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A MODEL-BASED ASSESSMENT OF THE COST IMPLICATIONS OF CLIMATE-RELATED R&D

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SUMMARY This paper addresses two basic issues related to technological innovation and climate stabilisation objectives: i) Can innovation policies be effective in stabilising greenhouse gas concentrations? ii) To what extent can innovation policies complement carbon pricing (taxes or permit trading) and improve the economic efficiency of a mitigation policy package? To answer these questions, we use an integrated assessment model with multiple externalities and an endogenous representation of technical progress in the energy sector. We evaluate a range of innovation policies, both as a stand-alone instrument and in combination with other mitigation policies. Even under fairly optimistic assumptions about the funding available for, and the returns to RD, our analysis indicates that innovation policies alone are unlikely to stabilise global concentration and temperature. The efficiency gains of combining innovation and carbon pricing policies are found to reach about 10% for a stabilisation target of 535 ppm CO2eq. However, such gains are reduced when more plausible (sub-optimal) global innovation policy arrangements are considered.

Keywords: Climate change, environmental policy, energy RD fund, stabilisation costs

JEL: H0, H2, H3, H4, O3, Q32, Q43, Q54

1. Introduction

The issue of the role and potential effectiveness of technological change for mitigating climate change has gained momentum in both the literature and the political debate over the past decade. Despite the many uncertainties around the magnitude of the impacts of technological change on mitigation costs, there is now broad agreement that innovation will be required to foster the needed decarbonisation of the economy. Furthermore, in the presence of both environmental and innovation externalities, the optimal set of climate policy instruments should include explicit R&D and possibly technology diffusion policies, in addition to carbon pricing policies that stimulate new technology purely as a side effect of internalising the environmental externality (Jaffe et al. (2005) and Bennear and Stavins (2007)). On the other hand, relying on R&D alone might be not sufficient to achieve stringent targets and/or to minimise mitigation costs, because such an approach would provide no direct incentives for the adoption of new technologies and, by focusing on the long term, would miss near-term opportunities for cost-effective emissions reductions (Philibert, 2003; Sandén and Azar, 2005; Fischer 2008).

Against this background, innovation and technology policies have received considerable attention from policymakers in the past few years. Proposals of international technology agreements have been put forward, that would encompass domestic and international policies to foster R&D and knowledge-sharing (Newell 2008). Innovation strategies have also been analysed in the context of climate coalition formation, suggesting that they are indispensable for improving the robustness of international agreements to control climate change (Barrett 2003). On the policy side, some climate-related scientific and technology agreements have emerged, including the Carbon Sequestration Leadership Forum, the Asia Pacific Partnership on Clean Development and Climate, and the International Partnership for a Hydrogen Economy. Most recently, the accord signed in Copenhagen at COP15 envisages a network of "Climate Innovation Centres" to facilitate collaboration on clean technologies between developed and developing nations.

Despite the growing interest for climate-related technological change, there is so far limited quantitative evidence on the role that innovation policies should play in a climate stabilisation policy package, as well as on the particular R&D areas that should be targeted. Popp (2006) has shown that combining carbon pricing and R&D policies can yield welfare gains, but that these are modest with respect to the optimal carbon tax case. Fischer and Newell (2008) find that an optimal portfolio of policies that includes, among others, emissions pricing and R&D can achieve significant efficiency gains.

Energy-economy-climate models used to evaluate mitigation policies have incorporated innovation mechanisms such as R&D investments only to a limited extent. This is a drawback, since the optimal policy mix is likely to depend on the returns to scale of energy technologies that are subject to learning (Gerlagh and van der Zwaan (2006)), and that are determined by the evolution of the whole energy system. Also, the limited analysis available of R&D investments required to comply with climate stabilisation objectives (Shock et al 1999, Davis and Owens 2003, Nemet and Kammen 2007) has been carried out mostly outside the realm of general equilibrium models. The main objective of this paper is to bring innovative input to the debate on the role of technology policy for climate change mitigation, focusing on the interplay between innovation and carbon pricing policies using the rich set-up allowed by integrated assessment models. To this end, we investigate several potential intervention strategies, with technology policies being used either as a substitute or as a complement to carbon pricing.

The rest of this paper is organised as follows. Section 2 provides a brief overview of the model used in this paper, WITCH, focusing on the various channels of endogenous technological change featured in the model and the types of innovation policies that can be assessed. Section 3 looks at the climate effectiveness of innovation policies, *i.e.* at the extent to which such policies *alone* can bring about emission reductions. Section 4 then turns to the economic effectiveness of innovation policies, *i.e.* the extent to which they can lower the economic costs of a climate policy package aimed at meeting a given climate change mitigation target. We assess the potential economic efficiency gains from hybrid innovation/carbon pricing policies relative to a pure carbon-pricing approach, and compare these potential efficiency gains to those achievable in practice when considering politically more realistic – but sub-optimal – policy combinations. Section 5 concludes the paper by summarising its main results.

2. Endogenous technological change and innovation policy options in WITCH

The analysis presented in the paper is carried out using the World Induced Technical Change Hybrid (WITCH) model, an energy-economy-climate model developed by the climate change group at FEEM. The model has been used extensively for economic analysis of climate change policies.[1] The Appendix to this paper provides a short introduction to the model, focusing in particular on the modelling of the channels that foster technological change.

WITCH is an economic model with an in-built representation of the energy sector, thus belonging to the class of fully integrated (hard link) hybrid models. It is a global model divided into 12 macro-regions. The model has two main distinguishing features in the context of the present analysis. The first one is a representation of endogenous technical change in the energy sector. Advancements in a range of carbon mitigation technologies are described by both innovation and diffusion processes. Learning-by-Researching (LbR) and Learning-by-Doing (LbD) shape the optimal R&D and technology deployment responses to given climate policies. In terms of innovation market failures, energy-related knowledge in a country depends not only on the country's own R&D investments but also on those made by others, *via* an international spillovers mechanism. For a given region, the magnitude of such spillovers depends on the distance of its R&D knowledge stock (cumulative past R&D) to the frontier, but also on its absorptive capacity which depends positively on its knowledge stock. This gives rise to a bell-shaped relationship between a country's R&D knowledge stock and spillovers, with the latter being lowest when the former is either very low (weak absorptive capacity) or very high (small distance to technological frontier) (for details, see Bosetti *et. al.,* 2008 and the Appendix of this paper). In turn, these international R&D spillovers provide a case for international R&D policies.

WITCH accounts for higher social returns from R&D by calibrating a higher marginal price of capital and assumes an exogenous crowding out of other forms of R&D. Thus, the implications of biased technical change are not considered here, but they have been evaluated in applications of WITCH on the direction and pace of technical progress (Carraro *et. al.* (2009a)) and on human capital formation (Carraro *et al.* (2009b)). Nevertheless, it should be noted that important additional R&D externalities, such as appropriability and knowledge protection issues, are not captured due to the aggregated structure of the model.

The second relevant modelling feature is the game-theoretic set up. WITCH is able to produce two different solutions. The first is the so-called globally optimal solution, which assumes that countries fully cooperate on global externalities. The second is a decentralised solution that is strategically optimal for each given region in response to all other regions' choices, and corresponds to a Nash equilibrium. This modelling feature

[1] See www.witchmodel.org for a list of applications and papers.

allows accounting for externalities due to all global public goods (CO_2, international knowledge spillovers, energy markets, etc...), making it possible to model free-riding incentives. It also allows exploring the environmental and economic effects of, and the potential interactions between different policies aimed at internalising the technological externality and/or the climate externality.

