this relationship is in principle ambiguous, this ambiguity depends on what technology is under consideration (see Baker et al. (2006b)). R&D aimed at cleaner and more efficient carbon technologies has increasing marginal benefits for moderate emissions reductions; however, this positive effect decreases and eventually drops to zero as the game gets tougher and stringent emission reductions have to be met. A different story holds for carbon-free technologies, where the effect of R&D is that of lowering the marginal cost curves for *any level of abatement*. So the issue of ambiguity in the sign could be interpreted more practically as: what type of technologies is technical change affecting in the model? When large emission cuts are at stake, carbon technologies have a lower margin for efficient improvement than carbon-free technologies (i.e. nuclear, renewables, carbon-free backstop) which would play a major role. In this case marginal benefits of innovation are increasing with the level of abatement. Conversely, in the case of moderate climate policy, efficiency improvement would play a relevant role. But again, in this case marginal benefits of innovation would hardly decrease in the range of abatement under consideration, given the small mitigation effort required. This argument justifies the increasing marginal benefits assumption that is behind our results.[4]

In contrast with Baker and Adu-Bonnah (2008), our result is independent of how stringent the climate target might be. Since the productivity gain from the low cost case is always twice that of the central case, the upside of an uncertain program outweighs the downside, notwithstanding the level of abatement. In the limit case when abatement is totally achieved by the backstop technology in both central and low cost cases, then uncertainty would not affect the optimal choice of R&D.

3. Numerical analysis

In this section we turn to the numerical analysis of the model. In order to investigate the role of uncertain technological change, we devise a version of the energy–economy–climate model WITCH featuring an R&D-driven carbon-free backstop technology. Innovation can lower the price of this otherwise non-competitive technology, but it is modeled in a stochastic setting in order to account for the uncertainty of the R&D outcome. We first introduce the backstop technology sector and then discuss numerical results for different simulation experiments.

3.1. Uncertain backstop technology in WITCH

WITCH—World Induced Technical Change Hybrid model—is an integrated assessment model for the analysis of climate change and energy issues. For a detailed description of the model see Bosetti et al.

[2] The traditional technology is eliminated from the marginal analysis for the Envelope Theorem since it is not affected by the innovation in the backstop technology as noted in the above discussion on the abatement cost functions separability. We thank an anonymous referee for clarifying this issue.

[3] This directly follows from the choice of investigating R&D efforts reducing the costs of a backstop, carbon-free, technology, as discussed in detail later in the paper.

[4] Mathematically, innovation shifting down abatement curve ensures that the value function of the minimization problem is convex in the shift. Thus, the cost asymmetry inequality shown in Eq. (10) holds because of Jensen inequality. We thank an anonymous referee for this remark.

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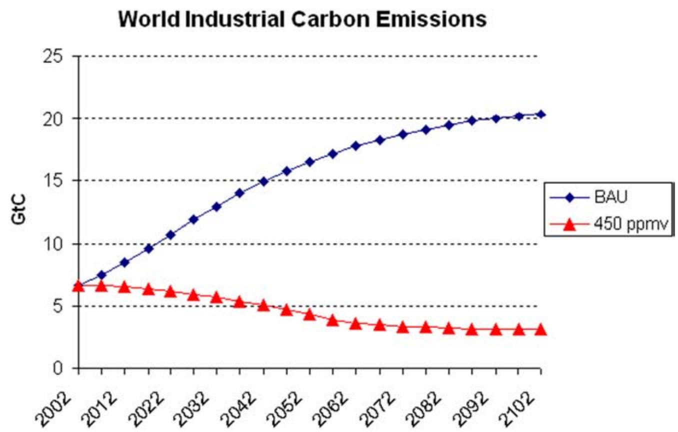

Fig. 1. CO_2 emissions in the BAU and 450 ppmv cases.

(2006, 2007). It is a regional model featuring an inter-temporal optimal growth top-down part that is hard linked with a bottom-up description of the energy sector. The energy sector is described by nested constant elasticity of substitution functions which describe the transformation of primary energy carriers into final energy services. World regions strategically interact in a game theoretic set-up by playing an open-loop Nash game on global externalities. Technological change is endogenous and acts both via energy efficiency R&D and learning-by-doing in power capacity. The model is solved numerically with GAMS/CONOPT.

The non-cooperative baseline predicts global CO_2 emissions to reach around 20 GtC by 2100, a figure in line with IPCC B2 SRES scenarios. These figures show how the free-riding incentives that characterize global stock externalities such as CO_2 make it difficult to achieve substantial emission reduction in a cost benefit analysis setting. Concerns over the risk of prolonged emissions put forward by climatologists and specialized bodies such as the IPCC justify the resort to cost effectiveness analysis of given climate goals. In this paper we focus on the specific target of stabilizing atmospheric CO_2 concentration to 450 ppmv (550 ppmv CO_2 equivalent) by 2100, a target probabilistically associated with that of maintaining within 2 °C the global temperature increase above pre-industrial level within the century.

As evident from Fig. 1, a climate policy of this kind entails significant emission reductions: for example, an emission path respecting the 450 ppmv target would curb emissions by 50% in 2030, and up to 85% by the end of the century. Such a scenario is clearly challenging, and will come at a cost in terms of economic growth, without adequate technological advancement.

For example, simulations using the WITCH model show that on the basis of currently existing technologies the stabilization effort would lead to a power generation mix such as the one shown in Fig. 2. Three technologies are believed to provide the low/zero carbon electricity indispensable in such a severe mitigation scenario. First, early deployment of advanced coal combined with CCS to achieve some of the needed reductions of emissions. Second, nuclear power that would become the predominant technology by mid-century, with almost half of the electricity share. Finally, renewables, expected to significantly contribute from the second half of the century. In

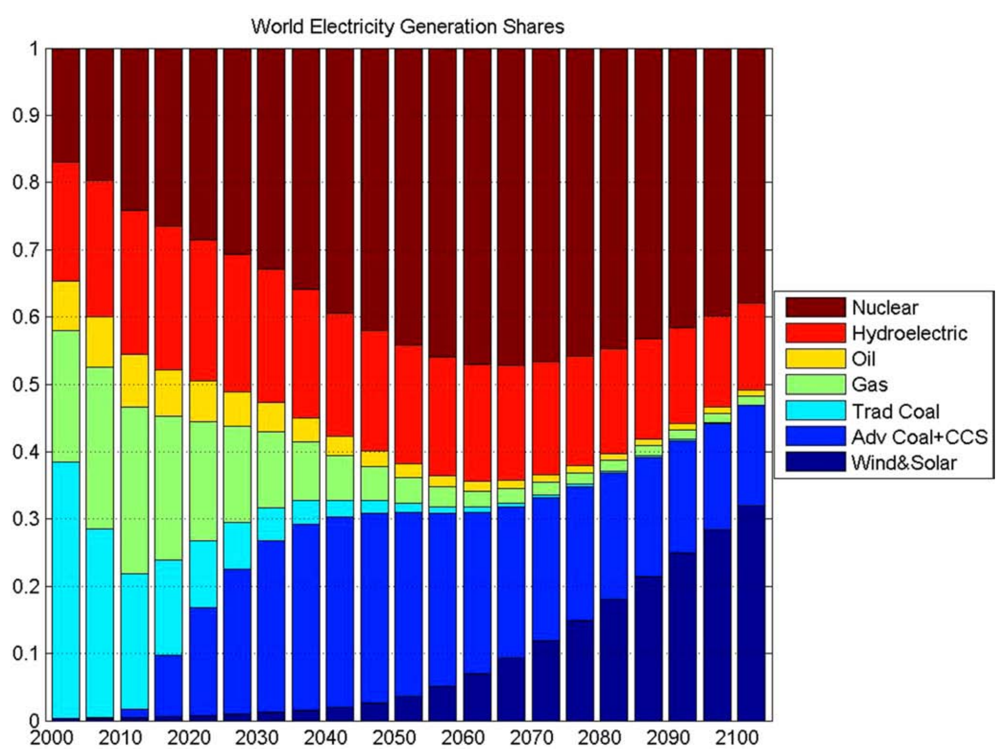

Fig. 2. Power generation shares in the 450 ppmv stabilization case. From top to bottom: nuclear, hydro, oil, gas, trad. coal, advanced coal + CCS, wind and solar.

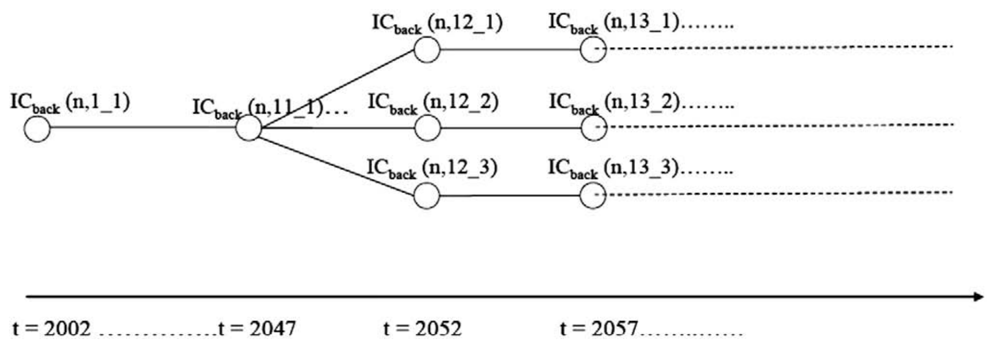

Fig. 3. Scenario tree in the stochastic version of WITCH. Variables, as IC$_{back}$ in this example, are redefined depending on nodes.

addition to this, given the comparatively greater difficulty in cutting emissions in the non-electricity sector, R&D-driven energy saving will also be indispensable.

A stabilization scenario of this kind appears ambitious, for a variety of reasons. First, it would imply considerable costs, quantifiable in a net present value output loss during this century of around 2% (at a constant discount rate of 5%). Second, current technologies face many constraints. A massive deployment of nuclear energy would entail increased waste management costs and proliferation risks: the lack of resolution of these problems—for instance through technological advances—means the scenario will be unlikely to develop. Similarly, the high land use demand of currently available renewables technologies in power generation, constitutes a serious challenge for the penetration target needed to stabilize at 450 ppmv. Unavoidably, any stringent stabilization scenario will call for innovation in non-carbon energy technologies. Future energy scenarios depending on such backstop technologies cannot be conceived without a focus on the crucial role of R&D investments as the main impulse fostering the required technological innovation.

We follow the lines of the toy model by introducing an R&D dependent backstop technology in WITCH. We model it as a power generation technology, that emits zero carbon per unit of electricity and is renewable in the sense that it doesn't rely on rapidly exhaustible natural resources. It could be thought of as a ground-breaking innovation such as fusion power, or more likely as a portfolio of advanced versions of technologies such as advanced solar power, new nuclear etc. We assume this representative technology to be currently uneconomical, but that its cost can be decreased by means of investments in innovation. This framework is coherent with the one used in the analytical model in the first part of the paper. The "traditional" nuclear power technology can be substituted by a cheaper (e.g. deployable on a larger scale) one, only if enough R&D investments are deployed.

Specifically, the investment cost for building a unit of power capacity ($/kW), IC$_{back}$, depends on cumulated R&D, KR&D$_{back}$, via a power formulation as follows[5]:

$$\mathrm{IC}_{\mathrm{back}}(n,t)=\frac{\mathrm{IC}_{\mathrm{back}}(n,0)}{(1+\mathrm{KR\&D}_{\mathrm{back}}(t,n))^{\eta}} \tag{5}$$

i.e. at time t, for region n, the investment cost decreases with the R&D capital depending on the learning parameter η.[6] The capital depreciates with rate δ and can be increased by investing in knowledge IR&D$_{back}$ through an innovation possibility frontier of this kind:

$$\begin{aligned}\mathrm{KR\&D}_{\mathrm{back}}(n,t+1)=&(1-\delta)\mathrm{KR\&D}_{\mathrm{back}}(n,t)\\&+a\mathrm{IR\&D}_{\mathrm{back}}(t,n)^{b}\mathrm{KR\&D}_{\mathrm{back}}(t,n)^{c}\end{aligned} \tag{6}$$

The presence of the stock in the possibility frontier ensures the "standing on shoulders" effect, and the exponents b and c sum up to less than one to model diminishing returns to research. Such a formulation has received empirical support for energy innovation by Popp (2004).

We assume that the backstop technology enters as a linear substitute of nuclear power in the energy sector nest; in this way we allow the new technology to displace the technology that most controversially contributed to carbon-free energy generation in the original formulation of the model; at the same time the nested CES structure of the electricity sector with higher than unity elasticities allows the phase out of all other power generation plants, although at a higher cost than would have otherwise happened assuming linear relations. To account for the industrialization lag that stands between research and commercialization, the backstop technology is assumed to be available from 2050 onwards only, even though we will test our result also for different entry periods.