Three types of innovation policies summarised in Table 1 are considered in this paper, which differ in the type of R&D they subsidise:

i) ***Energy intensity enhancing R&D investments (E.E.).*** The model assumes that an energy efficiency capital stock can be built through dedicated R&D investments, which is a substitute for physical energy (via a constant elasticity of substitution production function) in producing final energy demand.

ii) ***Wind, solar and Carbon Capture and Storage R&D investments (W+S & CCS).*** The investment costs of wind, solar and CCS can be decreased by innovation investments, *via* an LbR formulation that relates proportional increases in the knowledge capital to productivity improvements.

iii) ***Breakthrough technologies R&D investments (Advanced Techs).*** As with wind, solar and CCS, LbR decreases the cost of two non-commercial, advanced carbon-free technologies. These technologies can substitute for existing ones in the electricity and non-electricity sectors, respectively.

Acronym	**Innovation Policy Features**
E.E.	R&D for energy efficiency enhancement
W+S & CCS	R&D to improve productivity of wind, solar and CCS
Advanced Techs	R&D for advanced, breakthrough technologies

Table 1: The three types of innovation policies considered in this paper

These three types of innovation policies are assessed in terms of both their potential carbon emission abatement potential if used as stand-alone policies, and the economic efficiency gains they can generate when combined with an explicit climate stabilisation policy.

3. Climate effectiveness of innovation policies

We start by analysing the environmental effectiveness of standalone innovation policies, looking at their impact on carbon emission and concentration trajectories over the century. We simulate innovation policies assuming global R&D funds of various sizes are used to subsidize the three categories of Table 1. As a central value, we use a fund size equal to 0.08% of Global World Product (GWP). This share is consistent with the optimal R&D investments needed to comply with a stringent climate stabilisation policy in the WITCH model (Bosetti et. al. 2009a), and is in line with the peak level of public energy R&D expenditures achieved across the OECD area in the early 1980s. Similar values have also been suggested in other recent analyses (IEA, 2008). For robustness check, and in order to assess the maximum world emission reduction that could be achieved through a stand-alone innovation policy, we pursued additional experiments with incrementally larger funds amounting to up to 2% of GWP. The international R&D fund is assumed to be financed by contributions from OECD regions that are proportional to their GDP (0.08% in most of our analysis). In turn, each world region receives from the international R&D fund a subsidy which adds to its own regional R&D investments in innovation. The fund is distributed across regions on an equal per capita basis, although alternative distribution rules were also tested to check for robustness.

Figure 1 and 2 report CO_2 emissions and concentrations for the 4 innovation policies, as well as for the reference (BAU, no policy) and a climate stabilisation pathway at 450 CO_2 (535 CO2-e) ppmv. The main result is that all innovation policies fall short of generating the mitigation action needed to stabilise carbon concentrations. In all cases, the atmospheric stock of CO_2 keeps increasing and so does the global temperature, which remains rather close to the baseline case.

There are differences across innovation policies, however. The “Advanced Techs” R&D policy, under which two advanced technologies become competitive via R&D investments, yields the higher mitigation and manages to stabilise carbon emissions – albeit not concentrations. Given the improvements needed and commercialisation lags, these technologies become effectively available around mid-century, leading to some emission reductions afterwards. The “W+S & CCS” R&D policy achieves somewhat smaller reductions relative to BAU, and with a different time profile. Unlike new breakthrough technologies, wind, solar and CCS can quickly penetrate the market if supported by R&D subsidies, allowing some emission reductions during the first half of the century.

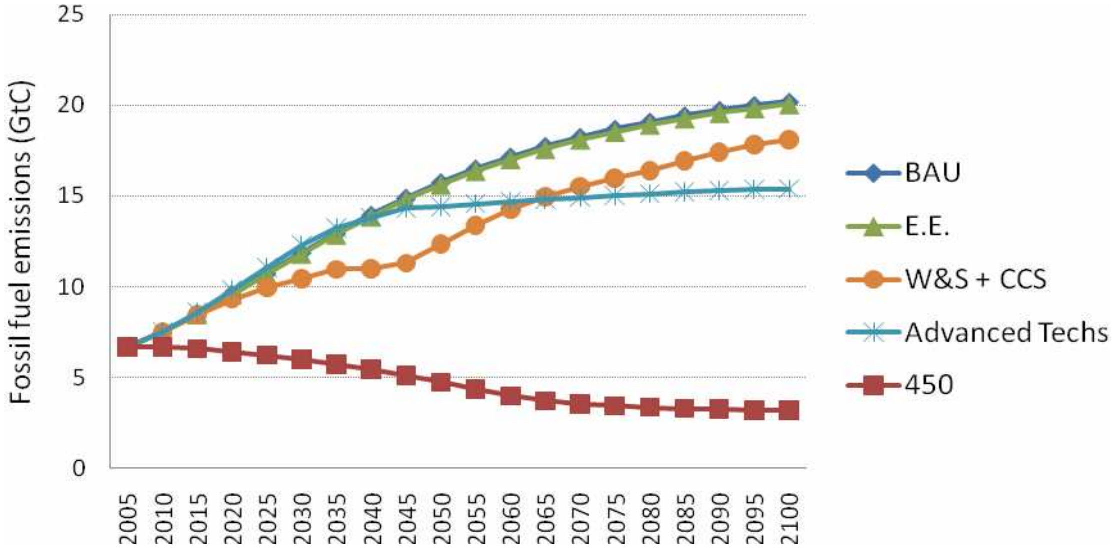

Figure 1. Fossil fuel emission paths under alternative innovation policies, compared with emission paths in the baseline and 450 ppm CO_2 only stabilisation cases.

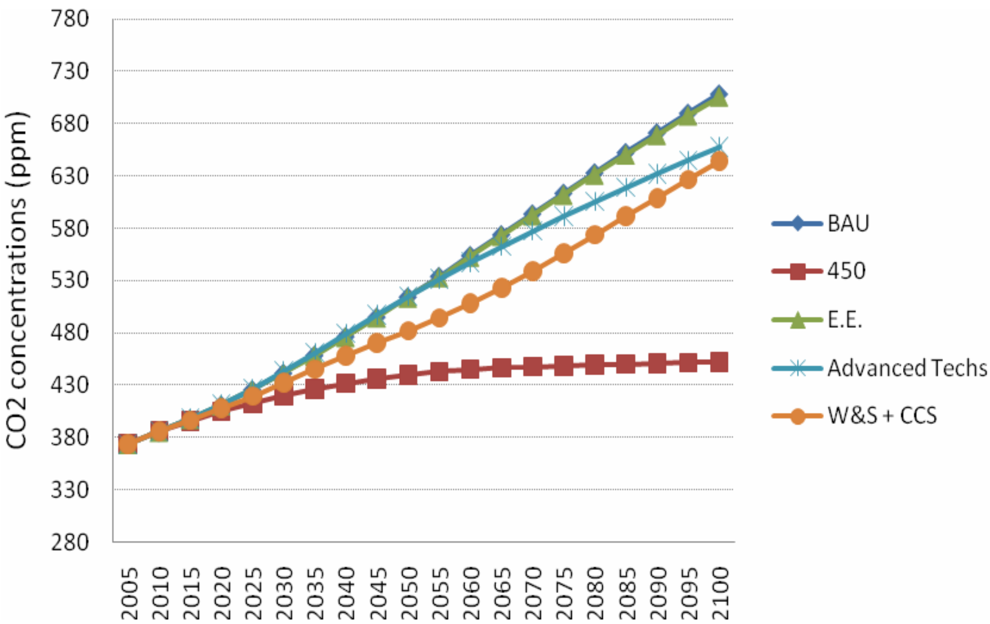

Figure 2. CO_2 concentration paths under alternative innovation policies, compared with emission paths in the baseline and 450 ppm CO_2 only stabilisation cases.

However, in the long term returns to R&D investments in both technologies are limited by the resource constraints in terms of site availability (for Wind and Solar) and storage repository (for CCS) . The last option, namely R&D dedicated to energy efficiency (E.E.), is almost ineffective for two reasons. First, some decline in energy intensity is already embedded in baseline scenarios, consistent with the dynamics of the last 50 years. As a consequence, achieving additional energy efficiency improvements *via* R&D is fairly expensive at the margin. Second, efforts to decarbonise the economy will ultimately be crucial to make a dent in emissions. This cannot be achieved through improvements in energy efficiency alone, and rather requires the progressive phasing-out of fossil-fuel-based energy technologies.

While the above simulations assume sizeable R&D spending, roughly four times higher than current public energy-related expenditures, one open question is whether even higher spending might overturn our conclusions. Likewise, mixed strategies combining all three types of R&D could in principle deliver higher returns, especially since alternative options differ in the time profile and long-run potential of the emission reductions they can achieve. We have therefore carried out a number of sensitivity analyses, varying the size and allocation of the technology fund. A very robust finding across all simulations is that the largest achievable reduction in emissions with respect to the baseline is in the order of 13%-14% in cumulated terms throughout the century, in the range of the "Advanced Techs" case discussed above. In particular, while a larger international R&D fund induces larger emission reductions over the medium term, its long-term impact is limited by declining marginal returns to R&D, as well as by the positive counteracting impact of the fund on world GDP and emissions.

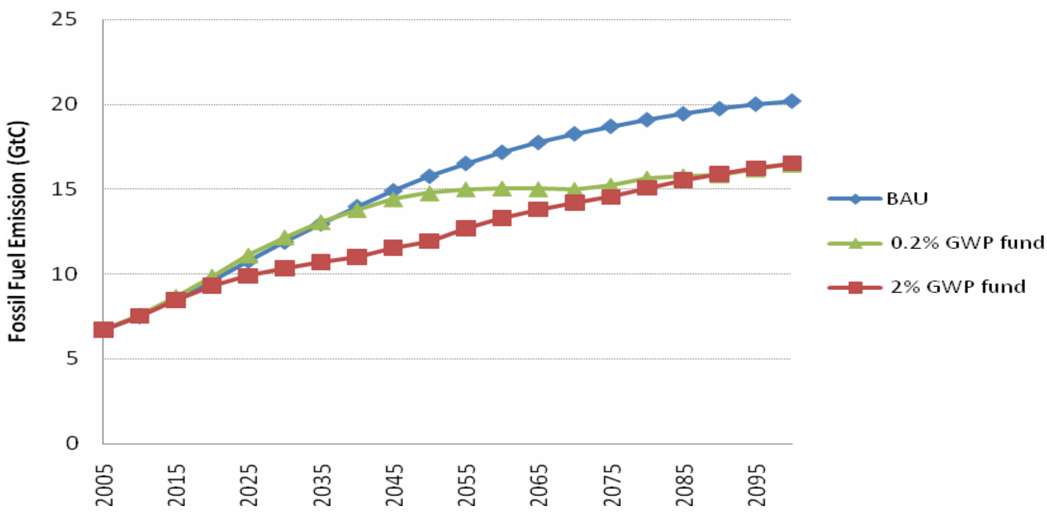

Figure 3. Fossil fuel emission paths for different sizes of a mixed innovation policy.

This is illustrated in Figure 3 through a comparison between two funds amounting to 2% of GWP and 0.2% respectively, both of which are assumed to subsidise equally all three types of R&D. Although the larger fund implies lower emissions in the medium term, by the end of the century the two innovation policies result in similar and growing emissions, due to the reallocation of consumption from earlier to later periods in time. Furthermore, the medium-term impact of a large R&D fund is insufficient to put world emissions, even for the first few decades, on a path consistent with long-run stabilisation of carbon concentrations at safe levels.

4. Economic efficiency gains from hybrid innovation/carbon pricing policies

Although the simulation results from the previous section clearly point to the lack of environmental effectiveness of R&D as a stand-alone policy, R&D may still contribute to reducing the cost of a climate policy package when used as a complement to carbon pricing policies. The main reason is illustrated in Figure 4, which shows the economic gains from a fund amounting to 0.08% of GWP used as a stand-alone policy. By internalising international technological externalities and forcing higher innovation investments in earlier periods, innovation policies deliver some welfare gains during the second half of the century, at the expenses of initial losses. While these gains are small under the "W+S & CCS" and "EE" innovation policies, they are sizeable in the "Advanced Techs" case, which as discussed before also achieves the largest emission reductions. Thus, R&D programs meant to facilitate the development of breakthrough technologies that can help decarbonise sectors such as transport appear to hold the largest emission-reduction and cost-reduction potential.

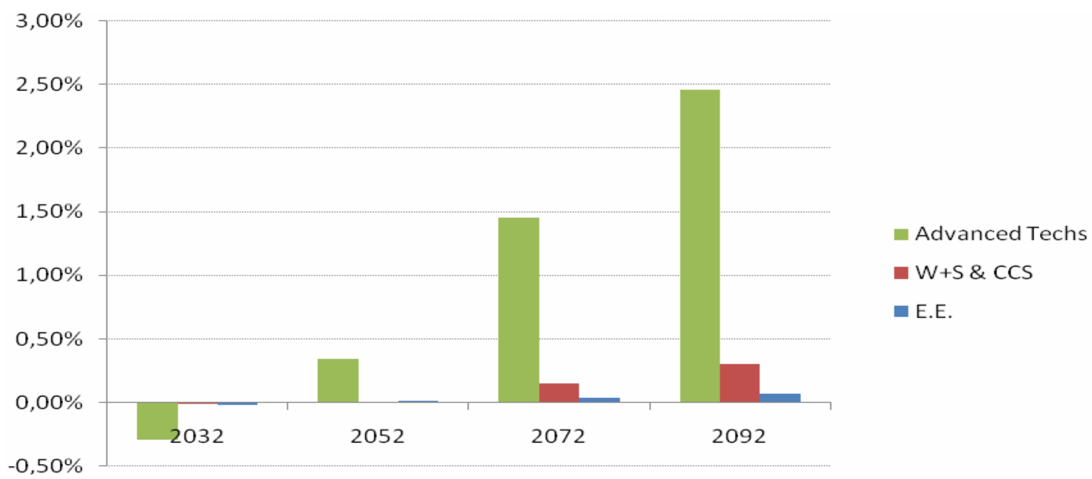

Figure 4. Economic benefits (% difference of global consumption with BAU) of stand-alone innovation policies, for an R&D fund equal to 0.08% of GWP.

It should be noted, however, that such policies still impose an economic cost in the first decades of the century, albeit a fairly small one in this case. Funds of larger sizes generate higher early penalties; for example, a fund of 2% of GWP as shown in Figure 3 would yield consumption losses of 2 to 3% and benefits only after 2060.

This section assesses the economic efficiency gains from hybrid carbon pricing/innovation policies in two steps. In a first step, we illustrate the innovation effects and economic impacts of a world carbon price alone under a 450 ppm CO_2 only (535 CO2 eq) carbon concentration stabilisation target[2]. In a second step, we estimate the economic gains from incorporating an R&D policy on top of that world carbon price.