Our primary interest in this paper is to analyze the effect of modeling uncertainty on the level of investments and on the costs of the policy. To account for this, we model the outcome of the R&D investments as uncertain: thus IC$_{back}(n,t,w)$ also depends on the state of the world, w. We assume that the effectiveness of R&D on decreasing the backstop costs can turn out to be either of the three following cases: in the "best" case (w=b) the investment cost of the backstop decreases with R&D as shown in Eq. (5); in the "failure" case (w=f) the investment cost of the backstop remains the same as the initial one, irrespective of the level of investments. This R&D failure case is equivalent to assume that the learning parameter η is equal to zero. Both these low and high cost states have the probability of occurring $\frac{1-p}{2}$ each. In the "central" case (w=c), with remaining p chances, the investment cost is the average of the two limit cases. To summarize:

$$\begin{aligned}\tfrac{1-p}{2}&:\mathrm{IC}_{\mathrm{back}}(n,t,b)=\frac{\mathrm{IC}_{\mathrm{back}}(n,0)}{(1+\mathrm{KR\&D}_{\mathrm{back}}(t,n))^{\eta}}\\p&:\mathrm{IC}_{\mathrm{back}}(n,t,c)=\frac{1}{2}\frac{\mathrm{IC}_{\mathrm{back}}(n,0)}{(1+\mathrm{KR\&D}_{\mathrm{back}}(t,n))^{\eta}}+\frac{1}{2}\mathrm{IC}_{\mathrm{back}}(n,0)\\\tfrac{1-p}{2}&:\mathrm{IC}_{\mathrm{back}}(n,t,f)=\mathrm{IC}_{\mathrm{back}}(n,0)\end{aligned} \tag{7}$$

This framework mimics the toy model presented in the previous section and allows us to control for the effect of R&D uncertainty. We can run the model for different values of p—the probability of the central case—and evaluate the consequences of uncertainty on innovation. In order to include in the model these concomitant alternative scenarios we develop an implicit[7] stochastic version of the WITCH model. All model variables, previously defined on regions, time and scenarios, are redefined on nodes belonging to a scenarios

[5] This specification is similar to that used for experience curves, and has been applied to backstops by Popp (2006).

[6] In this first application learning occurs independently at a regional level. As a future extension of the model we plan to include international spillovers of knowledge.

[7] Instead of accounting explicitly for the non-anticipative constraints, non-anticipativity is implicitly defined through characterization of predecessor/successor relationships among nodes in the scenario tree.

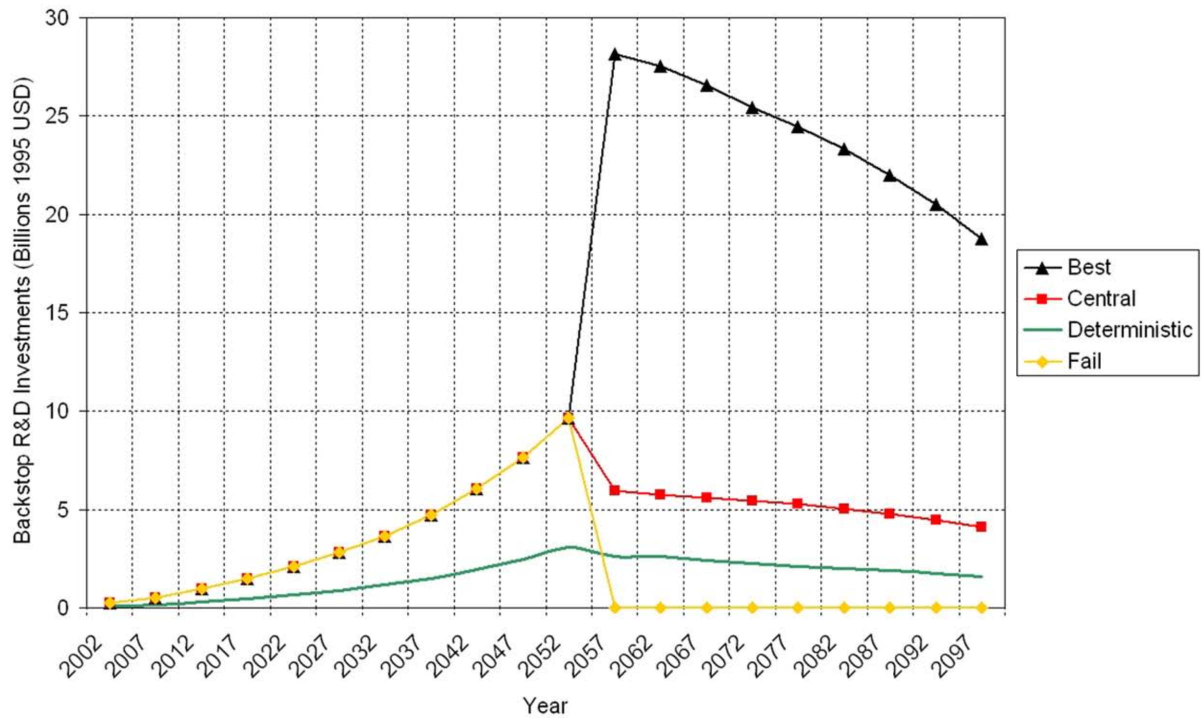

Fig. 4. R&D investments for backstop.

tree as the one depicted in Fig. 3. The objective function to be maximized for each region is the expected utility.

3.2. Numerical results

In this section we report results from the numerical exercise carried out with WITCH. A CO_2 only concentration target of 450 ppmv is assumed throughout the analysis. We compare the deterministic case with the uncertain formulation. The average of the latter coincides with the deterministic one to ensure the equivalence of the comparison exercise. In the uncertain formulation there is a 50% chance to achieve the central case and a 25% chance to achieve the failure and best cases, respectively. In accordance with the analytical analysis, we assume a risk-neutral social planner (we will then relax this assumption).

Since we are investigating the role of uncertainty on innovation, it is interesting to compare the R&D investments in the stochastic case and in the equivalent deterministic case, before uncertainty is resolved in 2050. Results of investments on innovation are presented in Fig. 4; the graph shows that optimal R&D investments are always higher in the stochastic formulation with respect to the deterministic

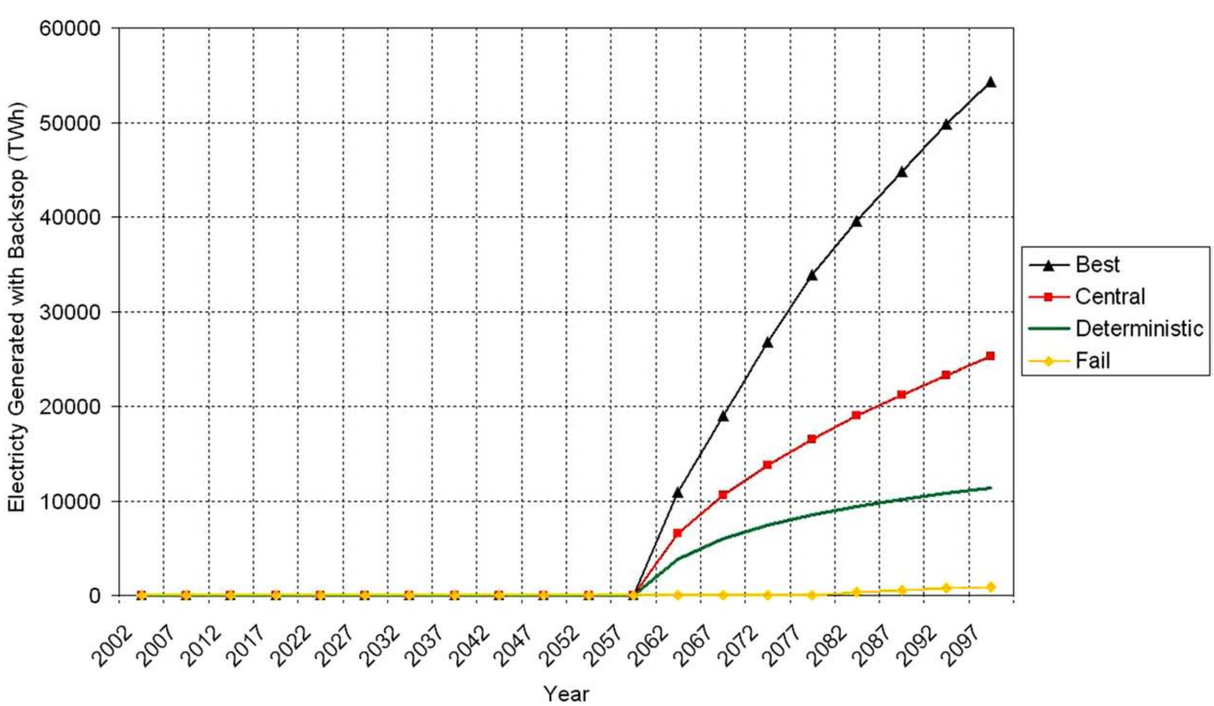

Fig. 5. Electricity with backstop.

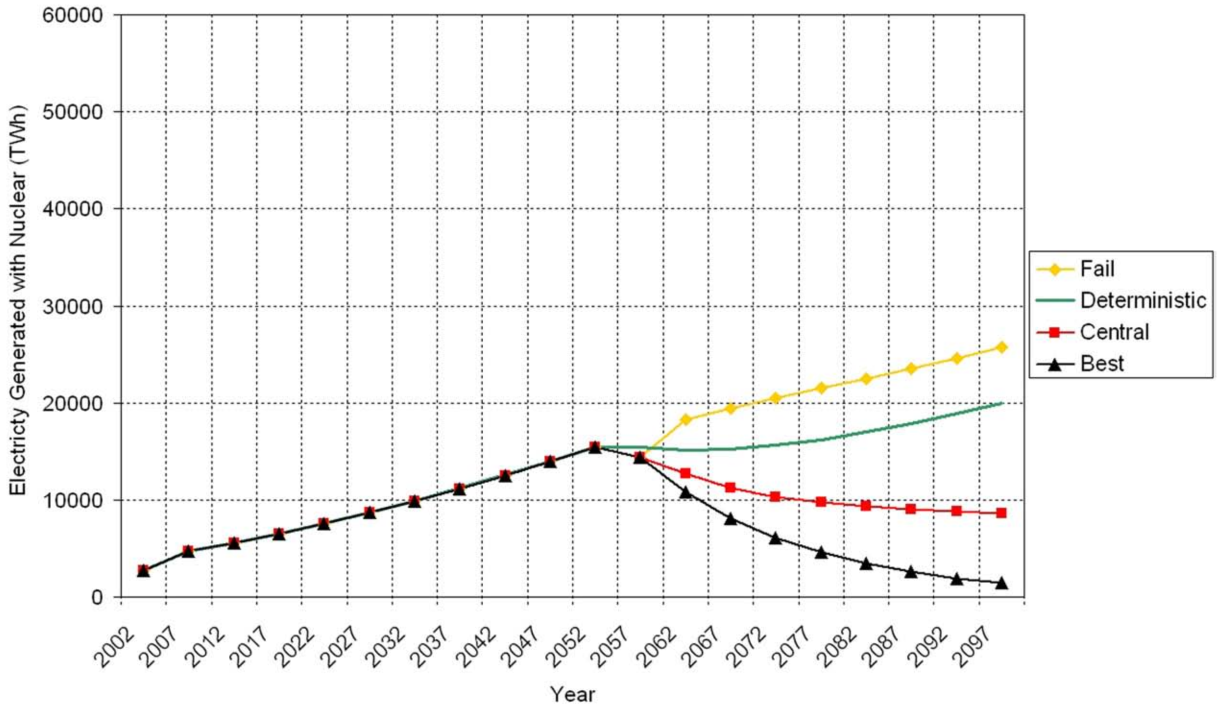

Fig. 6. Electricity with nuclear.

case before the resolution of uncertainty. The numerical analysis thus confirms that *modeling R&D as having an uncertain outcome induces more innovation effort*, as predicted by the analytical example outlined in Section 2. As expected, in the stochastic setting, once uncertainty is resolved, R&D is higher for the best case than for the central, and it is zero for the failure state.

To provide an insight into what different R&D investment paths imply in terms of technology adoption throughout the century, in Fig. 5 we show the values of electricity generated with the backstop technology in the various cases. From the last Figure we know that the R&D investments in the deterministic case are low compared to the stochastic one: such a reduced innovation effort sets back the competitiveness of the backstop technology. This translates into a lower deployment of the innovative technology in the deterministic case vis à vis the stochastic one, as is apparent from the graph (with the obvious exception of the R&D "failure" case).

As expected, the opposite behavior holds with regard to the existing technology competing with the backstop, i.e. nuclear power: the higher costs of the backstop technology lead to a higher nuclear power share in the deterministic formulation than in the uncertain one (except for the failure case, see Fig. 6). All in all, accounting for R&D uncertainty fosters the deployment of innovative technologies such as the backstop one. Through the path dependencies that characterize the evolution of technologies, this would act as a control on the negative externalities that affect the currently used technologies and define their limited deployment capacity. For example, in the WITCH model we explicitly account for waste management and proliferation risks (as well as uranium ore costs) as a global externality countries have incentives to free-ride on. The higher investments in innovation stemming from the uncertain characterization of R&D have the effect of reducing this externality.