4.1. Innovation and economic costs under a climate stabilisation policy alone

We begin by analysing the optimal investments in innovation when a stringent climate stabilisation policy is considered. A policy of this kind, although probably not sufficient to maintain the global temperature increase below the 2° Celsius threshold, does require an immediate and rapid decarbonisation trajectory, for which currently available mitigation options need to be supplemented with innovation in low carbon technologies, especially in the transportation sector. Thus, significant increases in R&D are found to be the optimal response to a stringent world cap-and-trade scheme. For example, as shown in Figure 5, public R&D expenditures are found to quadruple with respect to baseline and, as a share of GDP, to approach the peak levels of the early 1980s.[3] Most of the R&D undertaken is dedicated to the two breakthrough technologies, *i.e.* to decarbonisation, while R&D dedicated to energy efficiency improvements is comparatively smaller.

[2] We assume the existence of an international carbon market that equalizes marginal abatement costs. Emission allowances are allocated on an equal per capita basis.

[3] Bringing back public R&D spending to its early 1980s level is not inconsistent with IEA's most recent estimates of R&D spending needs, using a widely different framework (IEA, 2008). It is also worth noting that at the policy level, proposals to raise the energy R&D budgets considerably, even before committing to a cap-and-trade system, are apparently being made already. US President Obama recently committed to R&D tax exemptions and an additional investment of 1.2 USD Billions in basic energy-related research, see http://news.cnet.com/8301-11128_3-10202041-54.html

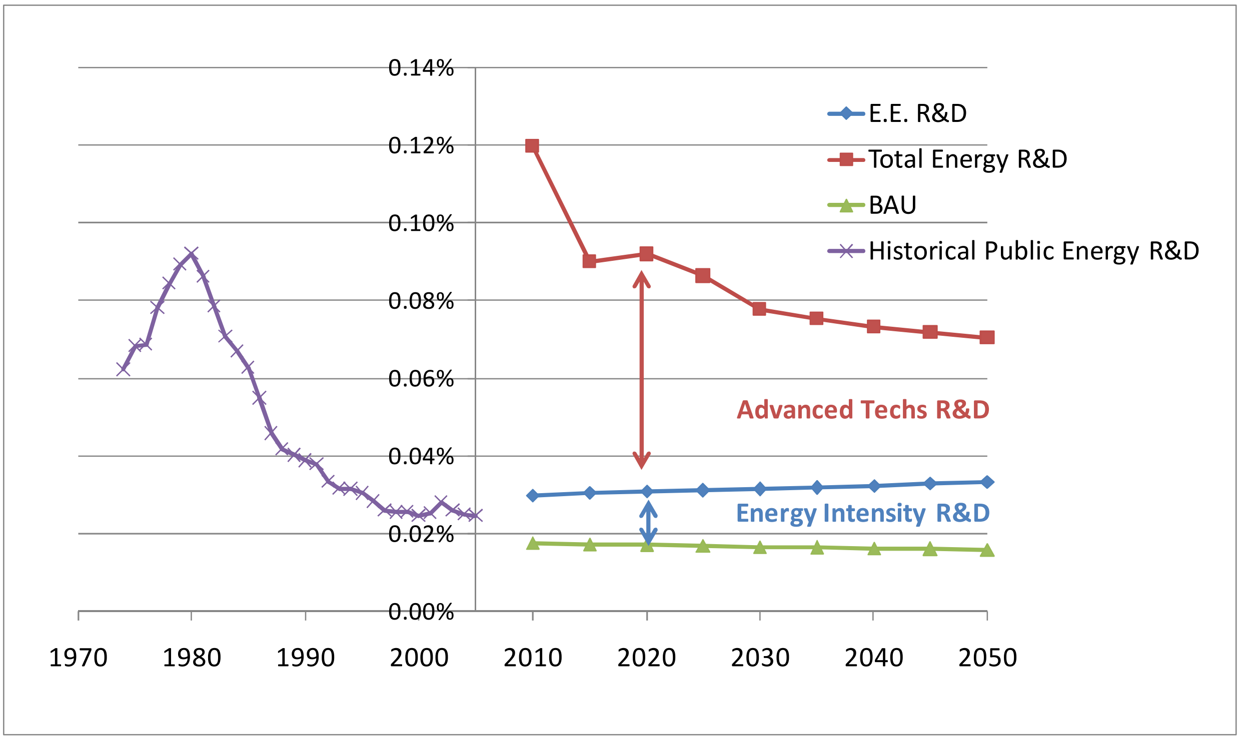

Figure 5. Energy R&D investments (as shares of GWP) in the baseline and the 450 ppm CO_2 (535 ppm CO_2eq) concentration stabilisation policy alone, compared with historical figures.

The response of R&D and technological change to carbon pricing, in particular the emergence of the advanced technologies, plays a major role in containing the costs of a climate stabilisation policy. This is illustrated in Figure 6, which compares the costs of the climate policy under alternative assumptions regarding investment possibilities in advanced technologies. One extreme scenario assumes that the possibility to invest in such breakthrough technologies is foregone altogether, while an intermediate scenario assumes that R&D investment is still possible in the non-electricity technology. Allowing R&D investments in the advanced technologies greatly reduces mitigation costs at distant horizons, especially beyond mid-century, at the cost of higher losses in the first decades, due to the large increase in R&D effort needed to bring about the breakthroughs. Overall, the difference in the economic costs of a stabilisation policy with and without the advanced technologies is in the order of 45%, using a 5% discount rate. A strong carbon price signal would still be needed in the short term (in the order of 100 $/tCO_2$ in 2030) to foster the large investments needed in both the available abatement opportunities and in the advanced technology R&D programs.

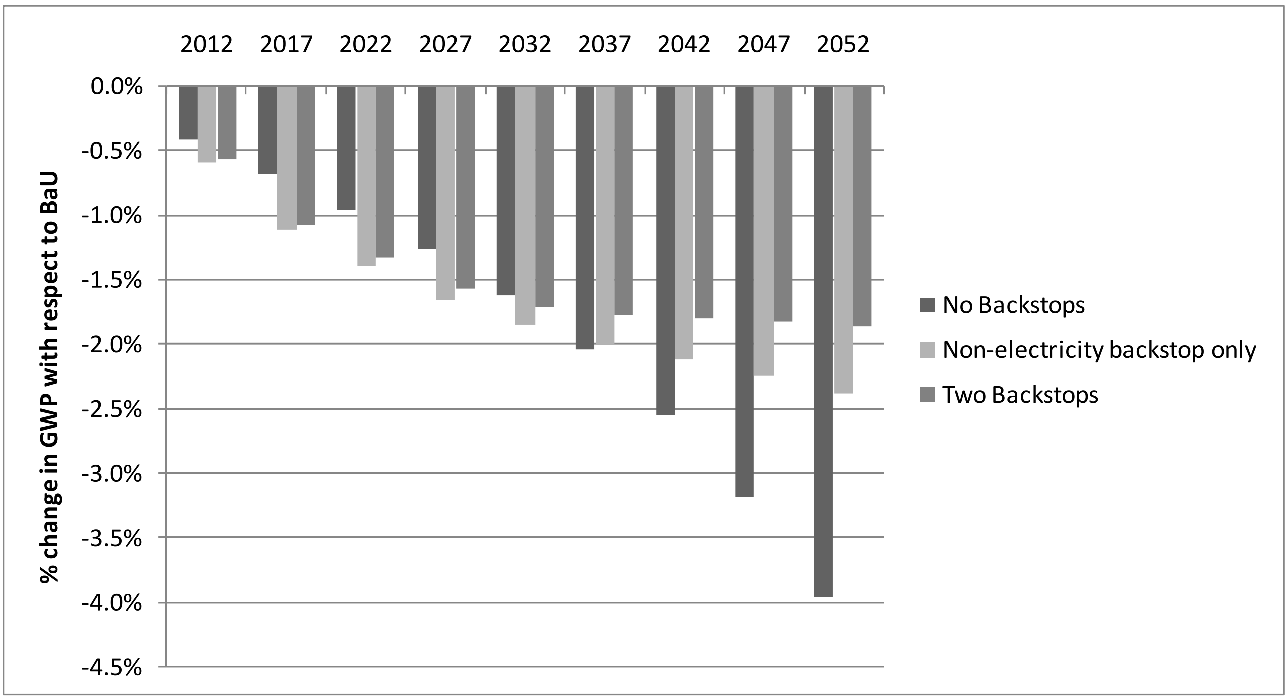

Figure 6. Costs (% GWP difference with BAU) of a 450 ppm CO_2 (550 ppm CO_2eq) concentration stabilisation policy under alternative assumptions regarding investment possibilities in advanced technologies.

The development of carbon-free technologies is especially important in the non-electricity sector, where the marginal costs of abatement are particularly high. Compared with a scenario where R&D investments can be made in both advanced technologies, a simulation where only the non-electricity carbon-free technology is available leads to a small increase in mitigation costs. These results highlight the importance of developing carbon-free technologies in the non-electricity sector, notably in transport, where currently commercially available mitigation options have only limited abatement potential. Also, the electric sector already possesses a fairly rich technology portfolio needed to achieve a stringent climate target, provided that nuclear, CCS and renewables can be deployed on a sufficiently large scale. This lowers the gains at the margin from investing in new advanced technologies in that sector.

4.2. Economic efficiency gains from optimal hybrid innovation/carbon pricing policies

Having shown that a carbon pricing approach would already induce sizeable increases in overall R&D spending, which in turn would significantly dampen mitigation costs, we now assess the economic efficiency gains from incorporating a global R&D policy on top of that world carbon price. This is done by comparing two cooperative solutions of the WITCH model, namely one featuring cooperation on both climate and R&D policies – *i.e.* combining a world carbon price and a global R&D investment strategy that internalises all international knowledge spillovers – and another assuming cooperation on climate policy only – *i.e.* the climate stabilisation policy considered in Section 4.1 above, which implicitly assumes non-cooperative behaviour of each region in setting their R&D spending.

Compared with cooperation on climate policy only, we find that an optimal policy with cooperation on both innovation and climate would yield somewhat higher energy R&D expenditures. As shown in Table 2, on average global R&D investments increase by about 9 Billions USD a year, or 9%. The largest increases occur in non-OECD countries: since these are far from the technological frontier, increased R&D spending enhances their ability to absorb the world knowledge pool. OECD countries also raise their innovation effort, although to a less extent, given their lower marginal returns to R&D investments. The highest change occurs during the initial periods, up to 2020.

	OECD	NON-OECD	WORLD
Climate policy	47.7	40.0	87.7
Optimal policy	49.3	46.3	95.6
% difference	3%	16%	9%

Table 2. Investments in energy R&D (Billions USD, average 2010-2050) for the two policies with cooperation on only climate and on both climate and innovation.

In economic terms, cooperation on both innovation and climate reduces the costs of climate mitigation. Global consumption losses (in net present value at 3% discount rate) are reduced from 1.92% to 1.72%, an efficiency gain of 10% or about 6 USD Trillions.

These numbers confirm that combining carbon pricing and R&D policies can yield welfare gains, but that carbon pricing alone could go a long way in determining the optimal investment portfolio consistent with climate stabilisation (Popp, 2006).

4.3. Economic efficiency gains from realistic hybrid innovation/carbon pricing policies

The 10% potential reduction in climate change mitigation costs from a global R&D policy estimated in the previous version is largely theoretical. Indeed, while cooperation on climate change "merely" requires setting up a single world carbon price, in principle cooperation on R&D requires an omniscient world social planner that sets an optimal level of global R&D and allocates it optimally across time, regions and types of R&D. This is extremely unlikely to be achievable in the real world, and as such the 10% represents at best an upper bound.[4]

It is therefore instructive to assess the economic efficiency gain that could be achieved by a more plausible global R&D policy, and to compare it with the maximum theoretical gain. To this end, we assume a global fund making a constant share of GWP, financed by OECD countries, allocated to each region on a per-capita basis, and spent only on breakthrough technologies, which we have shown have the largest cost-saving potential compared to alternatives. The results from such simulations in terms of efficiency gains carried out for a range of fund sizes are reported in Figure 7.

Unlike the optimal global R&D policy analysed in the previous paragraph, the simple R&D fund would only have a small impact on mitigation policy costs, reducing the global cost of meeting the stabilisation target by at most 3-3.5% relative to cooperation on climate policy only. The reduction in policy costs is highest – albeit small – for a fund of about 0.07% of GWP, roughly in line with the ones analysed through the paper. However, the gain is smaller than the one shown for the optimal case, given the different regional repartition. Higher spending is not found to be efficient due to decreasing marginal returns to R&D. Overall, the disappointingly small cost reduction achieved by the simple R&D fund compared with the maximum achievable savings highlights the importance of allocating spending optimally across time, regions and different types of R&D.

[4] It should be noted that the WITCH model's aggregate structure does not allow us to model issues related to private underinvestment in R&D, which could in principle increase the efficiency gains deriving from an R&D fund.

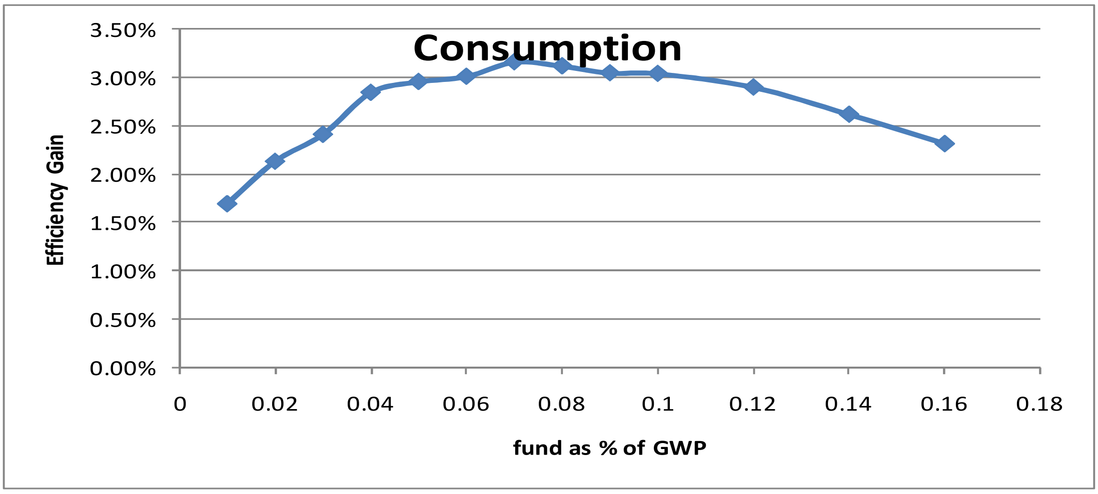

Figure 7. Economic efficiency gains (% difference in discounted consumption relative to cooperation on climate policy only) from a global R&D fund dedicated to breakthrough technologies, under a 450 ppm CO_2 (535 ppm CO_2eq) concentration stabilisation constraint and for different fund sizes.

4.4. Economic efficiency gains from optimal hybrid innovation/carbon pricing policies for a looser climate objective.

Our results so far have indicated that innovation is a key ingredient to climate stabilisation, and that substantial investments in energy-related R&D are needed to bring about the productivity changes required by low emission targets. As such, combining climate and innovation policies yields additional benefits, but those would be bounded by the high levels of investments already occurring in the climate scenarios. Indeed, our estimates have suggested that for a climate objective of 450 CO2 only (535 CO2-eq) the efficiency gains of coupling innovation and climate policies would at best equal 10%. However, the policy considered is a quite severe one, and one might wonder how results would change if a looser climate objective were considered.