The other issue we are dealing with in this paper is the effect of R&D uncertainty on the costs of complying to the climate policy. Are we miscalculating stabilization costs by neglecting uncertain efficacy of innovation in fostering a backstop technology? And, more generally, what is the role of a carbon-free power generation technology in determining these costs?

Numerical results again confirm the insights of the analytical model: *policy costs are always lower when accounting for uncertainty*, reaching a 2.3% gain by the end of the century with respect to the deterministic case. Although limited by the presence of an existing, largely deployable, carbon-free technology, such as the nuclear one, these cost variations indicate that modeling uncertainty explicitly alleviates the mitigation burden of the climate policy.

In order to test the results for robustness and to understand the effect of key assumptions, we have repeated simulations for a different set of assumptions on entry time and the level of risk aversion.[8]

In Fig. 7 we present the R&D results when we assume different entry times of the backstop technology ("early" in 2040, and "late" in 2060). The picture shows that early resolution of uncertainty on the efficacy of the R&D programme leads to a higher level of optimal R&D investments. The contrary holds in the case of late discovery of the program's effectiveness. Although the effect on the levels of investments is significant, entry time has a small impact on policy costs. As noted above, this result depends on the presence of the traditional carbon-free technology (nuclear) which has a buffer effect.

As a concluding analysis, we drop the assumption of risk neutrality and investigate what happens when the central planner is risk-averse. In this case, lower utility is attached to risky investments, and thus we expect to find an effect contrary to the results presented so far. We start by analysing the unit risk aversion case of logarithmic utility function. Numerical results show that R&D investments in the uncertainty case are indeed lower than for the reference risk-neutral analysis. The risk aversion increase roughly halves innovation effort: for example, R&D investments in 2050 drop from 10 to 5 USD billions. Despite this effect, they remain higher than for the certain case (that for example has 2.2 USD billions investments in 2050), thus confirming that the R&D fostering effect of uncertainty remain valid for central planners with unit risk version. Finally, we searched the risk aversion parameter for which R&D investments are equal in both the certain and uncertain cases. With the uncertainty parametrization used throughout the

[8] In order to preserve the base year consumption and savings figures we have adjusted the social time preference rate according to the new risk aversion value.

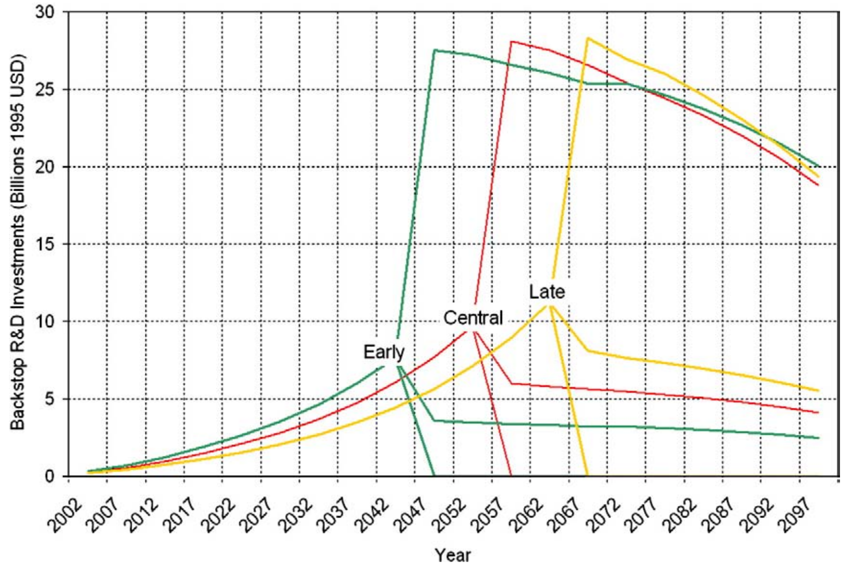

Fig. 7. Effect of entry time on backstop R&D investment.

paper, we find that a social planner with a CRRA utility function and a risk aversion coefficient of 1.5 invests in innovation equally in both the certain and uncertain cases. Higher risk aversions would result in lower innovation shares under uncertainty.

4. Conclusions

In this paper we have analyzed the issue of uncertain technological progress within environmental regulation. This is an important research topic given the relevance of technical change in the global warming literature and the uncertainty that characterizes all innovation processes, yet a poorly investigated one. We have analyzed optimal responses to uncertainty, in terms of R&D investments and climate policy costs, by modeling innovation as a backstop technology characterized by either a deterministic or an uncertain process. To this purpose, we have developed a simple analytical model and modified the hybrid integrated assessment model WITCH to account for a carbon-free backstop technology dependent on uncertain R&D realizations. We have performed a stochastic cost effectiveness analysis of a CO_2 stabilization policy of 450 ppmv.

Numerical results, in accordance with analytical insights, have shown how modeling innovation in a backstop technology as an uncertain process leads to higher optimal levels of R&D investments. A detailed representation of the energy sector has allowed us to capture path dependency in technological evolution, and therefore to account for the consequences of different innovation efforts on technology deployment and externality resolution. We have also shown how uncertainty lowers climate policy costs, although the rigidity of the energy sector—characterized by long-lasting investments with limited substitutability—is shown to constrain the contribution of a technology breakthrough solely in the electricity sector.

To check for the robustness of the results, we have tested the need to model R&D uncertainty as an endogenous process by letting the backstop entry time vary. We have shown how different timings of backstop availability affect R&D investments and policy costs in the expected direction but to a limited extent in terms of magnitude. Finally, the role of social planner risk aversion has been analyzed and shown to have a counterbalancing effect that reduces the gap in innovation investments with and without uncertainty.

In this first version of the model we have not considered the possibility of international spillover of knowledge. This is an issue that is relevant in both policy and modeling terms, as it can induce contrasting effects. We are investigating it in a follow-up analysis. Finally, future research includes the evaluation of innovation uncertainty on the choice of policy instruments with a specific focus on the role of free-riding.

Appendix A

Result 1. Within the analytical framework sketched in Section 2 we prove that the costs of complying to the environmental target diminish in uncertainty.

That is, labeling with V the optimal costs for the problem outlined in Eq. (1), we need to show that $\frac{dV}{dp}>0$.

The value function of the minimization problem is as follows:

$$V = C\left(I^*\right) + p\left[C_T\left(\mu_T^{C*}\right) + C_B^C\left(\mu_B^{C*}, I^*\right)\right] + \frac{1-p}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I^*\right)\right] + \frac{1-p}{2}C_T(\bar{\mu}) \tag{8}$$

From the envelope theorem we know that:

$$\frac{dV}{dp} = C_T\left(\mu_T^{C*}\right) + C_B^C\left(\mu_B^{C*}, I^*\right) - \frac{1}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I^*\right)\right] - \frac{1}{2}C_T(\bar{\mu}) \tag{9}$$

and so $\frac{dV}{dp}>0$ if

$$C_T\left(\mu_T^{C*}\right) + C_B^C\left(\mu_B^{C*}, I^*\right) > \frac{1}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I^*\right)\right] + \frac{1}{2}C_T(\bar{\mu}) \tag{10}$$

The right hand side of the equation is the sum of the minimized costs in the best and worst (failure) cases, respectively. Evaluating the best case function at a different abatement level, for instance at the one that is optimal for the central case, would yield higher costs, so we can write:

$$\frac{1}{2}\left[C_T\left(\mu_T^{C*}\right) + C_B^L\left(\mu_B^{C*}, I^*\right)\right] > \frac{1}{2}\left[C_T\left(\mu_T^{L*}\right) + C_B^L\left(\mu_B^{L*}, I^*\right)\right] \tag{11}$$

and thus, in order to prove Eq. (10) it suffices to show that:

$$C_T\left(\mu_T^{C*}\right) + C_B^C\left(\mu_B^{C*}, I^*\right) > \frac{1}{2}\left[C_T\left(\mu_T^{C*}\right) + C_B^L\left(\mu_B^{C*}, I^*\right)\right] + \frac{1}{2}C_T(\bar{\mu}) \tag{12}$$

We know that the central case abatement cost C_B^C is the average of the best and failure cases for any abatement. That is,

$$C_B^C\left(\mu_B^{C*}, I^*\right) = \frac{1}{2}C_B^L\left(\mu_B^{C*}, I^*\right) + \frac{1}{2}C_B^H\left(\mu_B^{C*}\right) \tag{13}$$

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Inserting this equation in the preceding one and rearranging terms we can rewrite the condition for costs diminishing in uncertainty as:

$$C_T\left(\mu_T^{C*}\right) + C_B^H\left(\mu_B^{C*}\right) > C_T(\overline{\mu}) \tag{14}$$

The LHS of the last equation is the cost of meeting the abatement target in the failure case with a suboptimal allocation of abatement between the technologies. By construction, abatement cost is minimized in this case by doing all the work with the traditional technology. Therefore the RHS is optimal and must have a lower cost than the suboptimal LHS.

Appendix B

Result 2. We investigate the sign of $\frac{dI^*}{dp}$, knowing that if $\frac{dI^*}{dp}<0$ then we have that R&D investments increase with uncertainty.

We focus on the case of an interior solution for the choice variable. Then, the optimality condition with respect to I ensures that the solution value satisfies:

$$\frac{dC(I^*)}{dI} + p\frac{dC_B^C(\mu_B^{C*}, I^*)}{dI} + \frac{1-p}{2}\frac{dC_B^L(\mu_B^{L*}, I^*)}{dI} = 0 \tag{15}$$

The marginal costs of innovation equate the marginal benefits from reduced abatement costs in the central and low cost cases, weighted by the probability of occurrence of both states.

Implicit differentiation with respect to p yields:

$$\begin{aligned}&\frac{d^2C(I^*)}{dI^2}\frac{dI^*}{dp} + p\frac{d^2C_B^C(\mu_B^{C*}, I^*)}{dI^2}\frac{dI^*}{dp} + \frac{dC_B^C(\mu_B^{C*}, I^*)}{dI} + \\ &+\frac{1-p}{2}\frac{d^2C_B^L(\mu_B^{L*}, I^*)}{dI^2}\frac{dI^*}{dp} - \frac{1}{2}\frac{dC_B^L(\mu_B^{L*}, I^*)}{dI} = 0\end{aligned} \tag{16}$$

Rearranging terms:

$$\begin{aligned}&\frac{dI^*}{dp}\left\{\frac{d^2C(I^*)}{dI^2} + p\frac{d^2C_B^C(\mu_B^{C*}, I^*)}{dI^2} + \frac{1-p}{2}\frac{d^2C_B^L(\mu_B^{L*}, I^*)}{dI^2}\right\} \\ &= -\frac{dC_B^C(\mu_B^{C*}, I^*)}{dI} + \frac{1}{2}\frac{dC_B^L(\mu_B^{L*}, I^*)}{dI}\end{aligned} \tag{17}$$

It is reasonable to assume convex cost functions in I (i.e. increasing marginal costs of innovation, and decreasing marginal benefits of innovation to abatement); the left hand side term of the expression is then positive, and the sign of $\frac{dI^*}{dp}$ is determined by the sign of the right hand side of the last equation.

The right hand side confronts the innovation marginal benefits for the central and low cost cases. From Eq. (2) we know that the marginal benefits in the low cost case are twice those of the central case. We can rewrite the right end side of Eq. (17) as follows:

$$\begin{aligned}&-\frac{dC_B^C(\mu_B^{C*}, I^*)}{dI} + \frac{1}{2}\frac{dC_B^L(\mu_B^{L*}, I^*)}{dI} = -\frac{dC_B^C(\mu_B^{C*}, I^*)}{dI} + \frac{dC_B^C(\mu_B^{L*}, I^*)}{dI} \\ &= MB^C(\mu_B^{C*}) - MB^C(\mu_B^{L*}) \lesseqgtr 0?\end{aligned} \tag{18}$$

We have obtained that the sign of $\frac{dI^*}{dp}$ depends on whether marginal benefits of R&D investments are increasing with abatement or not.

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Forestry and the carbon market response to stabilize climate

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Abstract

This paper investigates the potential contribution of forestry management in meeting a CO_2 stabilization policy of 550 ppmv by 2100. In order to assess the optimal response of the carbon market to forest sequestration, we couple two global models. An energy–economy–climate model for the study of climate policies is linked with a detailed forestry model through an iterative procedure to provide the optimal abatement strategy. Results show that forestry is a determinant abatement option and could lead to significantly lower policy costs if included. Linking forestry management to the carbon market has the potential to alleviate the policy burden of 50 ppmv or equivalently of $\frac{1}{4}$°C, and to significantly decrease the price of carbon. Biological sequestration will mostly come from avoided deforestation in tropical-forest-rich countries. The inclusion of this mitigation option is demonstrated to crowd out some of the traditional abatement in the energy sector and to lessen induced technological change in clean technologies.