As a final task, we investigate a climate objective of 550 CO2 only (650 CO2 –eq) and again compare the case of cooperation on climate only with that of cooperation on both climate and innovation. Table 3 (the counterpart of Table 2) shows the R&D investments in the two scenarios. Once again, the optimal policy envisages more investments in R&D than in the climate policy only. This time the global increase of investments is in the order of 20%, twice as much as for the more stringent climate objective, and also higher in levels (+12.6 Billions/yr), despite the fact that overall R&D investments are lower given the less ambitious climate target. The largest increase again occurs in developing countries, but developed ones also raise their levels of investments.

	OECD	NON-OECD	WORLD
Climate policy	35.2	29.4	64.6
Optimal policy	38.4	38.8	77.2
% difference	9%	32%	20%

Table 3. Investments in energy R&D (Billions USD, average 2010-2050) for the two policies with cooperation on only climate and on both climate and innovation.

In terms of macro-economic costs, the full cooperation and cooperation only on climate have consumption losses of 0.3% and 0.39% respectively. Thus, the relative efficiency gain is about 30%, significantly higher than for the more stringent climate policy. In levels, however, gains are smaller (3 Trillions compared to 6 Trillions) given that the looser climate policy has a substantially lower economic penalty.

5. Conclusion

This paper has used WITCH, a global integrated assessment model featuring a reasonably detailed representation of the energy sector and endogenous technological change, to assess the potential for innovation policies to address climate change or to lower the cost of doing so. Two main results stand out. First, innovation policies *alone* are unlikely to effectively control climate change. Even under large increases in global climate-related R&D spending and fairly optimistic assumptions regarding returns to R&D in new "breakthrough" technologies, emissions can be at best stabilised well above current levels and CO_2 concentration be reduced by about 50 ppm relative to baseline by 2100 (from over 700 ppm to about 650 ppm, or over 750 ppm CO_2eq). The decarbonisation of energy needed to meet stringent global emission reduction objectives has to be achieved at least partly by pricing carbon.

Second, relative to cooperation on emission reduction (through global carbon pricing) alone, international cooperation on R&D (through a global R&D policy that would internalise international knowledge spillovers and allocate worldwide spending optimally) might bring about additional benefits, of about 10% for a stringent climate policy and 30% for a looser one. However, such an optimal global R&D policy is hardly achievable in practice, and under more realistic assumptions about the allocation of spending across time, countries and types of R&D, the magnitude of economic efficiency gains becomes much smaller. This is because a world carbon price alone would already trigger large increases in R&D expenditures, which implies that further spending under a global R&D policy would run into decreasing marginal returns.

These findings are qualitatively robust to sensitivity analysis on key model parameters, notably returns to R&D, learning rates and international knowledge spillovers in the various technological areas (see Bosetti, *et al.*, 2009b). At the same time, some limitations to our analysis should be acknowledged, which call for caution in interpreting our quantitative results. While assumed away in this paper, increasing returns to R&D cannot be fully ruled out, and the magnitude of international R&D spillovers – a key justification for global policy intervention in climate-related R&D – remains highly uncertain for lack of empirical evidence. Also, the model assumes away some *domestic* innovation failures that in practice might provide a stronger case for R&D policy intervention than found in this paper. Such failures typically affect any type of innovation, but may be magnified in the area of climate change mitigation, such as appropriability problems (lack of credibility of intellectual property rights on key mitigation technologies that might emerge in the future), lack of credibility of carbon pricing policies (due to the impossibility for current governments to commit credibly to a future carbon price path), or failures specific to the electricity sector (network effects and thereby entry barriers associated with already installed infrastructure, cumulative nature of knowledge, …etc). It is however unclear whether the overall impact of credibility problems and lack of specific infrastructures would enhance or reduce R&D investments (different effects have sometimes opposite signs) and therefore would increase or reduce the effectiveness of technical change on climate change control. Further research is needed to explore these issues.

References

Barrett, S., (2003). "Environment and Statecraft". Oxford University Press, Oxford, UK.

Bennear, L. and R. Stavins (2007) “Second-best theory and the use of multiple policy Instruments”, *Environmental Resource Economics*, 37: 111–129

Bosetti, V., C. Carraro, R. Duval, A. Sgobbi and M. Tavoni (2009b). The Role of R&D and Technology Diffusion in Climate Change Mitigation: New Perspectives Using the WITCH Model. *OECD Economics Department Working Paper* No. 664.

Bosetti, V. C. Carraro, E. Massetti, M. Tavoni. (2008) "International Energy R&D Spillovers And The Economics Of Greenhouse Gas Atmospheric Stabilization", *Energy Economics,* 30, pp. 2912-2929

Bosetti, V., C. Carraro, E. Massetti, A. Sgobbi and M.Tavoni (2009a) "Optimal Energy Investment and R&D Strategies to Stabilise Greenhouse Gas Atmospheric Concentrations", *Resource and Energy Economics,* 31-2, pp. 123-137.

C. Carraro, E. Massetti and L. Nicita 2009a "How Does Climate Policy Affect Technical Change? An Analysis of the Direction and Pace of Technical Progress in a Climate-Economy Model", *The Energy Journal,* 30 (2), pp. 7-38.

C. Carraro, E. De Cian and M. Tavoni 2009b "Human Capital Formation and Global Warming Mitigation: Evidence from an Integrated Assessment Model" *CESIFO working paper* no. 2874, Munich.

Davis, G. and B. Owens (2003), “Optimizing the Level of Renewable Electric R&D Expenditures Using Real Options Analysis”, *Energy Policy*, Vol. 31, No. 15, pp. 1589-1608.

Gerlagh R, van der Zwaan B. 2006. “Options and instruments for a deep cut in CO2 emissions: Carbon dioxide capture or renewables, taxes or subsidies?” *Energy Journal,* 27 (3): 25-48.

Fischer C. (2008). "Emissions pricing, spillovers, and public investment in environmentally friendly technologies". *Energy Economics,* 30 (2), pp. 487-502

Fisher, C. and R. G. Newell (2008). Environmental and Technology Policies for Climate Mitigation, *Journal of Environmental Economics and Management,* Vol. 55, No. 2: 142-162

IEA (2008) "Energy Technology Perspectives 2008", OECD, Paris

Jaffe, A., R. Newell and R.Stavins (2005) “A tale of two market failures: Technology and environmental policy”, *Ecological Economics,* 54, 164– 174

Nemet, G. and D. Kammen (2007), “U.S. Energy Research and Development: Declining Investment, Increasing Need, and the Feasibility of Expansion”, *Energy Policy*, Vol. 35, No.1, pp. 746-755.

Newell, R.G. (2008), "International Climate Technology Strategies" Discussion Paper 08-12, Cambridge, Mass.: Harvard Project on International Climate Agreements.

Philibert, C. (2003). *Technology Innovation, Development and Diffusion*. OECD and IEA Information Paper. COM/ENV/EPOC/IEA/SLT(2003)4, *International Energy Agency*, Paris.

Popp D. (2006). “R&D subsidies and climate policy: Is there a ‘free lunch’?” *Climatic Change,* 77 (3-4): 311-41

Sandén, B. and C. Azar (2005). "Near-Term Technology Policies for Long-Term Climate Targets – Economy-Wide versus Technology Specific Approaches." *Energy Policy,* 33: 1557-1576.