Keywords: Forestry; Climate policy; Technological innovation

1. Introduction

This study examines the role that forestry may play in the context of atmospheric CO_2 stabilization. There is widespread research suggesting that biological sequestration of carbon can play an important role for reducing greenhouse gases (GHG) emissions through activities such as slowing the rate of deforestation, increasing the establishment of forests on old agricultural or degraded lands, and improving the management of existing and future timber (see, for example, Metz et al., 2001). Estimates of the range of potential costs of sequestration are fairly wide (Richards and Stokes, 2004), but there is also general consensus that forest sinks can be a valuable mitigation option. However, the nations of the Kyoto Protocol have thus far only haltingly incorporated forestry measures, and the Kyoto process only recently (at the 11th Conference of Parties in 2005) began considering how one of the measures with the largest potential, tropical forest conservation or prevention of deforestation (see, for this purpose, the proposal as in Moutinho et al., 2005) could be included.

There are several explanations for the limited role that forestry has so far played in abatement strategies. First, error bounds for measuring and monitoring carbon in forests are fairly large in developed countries with well-established measurement technologies (see Watson et al., 2000). Errors in calculating carbon storage are likely to be larger in developing countries that have devoted fewer resources to conducting forest inventories. Second, many concerns have been raised about issues such as additionality and permanence. Unlike abatement of energy emissions, carbon stored in forests is subject to future emissions due to harvesting or other natural disturbances. Third, it is widely assumed that allowing forestry options would reduce incentives to develop important abatement technologies, and these technologies are ultimately necessary to achieve a stable, albeit changed, climate. The first two questions have been widely addressed in a range of publications, including those of the Intergovernmental Panel on Climate Change (see Watson et al., 2000; Metz et al., 2001). However, no one has yet quantified the implications of a forest carbon

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sequestration program on the innovation of energy abatement technologies.

Recent research indicates that global policies meant to stabilize GHG concentrations in the future will require a vast bundle of measures to meet ambitious targets (Pacala and Socolow, 2004). Given the recent focus on stabilization policies and the apparent costs of achieving fairly stringent concentration targets, it is surprising that relatively few energy models have even incorporated forestry sequestration (see Rose et al., 2006). Sohngen and Mendelsohn (2003), do link a forestry model to an aggregate global climate—economy model (DICE; Nordhaus and Boyer, 2000), and their results suggest that forestry could provide nearly one-third of the world's carbon abatement over the coming century, but that study examined a fairly limited overall carbon abatement strategy, and it suggested that a large portion of the carbon sequestration in forests would occur later in the century (thus having little impact on energy abatement). With more stringent policies, carbon prices initially are expected to be higher, and forestry sequestration could have more important implications for the costs of the overall abatement program.

This paper develops an intertemporal optimization model of carbon abatement in the energy and land-using sectors to analyze the potential role that forests may play in climate stabilization policy. To accomplish this, we bring together a forestry and an energy–economy–climate model to evaluate the mitigation potential of forest sequestration and to measure the deriving feedback on ''traditional'' abatement options and on the carbon market as a whole. To put ourselves in a context of a global climate policy, we consider a target of a 550 ppmv CO_2 only stabilization (see International Panel on Climate Change (IPCC) (2001) for a scientific motivation of the target), and examine the abatement pathway with and without forestry sequestration.

Results show that forestry has important implications for the overall abatement strategy, and a profound effect on the carbon market (i.e., on the global costs of a climate policy), so that, for example, 50 additional ppmv–equivalently of $\frac{1}{4}$°C—are achieved at no extra cost. The numerical optimization estimates that forest sinks can contribute to one-third of total abatement by 2050 and decrease the price of carbon by 40% by 2050. This decisive reduction in the policy costs is mainly attained via avoiding deforestation in tropical forests in the first half of the century, though it could also be sustained in later periods by afforestation and enhanced forest management. The introduction of the forestry option is shown to have a visible influence on other abatement alternatives: in meeting a given policy target, forestry crowds out some abatement in the energy sector, so that, for example, improvements of the energy intensity of the economy are more modest in early periods. More importantly, policy-induced technological change in clean technologies such as renewables power generation is also reduced. Although the time needed for technological advancement may be considered as one reason to delay permanent emissions cuts, buying time with forestry appears to be an attractive mitigation option.

In order to produce results, the two world models are coupled via an iterative procedure that focuses on carbon quantities and prices. Various characteristics are at the basis of the originality of the present paper. First, the model's dynamic specification of the economy and the detail of the energy sector allow us to assess the dynamic feedbacks on the economic system as well as the evolution of energy technologies. This enables us to integrate forest carbon sinks into the control problem of GHG mitigation, so that investments in final good, energy technologies, energy R&D, and forestry are optimally chosen. The energy sector description and the presence of endogenous technological change—a central feature for climate change modeling; see Goulder and Mathai (2000)—puts us in the condition to assess how the inclusion of forestry incentives may affect induced technological change, an issue not yet investigated to our knowledge. Moreover, the intertemporal structure of the models is essential to understand the timing issue of the biological sequestration abatement option, which is a largely discussed one because of the non-permanence issue (managed forests do not sequester carbon permanently but release it back to the atmosphere if harvested).

Second, the regional disaggregation of both models allows us to account for distributional issues among countries (the so-called ''where'' dimension), an issue that has proved particularly central in the policy debate surrounding the forestry abatement option. Last but not least, contrary to current studies, by framing the analysis in a global mitigation policy context such as a 550 ppmv target, we are able to augment the cost-effectiveness literature introducing an additional measure designed to cover a stabilization wedge.

With respect to the existing literature, the approach that is the closest to ours is the one in Sohngen and Mendelsohn (2003). Their original analysis is, however, limited to a single world region and has incomplete technological detail. Similar to van't Veld and Plantinga (2005), they find forestry to have but a negligible feedback on the carbon market. Also, they find that forestry carbon offsets do not delay energy abatement. Conversely, Gitz et al. (2006) use a stochastic version of DIAM—a single region, least abatement costs model. They find, as in our case, a significant forestry–carbon market linkage.

This paper is divided as follows. Section 2 introduces both models and defines the coupling procedure. Section 3 presents numerical results, and Section 4 concludes.

2. Models and coupling

In this section, we present the two models that have been linked to analyze the role of forestry in contributing to the climate stabilization target of 550 ppmv CO_2 only. For the energy–economy side we use the World Induced Technical Change Hybrid model (WITCH) (Bosetti et al., 2006), a recently designed hybrid integrated assessment model for climate change issues. As for the forestry part, we use a global timber model built upon Sohngen et al. (1999).

2.1. The energy–economy–climate model

WITCH is a regional integrated assessment model structured to provide normative information on the optimal responses of world economies to climate damages and to model the channels of transmission of climate policy to the economic system. It is a hybrid model because it combines features of both top-down and bottom-up modeling: the top-down component consists of an intertemporal optimal growth model in which the energy input of the aggregate production function has been expanded to give a bottom-up-like description of the energy sector. World countries are grouped in 12 regions that strategically interact following a game-theoretic structure. A climate module and a damage function provide the feedback on the economy of carbon dioxide emissions into the atmosphere. The WITCH top-down framework guarantees a coherent, fully intertemporal allocation of investments that have an impact on the level of mitigation—R&D effort, investment in energy technologies, and fossil fuel expenditures. The regional specification of the model and the presence of strategic interaction among regions—through CO_2, exhaustible natural resources, and technological spillovers—allow us to account for the incentives to free-ride. By playing an open-loop Nash game, the investment strategies are optimized by taking into account both economic and environmental externalities. In WITCH, the energy sector has been detailed and allows a reasonable characterization of future energy and technological scenarios and an assessment of their compatibility with the goal of stabilizing GHG concentrations. Also, by endogenously modeling fuel (oil, coal, natural gas, uranium) prices, as well as the cost of storing the CO_2 captured, the model can be used to evaluate the implication of mitigation policies on the energy system in all its components. Finally, technical change in WITCH is endogenous and is driven both by learning-by-doing (LbD) and by energy R&D investments. These two factors of technological improvements act through two different channels: LbD is specific to the power generation costs, while R&D affects the non-electric sector and the overall system energy efficiency.

In this paper, we focus on a stabilization policy of 550 ppmv. In order to do so, we perform a cost-effectiveness analysis with a cap and trade policy instrument, and we set an equal per capita allocation system. We have an emission permit trading scheme that equalizes regional marginal abatement costs, creating a unique set of carbon prices. The model is solved to 2200 numerically in GAMS/CONOPT.

2.2. The forestry model

The forestry model is built upon the model described in Sohngen et al. (1999) and used by Sohngen and Mendelsohn (2003) to analyze global sequestration potential. The model used in this analysis contains an expanded set of timber types, as described in Sohngen and Mendelsohn (2006). There are 146 distinct timber types in 13 regions: each of the 146 timber types modeled can be allocated into one of three general types of forest stocks. First, moderately valued forests, managed in optimal rotations, are located primarily in temperate regions. Second, high-value timber plantations are managed intensively. Subtropical plantations are grown in the southern United States (loblolly pine plantations), South America, southern Africa, the Iberian Peninsula, Indonesia, and Oceania (Australia and New Zealand). Finally, low-valued forests, managed lightly if at all, are located primarily in inaccessible regions of the boreal and tropical forests. The inaccessible forests are harvested only when timber prices exceed marginal access costs. The forestry model maximizes the net present value of net welfare in the forestry sector.

One important component of the costs of producing timber and carbon are land rental costs. The model accounts for these costs by incorporating a series of land rental functions for each timber type. The rental functions account for land competition between forestry and agriculture, although they are not presently responsive to price changes in agriculture (see Sohngen and Mendelsohn (2006) for additional discussion of the land rental functions). Incentives for carbon sequestration are incorporated into the forestry model by renting carbon. The price of energy abatement is the value of sequestering and holding a ton of carbon permanently. The rental value for holding a ton of carbon for a year is determined as the path of current and future rental values on that ton that is consistent with the price of energy abatement currently. One of the benefits of using the rental concept for carbon sequestration is that the carbon temporarily stored can be paid while it is stored, with no payments accruing when it is no longer stored (i.e., if forest land is converted to agriculture, or if timber is harvested, leaving the forest in a temporarily low-carbon state). Furthermore, renting carbon does not penalize current forestland owners by charging them for emissions. We do, however, account for long-term storage of carbon in wood products by paying the price of carbon for tons when they are stored permanently after harvest. For simplicity, in this analysis, we assume that 30% of harvested wood is stored permanently, following Winjum et al. (1998).

2.3. Coupling

Given the complexities of the two models used in this paper, we have integrated them via an iterative procedure. In order to do so, we have augmented both models so that they could incorporate results from the other, and have run subsequent iterations until convergence, as measured by a sufficiently small rate of variation of carbon prices. We define this as being less than a 5% average deviation in prices and quantities from one scenario to the next. As expected, the initial high responses of both models—in terms of adjustments of carbon prices to the quantities sequestered in forests and vice versa—gradually shrink, and an equilibrium is achieved after 11 iterations. For prices, the average deviation is 3% whereas for quantities it is 4%. This way of interfacing two separate models is normally described as ''soft link'', and has been extensively used to couple energy system models and economic models to account for the mutual interactions between the energy sector and the whole economy.

To make the two models consistent, several additional adjustments were made. First, the different regions had to be matched. Coincidentally, the regional disaggregation is similar in the two cases—12 regions for the WITCH model, 13 for the forestry one—so that only minor adjustments were needed. Also, the WITCH model has 5-year time steps and the forestry model has 10-year time steps. To link the two, we utilized prices at the 10-year intervals provided by the WITCH model in the forestry model. We interpolated carbon sequestration rates between 10-year time increments from the forestry model when incorporating forest sequestration in the WITCH model. The forestry model has been augmented to comprise the time path of carbon prices, which is equalized across regions and given by the emissions permits prices of the cap and trade policy. To account for the non-permanence of the biological sequestration, carbon prices are transformed into annual storing values via rental rates. For more information, see Sohngen and Mendelsohn (2003). The energy–economy–climate model has been fed the carbon quantities sequestered by forests in each region by counting them in the carbon emission balances, as well as in the budget constraint—at the carbon price value.

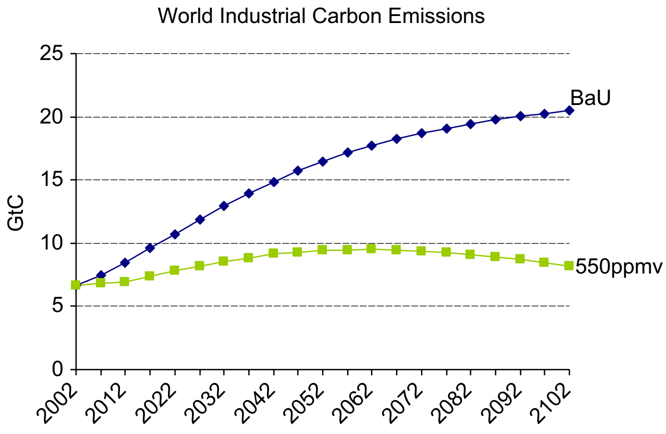

Fig. 1. Carbon emissions for business as usual and 550 ppmv policy.

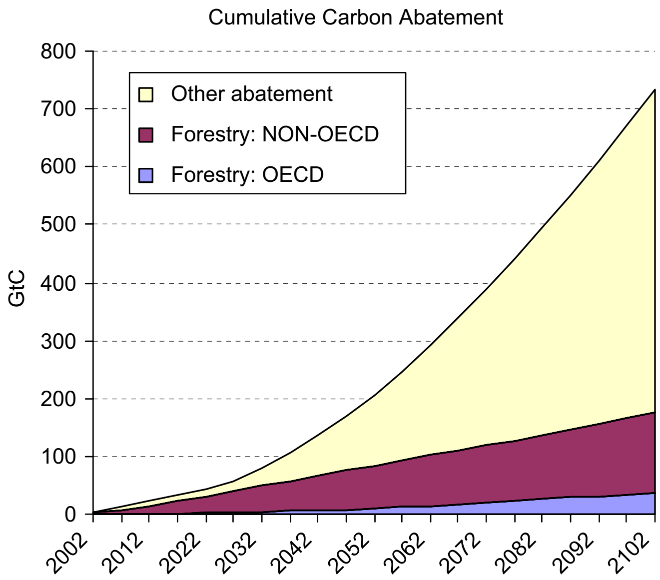

Fig. 2. Carbon abatement.

3. Results

In this section, we report the numerical results of the contribution of forestry management in meeting a CO_2 (only) stabilization policy of 550 ppmv by 2100. To give the feeling of what such a policy entails in terms of global warming mitigation, in Fig. 1 we show the time profile of carbon emissions for a business as usual (BaU) and a 550 ppmv policy resulting from using the WITCH with abatement only in the energy sector. In a no-policy scenario, emissions grow to 20 GtC by the end of the century, whereas for the 550 ppmv policy, emissions peak around 2050, falling by more than half after that with respect to BaU. The 550 ppmv policy reduces the carbon intensity in the economy considerably, and reduces the increase in global temperature by 2100 to 2.2 °C, from 2.9 °C in the BaU. Although this temperature is still higher than the IPCC advocated level of 2 °C, we concentrate on this target given its relevance, especially in terms of political feasibility.

We start by reporting the potential of forestry in contributing to the foreseen emission reductions, and then analyze the impacts on the carbon markets and the policy costs. Finally, we examine the retroactions on the energy abatement portfolio, with a particular look at the implications for induced technological change.

3.1. Sequestration in forests

Several studies in the forestry literature have estimated the sequestration potential for various given carbon prices, and most seem to agree that forestry can provide a significant share of abatement (Sedjo et al., 1995). As an example, it is worth remembering that tropical deforestation is a major source of GHG emissions, accounting for as much as 25% of global anthropogenic GHG emissions (Houghton, 2005).

Fig. 2 reports carbon abatement over the century accomplished by forestry in OECD and non-OECD countries vis-à-vis the overall abatement effort. The picture underlines an important role for biological sequestration: forests sequester around 75 GtC cumulative to 2050.

This estimate is consistent with the results presented in earlier IPCC reports (see, for example, Watson et al., 2000) but of course there are costs associated with this forestry effort. Overall, forestry contributes to one-third of total abatement to 2050, or three wedges in the words of Pacala and Socolow (2004). After the peak in emissions in 2050, the share of forestry in total abatement starts to decline (from 2050 to 2100 it increases by only 10% in absolute values), given that the target gets more stringent and permanent emission cuts in the energy sector are called for.

The largest share of carbon sequestration occurs in non-OECD countries during the early part of the century (Table 1). Around 63% of all of the carbon sequestered from 2002 to 2052 of the stabilization scenario results from reductions in deforestation in just a few regions, namely Latin America, East Asia, and Sub-Saharan Africa. Most of this carbon is due to reductions in deforestation. While consideration of policies to reduce deforestation has been shunned in earlier negotiations related to the Kyoto Protocol, they recently received significant attention as a result of discussions at COP 11 in Montreal.

Focusing on Latin America, East Asia, and Sub-Saharan Africa, where the bulk of deforestation currently is occurring (FAO, 2005), around 10.7 million hectares of forestland are estimated to be lost each year (Table 2). The carbon incentives in the stabilization scenario would reduce these losses to around 5.9 million hectares per year during the first decade, and they would essentially halt net forest losses by 2022. While developing policies to reduce deforestation efficiently would undoubtedly be a difficult task, these results suggest that the economic value of making these changes could be substantial.

Table 1
Regional forest carbon sequestration, 2025, 2055, 2095

	2022	2052	2092
	Mt C/yr		
OECD			
USA	42	144	193
OLDEURO	37	82	132
NEWEURO	8	18	29
CAJANZ	31	115	125
Total OECD	118	360	479
Non-OECD			
KOSAU	25	27	36
TE	179	117	134
MENA	73	49	31
SSA	270	175	106
SASIA	34	57	32
China	109	155	431
EASIA	451	481	371
LACA	391	326	330
Total non-OECD	1649	1746	1950
Total global	1766	2105	2429
C price	\$57	\$113	\$271

CAJANZ: Canada, Japan, and New Zealand. KOSAU: Korea, South Africa, and Australia. TE: Transition Economies. MENA: Middle East and North Africa. SSA: Sub-Saharan Africa. SASIA: India and South Asia. EASIA: South East Asia. LACA: Latin America and Caribbean.

The overall size of the carbon program increases over the century as carbon prices rise. It increases in both the OECD and the non-OECD regions, but the largest percentage gains occur in the OECD, where the annual carbon sink rises from 118 to 479 million t C/yr. In most non-OECD regions, the strength of the sink is actually declining because there are no longer opportunities to reduce deforestation, and forest growth on large areas of land that were reforested during the century is starting to slow. The one outlier is China, where sequestration expands. Sequestration dynamics in China tend to be more similar to OECD countries because it has large areas of temperate forests that have long growing cycles.

By reducing deforestation and promoting afforestation, a forest carbon sequestration program as part of a stabilization strategy would have strong impacts on total forestland area in the world, increasing it by 1.1 billion hectares relative to the baseline, or around 0.7 billion hectares above the current area of forests (Table 3). The largest share of increased forest area occurs in non-OECD countries. The stabilization scenario has complex results on timber harvests and prices. Initially, timber is withheld from the market in order to provide relatively rapid forest carbon sequestration through aging timber. As a result, global harvests decline by 14.5% relative to the baseline in 2022. However, over the century, more forests imply a larger supply of timber. By 2092 timber harvests increase by 26%. The changes in specific regions depend heavily on the types of forests (e.g., the growth function), the carbon in typical forests (e.g., biomass expansion factors), and economic conditions such as prices and costs. In contrast to the area changes, the largest increases in timber harvests (in relative and total terms) occur in OECD countries. OECD countries tend to have many species amenable to producing wood products.

3.2. *Optimal response of the carbon market*

We now focus on the general equilibrium effects of including forestry management as an abatement strategy. As a comprehensive measure of the influence of biological sequestration on the carbon market, we first examine what happens to the price of carbon when forestry is included into the policy. Fig. 3 shows the carbon price for the 550 ppmv policy throughout the century as found in the original version of the WITCH model (iter1), and after it has been coupled with the forestry model (iter11). Forest sinks substantially lower the cost of CO_2, for example by 40% in 2050, making a 550 ppmv policy cost as much as a 600 pmmv policy without including forestry. That is, carbon sinks achieve an additional 50 ppmv—or equivalently $\frac{1}{4}$°C—in 2100 at no extra cost.

To corroborate the idea that forestry can alleviate the compliance to the 550 ppmv target, in Fig. 4 we show the

Table 2
Net land area change in regions currently undergoing substantial deforestation, in million hectares per year

	FAO (2000–2005)	Projected for		
		2002–2012	2012–2022	2022–2032
Latin and Central America	−4.7	−2.3	−0.9	0.2
East Asia	−2.8	−1.2	−0.4	−0.1
Sub-Saharan Africa	−3.2	−2.4	−0.1	0.0
Total	−10.7	−5.9	−1.4	0.1

Table 3
Change in forestland area and change in annual timber harvests compared to the baseline

	2022	2052	2092	2022	2052	2092
	Million hectares			% Change in annual harvest		
OECD						
USA	1.5	23.1	94.2	1.2	−9.0	48.5
OLDEURO	11.5	34.9	51.9	−5.3	12.1	0.3
NEWEURO	2.6	7.8	11.6	−5.3	12.1	0.3
CAJANZ	−4.0	24.5	99.0	−3.8	−3.3	167.3
Total OECD	11.6	90.3	256.7	−3.3	3.0	54.1
Non-OECD						
KOSAU	5.1	17.7	49.1	11.3	34.5	42.1
TE	19.0	52.2	102.7	−20.8	8.9	−26.1
MENA	10.3	24.9	38.4	−63.9	−45.9	−6.7
SSA	37.2	90.7	137.0	−70.1	−52.9	−9.0
SASIA	5.2	18.8	32.3	−3.7	−3.9	13.0
China	8.6	41.9	115.4	−20.1	0.0	−98.8
EASIA	25.6	66.0	111.9	−63.3	−57.2	−48.9
LACA	42.9	129.3	262.4	−24.8	−7.1	15.5
Total non-OECD	153.8	441.5	849.2	−31.9%	−15.4%	−14.9%
Total	165.4	531.8	1105.9	−14.5%	−3.3%	25.9%

CAJANZ: Canada, Japan, and New Zealand. KOSAU: Korea, South Africa, and Australia. TE: Transition Economies. MENA: Middle East and North Africa. SSA: Sub-Saharan Africa. SASIA: India and South Asia. EASIA: South East Asia. LACA: Latin America and Caribbean.

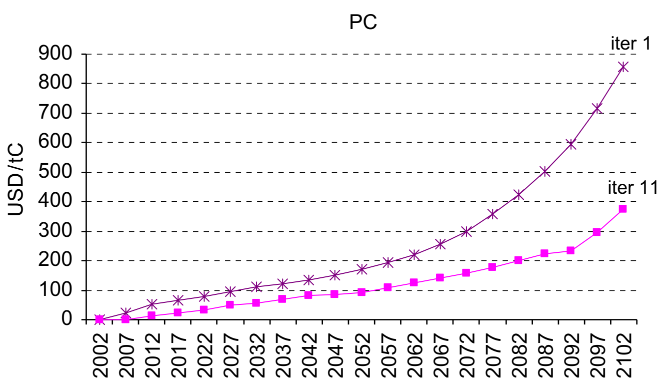

Fig. 3. Price of carbon with (iter11) and without (iter1) forestry.

policy costs with and without forestry. Again, forest sinks are shown to decrease policy costs: in particular, the policy burden is reduced and shifted ahead in the period to 2050,

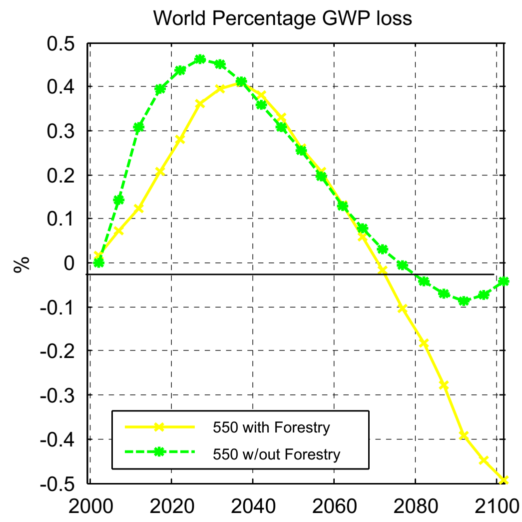

Fig. 4. Policy costs with and without forestry.

when the main action is via avoided deforestation. After 2070 the policy-induced benefits from avoided climate damages outweigh the costs of reducing emissions, and this effect is reinforced when forestry is an available mitigation option. All in all, the world policy cost in net present value decreases from 0.2% without forestry to 0.1% with forestry. This corresponds to a net present value saving to 2100 of almost $3.0 trillion (USD), which is nearly three times the present value cost of adding the forestry program of $1.1 trillion (USD).

One might wonder what are the distributional effects of including forestry for different regions. Two competing effects are at stake: on the one hand, forestry will benefit developing countries that are rich in tropical forests, given the role of avoided deforestation. On the other hand, the lower price of carbon will benefit countries that buy carbon market permits, and disadvantage sellers. Ultimately, the distributional effects will depend on the emissions allocation scheme adopted in the policy. For example, if one assumes that emissions are allocated based on an equal per capita rule, as we do in this paper, most of the emissions reductions are borne by the developed countries. Lower carbon prices with forestry included in the stabilization policy improve welfare in OECD countries by reducing their costs (from an undiscounted loss of 0.6% without forestry to 0.2% with forestry). On the contrary, non-OECD countries tend to be carbon permit sellers, and they have lower revenues when forestry is included as an option, although the difference in revenues is fairly small (from an undiscounted gain of 0.38% without forestry to 0.27% with forestry). It is worth noting that a different allowances allocation scheme would have changed the distributional results, though it would not have any impact on the carbon prices as they are determined by the world marginal abatement costs.