Schock, R., et al. (1999), “How Much is Energy Research & Development Worth as Insurance?” *Annual Review of Energy and Environment*, Vol. 24, pp. 487-512.

Appendix: description of the energy-economy-climate model WITCH

Full details on the WITCH model can be found in Bosetti, Carraro *et al.* (2006). The description below focuses on the overall model structure, and on the specification of endogenous technical change processes

Overall model structure

WITCH is a dynamic optimal growth general equilibrium model with a detailed ("bottom-up") representation of the energy sector, thus belonging to a new class of hybrid (both "top-down" and "bottom-up") models. It is a global model, divided into 12 macro-regions. A reduced form climate module (MAGICC) provides the climate feedback on the economic system. The model covers CO2 emissions but does not incorporate other GHGs, whose concentration is typically added exogenously to CO_2 concentration in order to obtain overall GHG concentration – a 450 ppm CO2 concentration scenario is roughly assumed to correspond to a 550 ppm overall GHG concentration scenario in the simulations below. In addition to the full integration of a detailed representation of the energy sector into a macro model of the world economy, distinguishing features of the model are:

- *Endogenous technical change*. Advancements in carbon mitigation technologies are described by both diffusion and innovation processes. Learning-by-Doing and Learning-by-Researching (R&D) processes are explicitly modelled and enable to identify the "optimal"[5] public investment strategies in technologies and R&D in response to given climate policies. Some international technology spillovers are also modelled.
- *Game-theoretic set up*. The model can produce two different solutions, a cooperative one that is globally optimal (global central planner) and a decentralised, non-cooperative one that is strategically optimal for each given region (Nash equilibrium). As a result, externalities due to global public goods (CO_2, international knowledge spillovers, exhaustible resources etc.) and the related free-riding incentives can both be accounted for, and the optimal policy response (world CO_2 emission reduction policy, world R&D policy)

[5] Insofar as the solution concept adopted in the model is the Nash equilibrium (see below), "optimality" should not be interpreted as a first-best outcome but simply as a second-best outcome resulting from strategic optimisation by each individual world region.

explored. A typical output of the model is an "optimal" carbon price path and the associated portfolio of investments in energy technologies and R&D under a given environmental target.[6]

Endogenous Technical Change (ETC) in the WITCH model

In WITCH, technical change is endogenous and is driven both by Learning-by-Doing (LbD) and Learning-by-Researching (LdR) through public R&D investments.[7] These two drivers of technological improvements display their effects through two different channels: LbD is specific to the power generation industry, while energy R&D affects overall energy efficiency in the economy and the cost of a backstop technology.

Learning-by-Doing

The effect of technology diffusion is incorporated based on experience curves that reproduce the observed negative empirical relationship between the investment cost of a given technology and cumulative 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:

$$SC\left(t+1\right) = A \cdot \sum_n K\left(n,t\right)^{-\log_2 PR} \quad , \qquad (1)$$

where SC is the investment cost of technology j, PR is the so-called progress ratio that defines the speed of learning, A is a scale factor and 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 $1/PR$. With several electricity production technologies, the model is flexible enough to change the power production mix and modify investment strategies towards the most appropriate technology for each given policy measure, thus creating the conditions to foster the LbD effects associated with emission-reducing but initially expensive electricity production techniques. Experience is assumed to fully spill over across countries, thus implying an innovation market failure associated with the non-appropriability of learning processes. Investment costs in renewable energy decline with cumulated installed capacity at the rate set by the learning curve progress ratios, which is equal to 0.87 — i.e. there is a 13% investment cost reduction for each doubling of world installed capacity.

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[6]A stochastic programming version of the model also exists to analyse optimal decisions under uncertainty and learning. However, it was not used within the context of this paper.

[7] Due to data availability constraints, only public R&D is modelled in the current version of WITCH. However, private R&D would be expected to respond in a qualitatively similar way to climate change mitigation policies.

Energy Intensity R&D

R&D investments in energy increase energy efficiency and thereby foster endogenous technical change. Following Popp (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:

$$ES(n,t) = \left[\alpha_H(n)HE(n,t)^{\rho} + \alpha_{EN}(n)EN(n,t)^{\rho}\right]^{1/\rho}, \tag{2}$$

where $EN(n,t)$ denotes the energy input, $HE(n,t)$ is the stock of knowledge and $ES(n,t)$ is the amount of energy services produced by combining energy and knowledge.

Assuming that obsolescence makes a fraction δ of past ideas not fruitful for the purpose of current innovation activity, the law of motion of the energy R&D stock is as follows:

$$HE(n,t+1) = HE(n,t)(1-\delta) + Z(n,t) \tag{3}$$

The stock of knowledge $HE(n,t)$ derives from energy R&D investments, $I_{R\&D}$, in each region, through an innovation possibility frontier where also international spillovers play a role:

$$Z(n,t) = a(n)I_{R\&D}(n,t)^b HE(n,t)^c SPILL(n,t)^d, \tag{4}$$

where $SPILL(n,t)$ is obtained by multiplying the world knowledge pool, KP, and the absorption capacity, γ, of each region *n*:

$$SPILL(n,t) = \gamma(n,t)\cdot KP(n,t) \tag{5}$$

Parameters *b*, *c* and *d* in equation (4) are calibrated parameters (the interested reader is referred to Bosetti et al, 2008 for a more detailed description of the modelling structure and calibration procedure).

Following Nordhaus (2003), and reflecting the high social returns from energy R&D, the return on energy R&D investment is assumed to be four times higher than that 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:

$$K_C(n,t+1) = K_C(n,t)(1-\delta_C) + (I_C(n,t) - 4\psi_{R\&D} I_{R\&D}(n,t)) \tag{6}$$

where K_c and I_c are physical capital stock and investments, respectively, and δ_C is the depreciation rate of the physical capital stock. New energy R&D is assumed to crowd out 50% of other R&D, as in Popp (2004).

R&D in Breakthrough Technologies

In the enhanced version of the model used for this paper, backstop technologies in both the electricity and non electricity sectors are developed and diffused in a two-stage process, through investments in R&D first and installed capacity in a second stage. A backstop technology can be better thought of as a compact representation of a portfolio of advanced technologies. These would ease the mitigation burden away from currently commercial options, but they would become commercially available only provided sufficient R&D investments are undertaken, and not before a few decades. This simplified representation maintains 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 modelling characterisation exist.

Concretely, the backstop technologies are modelled 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 etc.), without specifying the type of technology that will enter into the market. In line with the most recent literature, the emergence of these backstop technologies is modelled through so-called “two-factor learning curves”, in which the cost of a given backstop technology declines both with investment in dedicated R&D and with technology diffusion (see *e.g.* Kouvaritakis, Soria *et al.* 2000). This formulation is meant to overcome the limitations of single factor experience curves, in which the cost of a technology declines only through “pure” LbD effects from technology diffusion, without the need for R&D investment (Nemet, 2006). Nonetheless, modelling long-term and uncertain phenomena such as technological evolution is inherently difficult, which calls for caution in interpreting the exact quantitative results and for sensitivity analysis.[8]

Bearing this caveat in mind, the investment cost in a technology is assumed to be driven both by LbR (main driving force *before* adoption) and LbD (main driving force *after* adoption), with $P_{tec,t}$, the unit cost of technology tec at time t, being a function of the dedicated R&D stock $R\&D_{tec,t}$ and deployment $CC_{tec,t}$:

$$\frac{P_{tec,T}}{P_{tec,0}} = \left(\frac{R\&D_{tec,T-2}}{R\&D_{tec,0}}\right)^{-e} * \left(\frac{CC_{tec,T}}{CC_{tec,0}}\right)^{-f} \qquad (7)$$

where the *R&D stock* accumulates with the perpetual inventory method, accounting for standing-on-shoulders and spillover effects (see equations (3)-(5)) and CC is the cumulative installed capacity (or consumption) of the technology. A two-period (10 years) lag is assumed between R&D capital accumulation and its effect on the price of the backstop technologies, capturing in a crude way existing time lags between research and commercialisation. The two exponents are the LbD index (*-f*) and the Learning-by-Researching index (*-e*). 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 *f,e, lr* and *lrs* can be expressed as follows:

$$1 - lr = 2^{-f} \text{ and } 1 - lrs = 2^{-e} \qquad (8)$$

The initial prices of the backstop technologies are set at roughly 10 times the 2002 price of commercial equivalents. The cumulative deployment of the technology is initiated at 1000 TWh, an arbitrarily low value (Kypreos, 2007). The backstop technologies are assumed to be renewable in the sense that the fuel cost component is negligible. For power generation, it is assumed to operate at load factors (defined as the ratio of actual to maximum potential output of a power plant) comparable with those of baseload power generation.