3.3. *Implications for energy abatement and technological change*

An issue that has played a political relevance in the decision to keep forestry outside the Kyoto Protocol is the danger that the emissions constraint on the energy system might be relaxed too much: the deployment of clean technologies that can reduce emissions permanently might be delayed, and accordingly the investments in innovation that are needed to make new technologies competitive. Given the low turnover of energy capital stock, as well as the lengthy process before commercialization of advanced technologies, this is a justified reason of concern. The energy sector description and the endogenous technological change feature of the WITCH model allow us to check for the variations in energy abatement due to forestry.

In Fig. 5 we show the evolution of the world primary energy intensity, an aggregate indicator that summarizes the energy efficiency of the economy. Results are presented for the BaU scenario, and the 550 ppmv policy with and without forestry. As expected, the climate target induces more reductions in energy intensity with respect to the BaU scenario. However, this reduction is more moderate when we include the forestry abatement option: the energy intensity remains close to the BaU in the first 2–3 decades of this century, when avoided deforestation is significantly contributing to abatement, and then approaches the no-forestry path, as the emissions cuts in the energy sector become more predominant. We thus provide evidence of a delay in energy abatement, though limited to the very first part of the century. For example, the initial deployment of coal power plants with carbon capture and storage is postponed from 2015 (without forestry) to 2030 (with forestry). Similarly, the share of nuclear power is lower with forestry. Such a setback of low-carbon technologies can be seen either as harmful for the global warming cause or optimistically as a bridge solution in the wait to develop more consolidated, yet currently uneconomical, technologies.

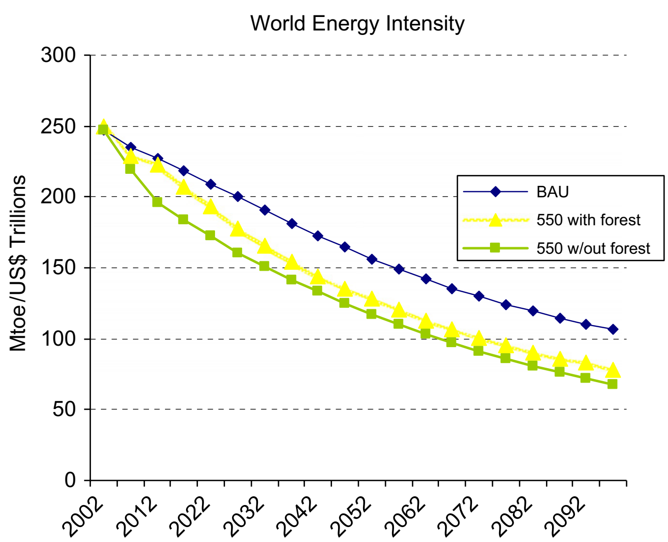

Fig. 5. Energy intensity of the economy.

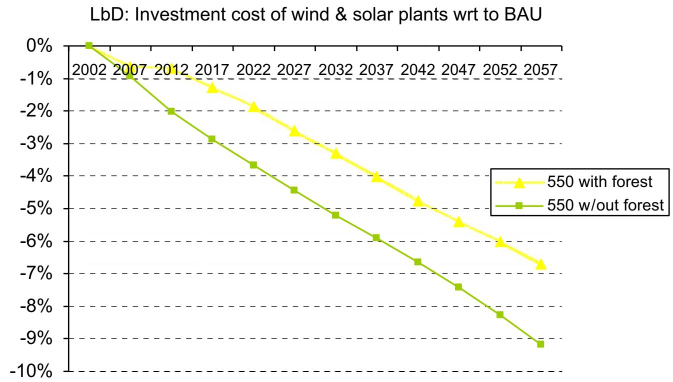

Fig. 6. Induced technological change with and without forestry.

We can try to answer this question by looking at what happens to the policy-induced technological change in the model. As mentioned in Section 2.2, WITCH features endogenous technological change via both LbD and energy R&D. In Fig. 6 we show the forestry inclusion implications for LbD: we plot the percentage variations in the investment costs of wind and solar power plants with respect to the BaU case, either with or without forestry. Forest sinks hamper the capacity of the 550 ppmv policy to induce technological change, as testified by the lower decrease in renewable costs due to the lower capacity deployment. Also, energy R&D investments are decreased by forestry, by roughly 10% (not shown). Although these are not vast variations in absolute figures, technological innovation could play a crucial role in hedging against possible future revisions of the climate targets, for example in case more pessimistic evidence about global warming emerges. Inevitably, in meeting given emission caps forestry crowds out other abatement; accompanying technological policies might be desirable to ensure a contemporaneous emergence of innovative technologies.

4. Conclusions

This paper evaluates the potential of forest sequestration within the context of stabilizing future concentrations of atmospheric carbon at 550 ppmv CO_2, and it assesses the feedback of forest sequestration on "traditional" energy abatement options. Although numerous studies have estimated the mitigation contribution of forest sinks, understanding how forest sequestration integrates with other climate change options has received little attention. Contemporaneous determination of carbon prices and sequestration in forests, and on the general equilibrium consequences, is thus a largely unexplored area of research. The current paper is a significant contribution as it provides insights of the effects of including forest management on the optimal carbon market responses, the energy technology evolution, and induced technological change.

Results show that forestry is an important abatement option, and that its inclusion into an international policy agreement can have a profound effect on the global costs of a climate policy, allowing a free saving of 50 ppmv in 2100, corresponding to $\frac{1}{4}$°C. In particular, we find that the total costs of the forestry program are \$1.1 trillion (USD) and the benefits, in terms of additional gross world product relative to meeting the same carbon constraint without forestry, are \$3.0 trillion (USD). Forest sequestration actions in the first half of the century, mainly from avoiding deforestation, could contribute one-third of total abatement effort, and could provide additional benefits throughout the entire century. Forest sinks have the potential to reduce the price of traded carbon permits, and the overall cost of the policy in terms of income losses, by half. However, in meeting the emissions reductions target, forestry crowds out some of the abatement in the energy sector for the first 2–3 decades. For example, deployment a potentially relevant energy abatement technology such as carbon capture and storage is delayed by 15 years. Policy-induced technological change in clean technologies such as renewables power generation is also reduced. Policy makers should consider developing targeted policies to help achieve the technological advancement to hedge against unknown risks, but they can make substantial headway towards achieving climate stabilization now with forest carbon sequestration.

These results provide a first step towards fuller consideration of land-based carbon sequestration in energy models. Future work should consider several improvements over this analysis. First, for example, future analysis should more carefully consider competition with agriculture and other land uses. Sequestration or abatement in the agricultural sector could provide important competing options for meeting stabilization targets, and thus are important to consider as well. Second, the endogenous effects of an increase in global temperature on the capacity of forests to sequester carbon can provide a more complete assessment of the problem. Third, biomass energy provides an additional competing land use that could have implications for these results.

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Appendix. The WITCH model

This section contains an overview of the WITCH model. For a complete description the reader is referred to Bosetti, Massetti and Tavoni (2006), and subsequent papers, that can be freely downloaded from the model website www.feem-web.it/witch.

Overview

WITCH is a regional integrated assessment model designed to identify the best responses of world economies to climate damages and to model the channels of transmission of climate policy into the economic system. The model has been used extensively for the analysis of the economics of climate change policies.

Several features distinguish the model. First, WITCH is based on a top-down framework that guarantees a coherent, forward-looking, fully intertemporal allocation of investments in physical capital and in R&D. Second, the model accounts for most actions that have an impact on the level of GHG mitigation – e.g. R&D expenditures, investment in carbon-free technologies, purchases of emissions permits or expenditure for carbon taxes – and can thus be used to evaluate optimal economic and technological responses to different policy measures. Third, the regional specification of the model and the presence of strategic interaction among regions – as for example through learning spillovers in wind & solar technologies, R&D spillovers or climate damages – allows us to account for the incentives to free-ride in the choice of optimal investments. This allows to inform policy makers on the optimal policy portfolio that is needed to overcome the various market failures (e.g. both environmental and innovation ones). Finally, technological change is modeled both via innovation and diffusion processes, so that policy induced technological advancements are evaluated.

A key feature of WITCH is that it explicitly models the interdependency of all countries' climate, energy and technology policies. The investment strategies are thus optimized by taking into account both economic and environmental externalities (e.g. CO_2, exhaustible resources, international R&D spillovers, etc). The investment profile for each technology is the solution of an intertemporal game among the 12 regions. More specifically, these 12 regions behave strategically with respect to all decision variables by playing an open-loop game that provides the Nash equilibrium. The equilibrium is open loop because a region optimizes its welfare function by determining the value of its decision variables from period 1 to period T. There is no feedback from future states of the world. The equilibrium is a fixed point and therefore a Nash equilibrium. From a top-down perspective, this enables us to analyze both the geographical dimension (e.g. rich vs. poor regions) and the time dimension (e.g. present vs. future generations) of climate policy.

Model Structure

WITCH is a Ramsey-type neoclassical optimal growth hybrid model defined for 12 macro regions of the world, as shown in Figure 1. For each of these regions a central planner chooses the optimal time paths of the control variables – investments in different capital stocks, in R&D, in energy technologies and consumption of fossil fuels – so as to maximize welfare, defined as the regional present value of log per capita consumption. Output is produced by aggregating factors via nested Constant Elasticity of Substitution (CES) functions as shown in Figure 2. Elasticity of substitution values are also reported. In particular, gross output of region *n* at time *t* is obtained by combining a Cobb-Douglas bundle of capital accumulated for final good production K_C and labour L with energy services ES. Net output is obtained by accounting for the climate feedback Ω on production, and by subtracting expenditure for natural resources and carbon capture and sequestration (CCS) as shown in equation (1):

$$
\begin{aligned}
Y(n,t) = {} & \frac{TFP(n,t)\left[\alpha(n)\cdot\left(K_C^{1-\beta(n)}(n,t)L^{\beta(n)}(n,t)\right)^{\rho}+(1-\alpha(n))\cdot ES(n,t)^{\rho}\right]^{1/\rho}}{\Omega(n,t)} \\
& -\sum_f\left(P_f(n,t)\,X_{f,extr}(n,t)+P_f^{\text{int}}(t)\,X_{f,netimp}(n,t)\right) \\
& -P_{CCS}(n,t)CCS(n,t)
\end{aligned} \qquad 1)
$$

TFP represents total factor productivity which evolves exogenously over time. Expenditure on fuels – indexed by *f* – enter either as extraction costs, $X_{f,extr}$, or as net imports, $X_{f,imp}$. In particular if a country is a net oil exporter, this latter variable is negative and measures revenues from fuels exports. The cost of transporting and storing the captured CO_2 is endogenous and depends on the quantity captured and injected in each region.

Consumption of the single final good *C* is obtained via the economy budget constraint:

$$
C(n,t)=Y(n,t)-I_C(n,t)-\sum_j I_{R\&D,j}(n,t)-\sum_j I_j(n,t)-\sum_j O\&M_j(n,t) \qquad (2)
$$

i.e., from output *Y* we subtract investment in final good I_C , in energy R&Ds and in each energy technology – labelled by *j* – as well as expenditure for Operation and Maintenance, denoted with *O&M*.

The use of fossil fuels generates CO_2 emissions, which are computed by applying stoichiometric coefficients to energy use. The quantity of carbon captured with carbon-capture and sequestration (CCS) technologies is subtracted from the carbon balance. Emissions are fed into a stylized three-box climate module (the dynamics of this module is described in Nordhaus and Boyer, 2000) which yields the magnitude of temperature increases relative to pre-industrial levels. The increase in temperature creates a wedge between gross and net output of climate change effects through the region-specific quadratic damage function *Ω*.

Non-cooperative Solution

In WITCH policy decisions adopted in one region of the world affect what goes on in all the other regions. This implies that the equilibrium of the model, i.e. the optimal inter-temporal investment profiles, R&D strategies and direct consumption of natural resources, must be computed by solving a dynamic game. World regions interact through five channels.

First, at each time period, the prices of oil, coal, gas and uranium depend on the consumption in all regions of the world. Thus, investment decisions, consumption choices and R&D investment in any country at any time period indirectly affect all other countries' choices. Consider, for example, the impact of a massive reduction of oil consumption in the USA and in Europe alone, possibly stimulated by policies that promote the deployment of biofuels. The resulting lower oil prices would modify energy demand in the rest of the world, probably stimulating higher emissions that would reduce the innovative actions of first movers. We thus describe rebound effects not only inside a region but also across regions. Second, at any time period, CO_2 emissions from each region change the average world temperature and this affects the shadow value of carbon emissions in all other regions. Third, investment decisions in each electricity generation technology in each country at each time, affect other regions by changing the cumulative world installed capacity which in turns affects investment costs via Learning-by-Doing. The fourth channel of interaction derives from the international R&D spillovers that affect the costs of advanced biofuels. Finally, the fifth channel is at work if the model is used to analyze the effects of emissions trading. With an active emission permits market, regions interact via this channel. Marginal abatement costs are equalized across regions, with all the obvious consequences for R&D efforts and investment choices.

WITCH incorporates these channels of interaction to characterize the interdependency of all countries' climate, energy and technology policies. We model the interactions among world regions as a non-cooperative Nash game, which is solved recursively and yields an Open Loop Nash Equilibrium. The solution algorithm works as follows. At each new iteration, the social planner in every region takes the behaviour of other players produced by the previous iteration as given and sets the optimal value of all choice variables; this newly computed level of variables is stored and then fed to the next round of optimizations. The process is iterated until each region's behaviour converges in the sense that each region's choice is the best response to all other regions' best responses to its behaviour. Convergence is rather fast (around fifty iterations) and the uniqueness of the solution has been tested using alternative starting conditions. The way in which the algorithm is constructed makes the solution invariant to different orderings of the regions.

Energy Sector

Figure 2 provides a diagrammatic description of the structure of the energy sector in WITCH and identifies the main technologies for the production of electric and non electric energy.

Energy services *ES*, an input of (1), combines energy with a variable, *HE*, that represents technological advances stemming from investment in energy R&D for improvements in energy efficiency. As in Popp (2004), an increase in energy R&D efforts improves the efficiency with which energy, *EN*, is translated into energy services, *ES* (e.g. more efficient car engines, trains, technical equipment or light bulbs).

EN is an aggregate of electric, *EL*, and non-electric energy, *NEL*. Contrary to what is specified in other top-down growth models – such as DEMETER (Gerlagh and van der Zwaan, 2004) and MIND (Edenhofer *et al.* 2005) – in WITCH energy demand is not exclusively defined by electricity consumption. We believe this is an important distinction as reducing emissions is traditionally more challenging in the non-electric sector, and its neglect would seriously over-estimate the potential GHG control achievements.

Non-electric energy is obtained by linearly adding coal and traditional biomass and an oil-gas-biofuels *(OGB)* aggregate. The use of coal in non-electric energy production *(COALnel)* is quite small and limited to a few world regions, and is thus assumed to decrease exogenously over time in the same fashion as traditional biomass (*TradBiom*). The oil-gas-biofuels aggregate combines oil *(OILnel*), biofuels (*Biofuels*) and natural gas (*GASnel*) sources. In WITCH, ethanol is produced from sugar cane, wheat or corn (*Trad Biofuel*), or from cellulosic rich biomass (*Advanced Biofuel*).[1] The two different qualities of ethanol add up linearly so that only the cheaper one is used.

As for the use of energy for electricity production, nuclear power (*ELNUKE*) and renewable sources in the form of wind turbines and photovoltaic panels (*ELW&S*) are combined with fossil fuel-based electricity (*ELFF*), the output of thermoelectric plants using coal, oil and natural gas (*ELCOAL*, *ELOIL* and *ELGAS*). In this way, we are able to distinguish more interchangeable power generation technologies, such as the fossil-fuelled ones, from the others. Coal-based electricity is obtained by the linear aggregation of traditional pulverized coal technologies *(ELPC)* and integrated gasification combined cycle production with CCS *(ELIGCC).* Hydroelectric power (*ELHYDRO*) is added to the total electric composite; because of its constrained deployment due to limited site availability, we assume that it evolves exogenously, in accordance with full resource exploitation.

One might note that by using a CES function we aggregate the various forms of energy in a non-linear way. This kind of aggregation is commonly used in economic models, to represent a less than infinite substitutability among factors: moving away from an established energy mix costs

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[1] Cellulosic feedstock comprises agricultural wastes (wheat straw, corn stover, rice straw and bagasse), forest residue (underutilized wood and logging residues, dead wood, excess saplings and small trees), energy crops (fast growing trees, shrubs, grasses such hybrid poplars, willows and switchgrass). For a description of the cellulosic ethanol production see IEA (2004b).

more than it would in a least cost minimization framework. This is also in agreement with econometric studies on inter-fuel substitution, which find little connection between energy consumption and own and cross energy prices. CES function bundling allows for contemporaneous investments in different technologies which conform to base-year calibrated factor shares and chosen elasticity of substitution, in contrast to linear aggregation where exogenous constraints on single (or a combination of) technologies are needed to return a portfolio of several investments. Finally, one should keep in mind that in economic models such as WITCH energy itself is an intermediate input, an aggregation of factors of production (capital, resources etc).

For each technology *j* (wind and solar, hydroelectric, nuclear, traditional coal, integrated gasification combined cycle (IGCC) with CCS, oil and gas) at time *t* and in each region *n*, electricity is obtained by combining three factors in fixed proportions: (i) the installed power generation capacity (*K*) measured in power capacity units, (ii) operation and maintenance equipment (*O&M*) in final good units and (iii) fuel resource consumption (*X*) expressed in energy units, where appropriate. The resulting Leontief technology is as follows:

$$EL_j(n,t) = \min\{\mu_j(n)K_j(n,t); \tau_j(n)O\&M_j(n,t); \varsigma_j X_{j,EL}(n,t)\} \tag{3}$$

The parameters governing the production function take into account the technical features of each power production technology. Thus μ translates power capacity into electricity generation (i.e. from TW to TWh) through a plant utilization rate (hours per year) which allows us to take into consideration the fact that some technologies - noticeably new renewables such as wind and solar power - are penalized by comparatively lower utilization factors; τ differentiates operation and maintenance costs among technologies, i.e. nuclear power is more expensive to run and maintain than a natural gas combined cycle (NGCC); finally, ς measures (the reciprocal of) power plant fuel efficiencies and yields the quantity of fuels needed to produce a KWh of electricity. *ELHYDRO* and *ELW&S* are assumed to have efficiency equal to one, as they do not consume any fuel: the production process thus reduces to a two-factor Leontief production function.

It is important to stress the fact that power generation capacity is not equivalent to cumulated investment in that specific technology, as different plants have different investment costs in terms of final output. That is:

$$K_j(n,t+1) = K_j(n,t)(1-\delta_j) + \frac{I_j(n,t)}{SC_j(n,t)} \tag{4}$$

where δ_j is the rate of depreciation and SC_j is the final good cost of installing power generation capacity of type *j*, which is time and region-specific. It is worth noting that depreciation rates δ_j are set consistently with the power plants' lifetime, so that again we are able to take into account the technical specifications of each different electricity production technology.

In WITCH the cost of electricity generation is endogenously determined. WITCH calculates the cost of electricity generation as the sum of the cost of capital invested in plants and the expenditures for O&M and fuels. Since the cost of capital is equal to its marginal product, as capital is accumulated capital-intensive electricity generation technologies, such as nuclear or wind and solar, become more and more preferable to variable cost-intensive ones such as gas. Indeed, whereas at the beginning of the optimization period regions with high interest rates – such as the developing ones – disfavour capital-intensive power generation technologies, in the long run the model tends to prefer capital-intensive to fuel-intensive electricity production. Note that this feature is not shared by energy system models, as they are not able to ensure capital market equilibrium (see Bauer, 2005). Since investment costs, O&M costs, fuel efficiency for each technology and fuel prices are region-specific, we obtain a high degree of realism in constructing relative prices of different ways of producing electricity in the 12 regions considered.[2]

Exhaustible Resources

Four non renewable fuels are considered in the model – coal, crude oil, natural gas and uranium - whose cost follows a long-term trend that reflects their exhaustibility. We abstract from short-term fluctuations and model the time path of the resource *f* price starting from a reduced-form cost function that allows for non-linearity in the ratio of cumulative extraction to available resources.[3] Initial resource stocks are region specific and so are extraction cost curves. Thus, for each fuel *f* we have:

$$c_f(n,t) = q_f(n,t)\left(\chi_f(n) + \pi_f(n)\left[Q_f(n,t-1)/\overline{Q}_f(n,t)\right]^{\psi_f(n)}\right) \quad (5)$$

where c is the regional cost of resource f, depending on current extraction q_f as well as on cumulative extraction Q_f and on a region-specific markup, $\chi_f(n)$; $\overline{Q}_f$ is the amount of total resources at time t and $\pi_f(n)$ measures the relative importance of the depletion effect. Assuming competitive markets, the domestic price $P_f(n,t)$ is equal to the marginal cost:

$$\begin{aligned} &P_f(n,t) = \chi_f(n) + \pi_f(n)\left[Q_f(n,t-1)/\overline{Q}_f(n,t)\right]^{\psi_f(n)} \\ &Q_f(n,t-1) = Q_f(n,0) + \sum_0^{t-1} X_{f,extr}(n,s) \end{aligned} \quad (6)$$

The second expression represents cumulative extraction and $X_{f,extr}(n,t)$ is the amount of fuel f extracted in region n at time t. Fuels are traded among regions at an international market clearing price $P_f^{\text{int}}(t)$. Each region can thus opt for autarky or trade in the market, either as a net buyer or a net seller of fuels. The net import of fuels $X_{f,netimp}(n,t)$ takes on positive values when the region trades as a net buyer, and negative values when it trades as a net seller.

CO_2 Emissions

Since WITCH offers the possibility of tracking the consumption of fossil fuels, GHGs emissions that originate from their combustion are derived by applying the corresponding stoichiometric coefficients to total consumption. Even though we presently use a climate module that responds only to CO_2 emissions, a multi-gas climate module can easily be incorporated in WITCH thus allowing the introduction of gas-specific emissions ceilings.[4] For each region *n*, CO_2 emissions from the combustion of fossil fuels are derived as follows:

$$CO_2(n,t) = \sum_f \omega_{f,CO_2} X_f(n,t) - CCS(n,t) \quad (7)$$

[2] To our knowledge, the endogenous determination of electricity prices is a novelty in optimal growth integrated assessment models.

[3] Hansen, Epple and Roberds (1985) use a similar cost function that allows for non-linearity also in the rate of extraction.

[4] As in Nordhaus and Boyer (2000) we take into account GHGs emissions other than CO_2 by including an exogenous radiative forcing when computing temperature deviations from pre-industrial levels. Thus, when we simulate GHG stabilization policies we consider this additional component and accordingly constrain CO_2 emissions to a global target.

where ω_{f,CO_2} is the stoichiometric coefficient for CO_2 emissions of fuel *f* and CCS stands for the amount of CO_2 captured and sequestered while producing electricity in the coal IGCC power plant. The stoichiometric coefficient is assumed to be positive for traditional biofuels and negative for advanced biofuels, in line with IEA (2004b). As noted above, when analyzing climate policy, regions and/or countries may be allowed to trade their emissions allowances in a global or regional carbon market.

Finally, WITCH's climate module delivers emissions from land use change that are added to emissions from combustion of fossil fuels to determine atmospheric concentrations as in Nordhaus and Boyer (2000).

Endogenous Technical Change (ETC)

In standard version of WITCH, technical change is endogenous and is driven both by Learning-by-Doing (LbD) effects and by energy R&D investments (LbR). These two sources of technological improvements act through two different channels: LbD is specific to the power generation industry, while R&D affects the overall system energy efficiency.

We incorporate the effect of technology diffusion using experience curves, that reproduce the observed empirical relation according to which the investment cost of a given technology decreases with the accumulation of installed capacity. Specifically, the cumulative installed world capacity is used as a proxy for the accrual of knowledge that affects the investment cost of a given technology:

$$SC\ (t+1) = A\ \cdot \sum_n K\ \ (n,t)^{-\log_2 PR} \qquad \textbf{[8]}$$

here *PR* is the progress ratio that defines the speed of learning, K is the cumulative installed capacity for region *n* at time *t*. With every doubling of cumulative capacity the ratio of the new investment cost to its original value is constant and equal to *PR*. With several electricity production technologies, the model is flexible enough to change the power production mix and invest in the more appropriate technology for each given policy measure, thus creating the conditions to foster the LbD effects associated with the clean but yet too pricey electricity production techniques. It should be noted that we assume complete spillovers of experience across countries, thus modeling the innovation market failure of non-appropriability of learning processes.

As for LbR, we model endogenous technical change through investments in energy R&D that increase energy efficiency. Following Popp (2004), technological advances are captured by a stock of knowledge combined with energy in a constant elasticity of substitution (CES) function, thus stimulating energy efficiency improvements:

$$ES(n,t) = \left[\alpha_H(n)HE(n,t)^{\rho} + \alpha_{EN}(n)EN(n,t)^{\rho}\right]^{1/\rho} \qquad \textbf{[9]}$$

The stock of knowledge $HE(n,t)$ derives from energy R&D investments in each region through an innovation possibility frontier characterized by diminishing returns to research, a formulation proposed by Jones (1995) and empirically supported by Popp (2002) for energy-efficient innovations in the US:

$$HE(n,t+1)\ =\ aI_{R\&D}(n,t)^b HE(n,t)^c + HE(n,t)(1-\delta_{R\&D}) \qquad \textbf{[10]}$$

with $\delta_{R\&D}$ being the depreciation rate of knowledge. As social returns from R&D are found to be higher than private ones in the case of energy R&D, the positive externality of knowledge creation is accounted for by assuming that the return on energy R&D investment is four times higher than the one on physical capital. At the same time, the opportunity cost of crowding out other forms of

R&D is obtained by subtracting four dollars of private investment from the physical capital stock for each dollar of R&D crowded out by energy R&D, $\psi_{R\&D}$, so that the net capital stock for final good production becomes:

$$K_C(n,t+1) = K_C(n,t)(1-\delta_C) + (I_C(n,t) - 4\psi_{R\&D} I_{R\&D}(n,t)) \qquad \textbf{[11]}$$

where δ_C is the depreciation rate of the physical capital stock. We assume new energy R&D crowds out 50% of other R&D, as in Popp (2004). This way of capturing innovation market failures was also suggested by Nordhaus (2003).