[8] This is especially true when looking at the projected carbon prices and economic costs at long horizons – typically beyond 2030, while the short-run implications of long-run technological developments are comparatively more robust across a range of alternative technological scenarios.

This formulation has received significant attention from the empirical and modelling literature in the recent past (see, for instance, Criqui, Klassen *et al.* 2000; Bahn and Kypreos, 2003; Söderholm and Sundqvist, 2003; Barreto and Klaassen, 2004; Barreto and Kypreos, 2004; Klassen, Miketa *et al.* 2005; Kypreos, 2007; Jamasab, 2007; Söderholm and Klassen, 2007). However, estimates of parameters controlling the learning processes vary significantly across available studies. Here, averages of existing values are used, as reported in Table A1.

Technology	**Author**	**LbD**	**LbR**
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%
WITCH		*10%*	*13%*

Table A1: Learning ratios for diffusion (LbD) and innovation (LbR) processes

For WITCH we take averages of the values in the literature, as reported in the last row of the table.

The value chosen for the LbD parameter is lower than those typically estimated in single factor experience curves, since here technological progress results in part from dedicated R&D investment. This more conservative approach reduces the role of "autonomous" learning, which has been seen as overly optimistic and leading to excessively low costs of transition towards low carbon economies.[9]

[9] Problems involved in estimating learning effects include: *i)* selection bias, *i.e.* technologies that experience smaller cost reductions drop out of the market and therefore of the estimation sample; *ii)* risks of reverse causation, *i.e.* cost reductions may induce greater deployment, so that attempts to force the reverse may lead to disappointing learning rates *a posteriori*; *iii)* the difficulty to discriminate between "pure" learning effects and the impact of accompanying R&D as captured through two-factor learning curves; *iv)* the fact that past cost declines may not provide a reliable indication of future cost reductions, as factors driving both may differ; *v)* the use of price – as opposed to cost – data, so that observed price reductions may reflect not only learning effects but also other factors such as strategic firm behaviour under imperfect competition.

Backstop technologies substitute linearly for nuclear power in the electricity sector, and for oil in the non-electricity sector. Once backstop technologies become competitive thanks to dedicated R&D investment and pilot deployments, their uptake is assumed to be gradual rather than immediate and complete. These penetration limits are a reflection of inertia in the system, as presumably the large deployment of backstops would require investment in infrastructures and wide reorganisation of economic activity. 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.

The WITCH model has been extended to carry out the analysis presented in this paper to include additional channels for technological improvements, namely learning through research or "Learning-by-Researching" (LbR) in existing low carbon technologies (wind and solar electricity, electricity from integrated gasifier combined cycle (IGCC) plants with carbon capture and storage (CCS)). For both technologies we assume investment costs decline with cumulated dedicated R&D with a learning ratio of 13% .

Appendix References

Barreto, L. and S. Kypreos (2004). "Endogenizing R&D and market experience in the "bottom-up" energy-systems ERIS model." Technovation 2: 615-629.

Bosetti, V., C. Carraro, R. Duval, A. Sgobbi and M. Tavoni (2009). The Role of R&D and Technology Diffusion in Climate Change Mitigation: New Perspectives Using the WITCH Model. OECD Economics Department Working Paper No. 664.

Bosetti, V., C. Carraro, M. Galeotti, E. Massetti and M. Tavoni (2006). "WITCH: A World Induced Technical Change Hybrid Model." *The Energy Journal*. Special Issue on Hybrid Modeling of Energy-Environment Policies: Reconciling Bottom-up and Top-down: 13-38.

Bosetti, V., E. Massetti and M. Tavoni (2007). The WITCH Model: Structure, Baseline, Solutions. FEEM Working Paper Series. 10/2007, FEEM, Milan.

Bosetti, V. C. Carraro, E. Massetti, M. Tavoni (2008). "International Energy R&D Spillovers and The Economics Of Greenhouse Gas Atmospheric Stabilization". Energy Economics, 30 2912–2929, doi:10.1016/j.eneco.2008.04.008

Criqui, P., G. Klassen and L. Schrattenholzer (2000). The efficiency of energy R&D expenditures. Economic modeling of environmental policy and endogenous technical change, Amsterdam, November 16-17, 2000.

Edenhofer, O., N. Bauer and E. Kriegler (2005), "The Impact of Technological Change on Climate Protection and Welfare: Insights from the Model MIND", Ecological Economics, 54, 277–292.

Gerlagh R. and B.C.C. van der Zwaan (2004), "A Sensitivity Analysis on Timing and Costs of Greenhouse Gas Abatement, Calculations with DEMETER", Climatic Change, 65, 39 71.

IEA (2004b), “Biofuels for Transport – An International Perspective”, OECD/IEA, Paris

Hansen, L., D. Epple and W. Roberds (1985), “Linear Quadratic Duopoly Models of Resource Depletion”, in: T.J. Sargent (ed.), Energy, Foresight, and Strategy, Washington D.C.: Resources for the Future.

Jamasab, T. (2007). "Technical change theory and learning curves: patterns of progress in electric generation technologies." *The Energy Journal* 28(3).

Jones, C. (1995). "R&D Based Models of Economic Growth." *Journal of Political Economy* 103: 759-784.

Klassen, G., A. Miketa, K. Larsen and T. Sundqvist (2005). "The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom." *Ecological Economics* 54(2-3): 227-240.

Kouvaritakis, N., A. Soria and S. Isoard (2000). "Endogenous Learning in World Post-Kyoto Scenarios: Application of the POLES Model under Adaptive Expectations." *International Journal of Global Energy Issues* 14(1-4): 228-248.

Kypreos, S. (2007). "A MERGE model with endogenous technical change and the cost of carbon stabilization." *Energy Policy* 35: 5327-5336.

Nemet, G. F. (2006). "Beyond the learning curve: factors influencing cost reductions in photovoltaics." *Energy Policy* 34(17): 3218-3232.

Nordhaus, W.D. and J. Boyer (2000), Warming the World, Cambridge: MIT Press.

Nordhaus, W. D. (2003). Modelling Induced Innovation in Climate Change Policy. Technological Change and the Environment. A. Grubler, N. Nakicenovic and W. D. Nordhaus. Washington D.C., Resources for the Future.

Popp, D. (2004). "ENTICE: endogenous technological change in the DICE model of global warming." *Journal of Environmental Economics and Management* 48: 742–768.

Söderholm, P. and G. Klassen (2007). "Wind power in Europe: a simultaneous innovation-diffusion model." *Environmental and Resource Economics* 36(2): 163-190.