Breakthrough technologies

We introduce backstop technologies in both the electric and non electric sectors. Backstop technology can be better thought of as a compact representation of a portfolio of advanced technologies, that would ease the mitigation burden away from currently commercial options, though it would become available not before a few decades and only provided sufficient R&D investments are undertaken. This representation has the advantage of maintaining simplicity in the model by limiting the array of future energy technologies and thus the dimensionality of techno-economic parameters for which reliable estimates and meaningful modeling characterization exist. We therefore model the backstop as “cumulative”, using historical and current expenditures and installed capacity for technologies which are already researched but are not yet viable (e.g. fuel cells, advanced biofuels, advanced nuclear technologies,…), without specifying the type of technology that will enter into the market.

We follow the most recent characterization in the literature, modelling the costs of the backstop technologies with a two-factor learning curve in which the price of the technologies declines both with investments in dedicated R&D and with technology diffusion (see, e.g., Kouvaritakis, Soria et al., 2000). This improved formulation is meant to overcome the main criticism of the single factor experience curves (Nemet, 2006) by providing a more structural -R&D investment led- approach to the penetration of new technologies, and thus to ultimately better inform policy makers on the innovation needs in the energy sector. Modeling of long term and uncertain phenomena such as technological evolution calls for caution in the interpretation of exact quantitative figures, and to accurate sensitivity analysis. The model parsimony allows for tractable sensitivity studies. One should nonetheless keep in mind that economic implication of climate policies as well as carbon price signals are influenced by innovative technologies availability only after 2030.

More specifically, we model the investment cost in a technology *tec* as being influenced by a learning by researching process (main driving force before adoption) and by learning by doing (main driving force after adoption). $P_{tec,t}$, the unit cost of technology *tec* at time *t* is a function of deployment, $CC_{tec,t}$ and dedicated R&D stock, $R\&D_{tec,t}$ as described in equation 14:

$$\frac{P_{tec,T}}{P_{tec,0}} = \left(\frac{R\&D_{tec,T-2}}{R\&D_{tec,0}}\right)^{-c} * \left(\frac{CC_{tec,T}}{CC_{tec,0}}\right)^{-b} \qquad [\ 12]$$

where the *R&D stock* accumulates with the perpetual rule and CC is the cumulative installed capacity (or consumption) of the technology.

We assume a two-period time interval (i.e. 10 yrs) between R&D knowledge investments have an effect on the price of the backstop technologies. This is to account for time lags between research and commercialization.

The two exponents are the learning by doing index ($-b$) and the learning by researching index ($-c$). They define the speed of learning and are derived from the learning ratios. The learning ratio lr is the rate at which the generating cost declines each time the cumulative capacity doubles, while lrs is the rate at which the cost declines each time the knowledge stock doubles. The relation between b, c, lr and lrs can be expressed as follows:

$1-lr = 2^{-b}$ and $1-lrs = 2^{-c}$ [13]

We set the initial prices of the backstop technologies at roughly 10 times the 2002 price of commercial equivalents. The cumulative deployment of the technology is initiated at 1000 TWh and 1 EJ respectively, an arbitrarily low value (Kypreos, 2007). The backstop technologies are assumed to be renewable in the sense that the fuel cost component is negligible; they are assumed to operate at load factors comparable with those of baseload power generation technologies.

This formulation has received significant attention from the empirical and modelling literature in the most recent past (see, for instance, Criqui, Klassen et al., 2000; Barreto and Kypreos, 2004; Klassen, Miketa et al., 2005; Kypreos, 2007; Jamasab, 2007; Söderholm and Klassen, 2007), but estimates of parameters controlling the learning processes vary significantly across studies. In this formulation, we take averages of the values in the literature, as reported in **Errore. L'origine riferimento non è stata trovata.** Note that the value chosen for LbD parameter is lower than those normally estimated in single factor experience curves, since part of the technology advancement is now led by specific investments. This more conservative approach reduces the role of black box autonomous learning, which has been criticized for being too optimistic and leading to excessively low costs of transition towards low carbon economies.

Table 1: Learning ratios for diffusion (LbD) and innovation (LbS) processes

Technology	Author	Lbd	LbS
Wind	Criqui et al 2000	16%	7%
	Jamasab 2007	13%	26%
	Soderholm and Klassens 2007	3.1%	13.2%
	Klassens et al 2005		12.6%
PV	Criqui et al 2000	20%	10%
Solar Thermal	Jamasab 2007	2.2%	5.3%
Nuclear Power (LWR)	Jamasab 2007	37%	24%
CCGT (1980-89)	Jamasab 2007	0.7%	18%
CCGT (1990-98)	Jamasab 2007	2.2%	2.4%
Backstop EL		*10%*	*13%*
Backstop NEL		*7%*	*13%*

Backstops substitute linearly nuclear power in the electric sector, and oil in the non-electric one. We assume that once the backstop technologies become competitive thanks to dedicated R&D investment and pilot deployments, their uptake will not be immediate and complete, but rather there will be a transition/adjustment period. These penetration limits are a reflection of inertia in the system, as presumably the large deployment of backstops will require investment in infrastructures and the re-organization of the economic system. The upper limit on penetration is set equivalent to

5% of the total consumption in the previous period by technologies other than the backstop, plus the electricity produced by the backstop in the electricity sector, and 7% in the non electricity sector.

Spillovers in knowledge and experience

The effect of international spillovers is deemed to be very important, and its inclusion in integrated assessment models desirable, since it would allow for a better representation of the innovation market failures and for specific policy exercises.

In addition to spillovers of experience, WITCH includes spillovers in knowledge for energy efficiency improvements (Bosetti et al, 2007).

The amount of spillovers entering each world region depends on a pool of freely available knowledge and on the ability of each country to benefit from it, i.e. on its absorption capacity and knowledge accumulates according to the standard capital accumulation perpetual rule. Knowledge acquired from abroad combines with domestic knowledge stock and investments and thus contributes to the production of new technologies at home.

More specifically, we assume that a technological frontier is determined by the combined efforts in energy efficiency R&D of the group of high income countries. By assuming a technological frontier determined by more than one country, we avoid the case of one single world leader, which cannot absorb any valuable knowledge from its followers, which is highly unrealistic when not dealing with a specific industry. Furthermore, we assume that only a fraction of the knowledge pool can be absorbed by each country. The spillover of international knowledge in region n at time t is given by equation 14:

$$SPILL(n,t) = \frac{HE(n,t)}{\sum_{n \in HI} HE(n,t)} * \left[\left(\sum_{n \in HI} HE(n,t)\right) - HE(n,t)\right] \qquad \textbf{[14]}$$

Where the second term represents the technological frontier, determined by the combined efforts in energy efficiency R&D of the group of high income countries, HI; and the first term represents regional absorption capacity, a function of the distance of EE R&D capital accumulated in each region from the technological frontier.

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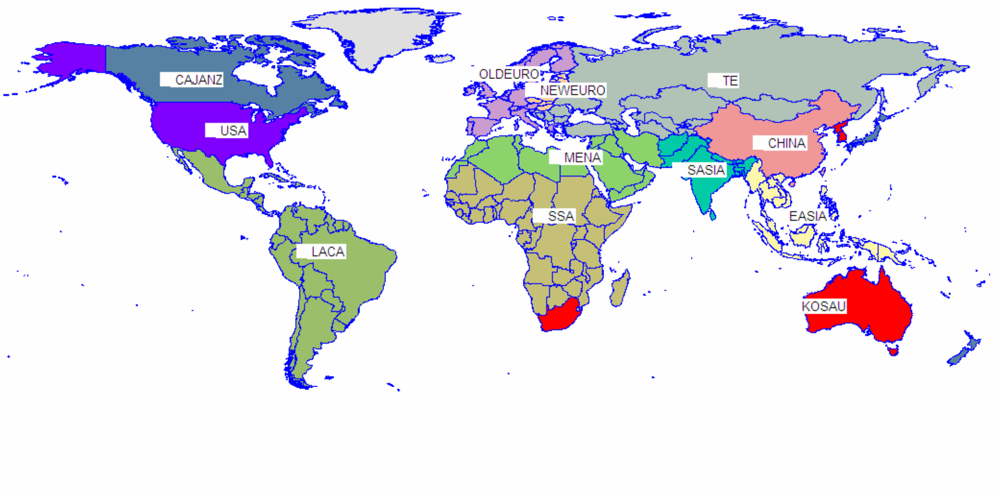
Figures

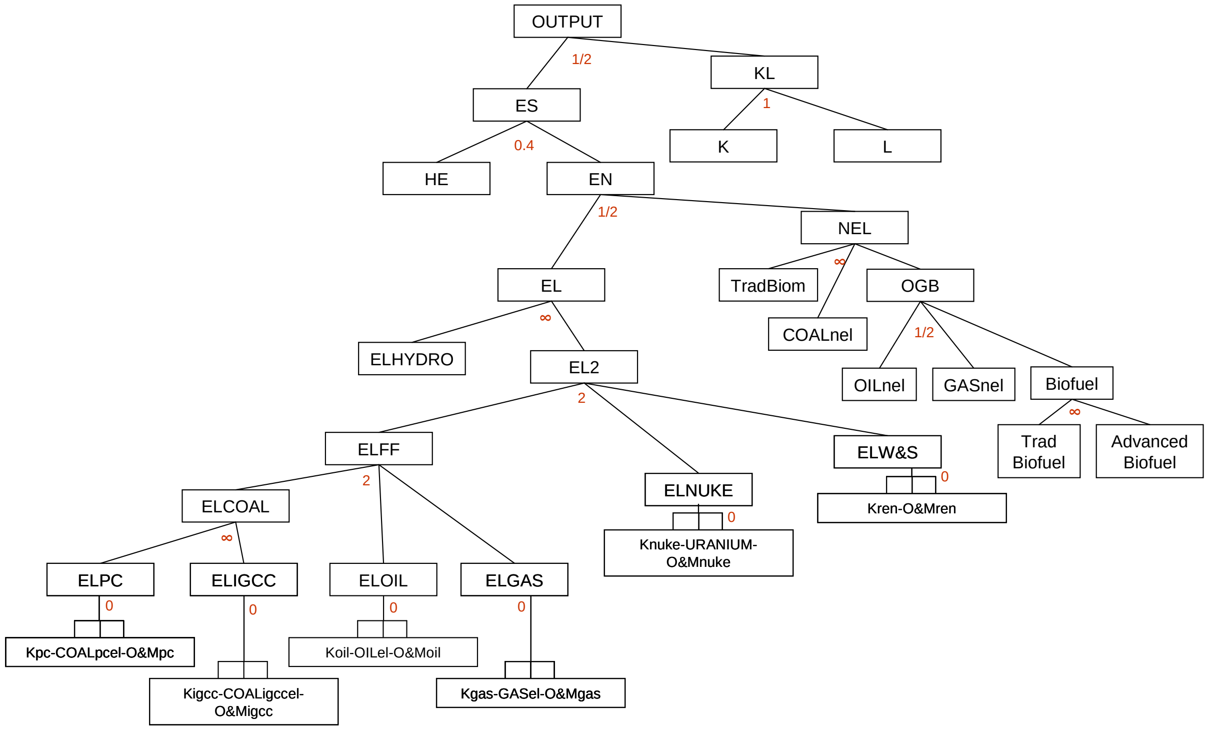
Figure 1: World Regions in the WITCH Model



Regions:

1) **CAJANZ (Canada, Japan, New Zealand)**
2) **USA**
3) **LACA (Latin America, Mexico and Caribbean)**
4) **OLDEURO (Old Europe)**
5) **NEWEURO (New Europe)**
6) **MENA (Middle East and North Africa)**
7) **SSA (Sub-Saharan Africa excl. South Africa)**
8) **TE (Transition Economies)**
9) **SASIA (South Asia)**
10) **CHINA (including Taiwan)**
11) **EASIA (South East Asia)**
12) **KOSAU (Korea, South Africa, Australia)**

Figure 2: Production Nest and the Elasticity of Substitution values



Legenda:

KL= capital-labour aggregate

K = capital invested in the production of final good

L = Labour

ES = Energy services

HE = Energy R&D capital

EN = Energy

EL = Electric energy

NEL = Non-electric energy

OGB = Oil, Gas and Biofuel nest

ELFF = Fossil fuel electricity nest

W&S= Wind and Solar

ELj = Electricity generated with technology j

TradBiom= Traditional Biomass

Kj = Capital for generation of electricity with technology j

O&Mj = Operation and Maintenance costs for generation of electricity with technology j

'FUELj'el = Fuel use for generation of electricity with technology j

'FUELj'nel = Direct fuel use in the non-electric energy use