THE ROLE OF R&D AND TECHNOLOGY DIFFUSION IN CLIMATE CHANGE MITIGATION: NEW PERSPECTIVES USING THE WITCH MODEL

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Abstract

This paper uses the WITCH model, a computable general equilibrium model with endogenous technological change, to explore the impact of various climate policies on energy technology choices and the costs of stabilising greenhouse gas concentrations. Current and future expected carbon prices appear to have powerful effects on R&D spending and clean technology diffusion. Their impact on stabilisation costs depends on the nature of R&D: R&D targeted at incremental energy efficiency improvements has only limited effects, but R&D focused on the emergence of major new low-carbon technologies could lower costs drastically if successful – especially in the non-electricity sector, where such low-carbon options are scarce today. With emissions coming from multiple sources, keeping a wide range of options available matters for stabilisation costs more than improving specific technologies. Due to international knowledge spillovers, stabilisation costs could be further reduced through a complementary, global R&D policy. However, a strong price signal is always required.

JEL classification: H0; H2; H3; H4; O3; Q32; Q43; Q54.

Keywords: Climate policy; Energy R&D; Fund; Stabilisation costs.

February 2009

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1. This paper is part of the research work being developed within the Sustainable Development Research Program of the Fondazione Eni Enrico Mattei and the Climate Impacts and Policy Division of the EuroMediterranean Center on Climate Change. It has been carried out in cooperation with the Economics Department of the OECD, Paris. We are very grateful to participants at seminars at OECD and in Milan, Venice, Paris Dauphine and Bern for helpful comments and suggestions. The usual disclaimer applies. Contact: valentina.bosetti@feem.it.

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1. Introduction and summary of main findings

Any cost-effective policy framework to address climate change should foster efficient R&D, innovation and diffusion of greenhouse gas (GHG) emission-reducing technologies. Technological progress will be needed both to bring down the cost of available technologies which in many key emitting areas remains significantly more expensive than the fossil-fuel based technologies they could potentially displace, and to expand the pool of available technologies and their mitigation potential (Anderson, 2006; IEA, 2008). Currently, it would appear that the scope and scale of low-carbon technologies envisaged for the future might be limited (Anderson, 2006). Most are of a specific rather than general purpose nature, with their potential use being restricted to a narrow range of economic activities (*e.g.* wind, solar and nuclear energy to power generation, hydrogen and biofuels to transport etc.). Furthermore, constraints remain (*e.g.* related to energy storage possibilities) on the extent to which emissions from any industry could be abated through the use of one single mitigating option. For these reasons, a broad portfolio of technological options will probably have to be involved in mitigating climate change (see *e.g.* Pacala and Socolow, 2004).[2]

Speeding up the emergence and deployment of low-carbon technologies will ultimately require increases in, and reallocation of, the financial resources channelled into energy-related R&D. Average public energy-related R&D expenditure across the OECD has declined dramatically since its peak in the early 1980s, and even though no comprehensive data exist on private sector energy-related R&D, available evidence suggests that its share in overall private R&D spending is low compared with other sectors and decreasing over the past two decades (IEA, 2008).[3] More broadly, climate change mitigation will involve increased expenditure at all stages of the technology development process, ranging from R&D upstream to demonstration, deployment, and ultimately diffusion downstream. In particular, empirical evidence suggests that most emerging low-carbon energy technologies are subject to sizeable “learning effects”, *i.e.* their costs decrease as experience accumulates through cumulative production (see below). In that context, significant technology deployment costs may have to be incurred before low-carbon technologies can become competitive at market prices.[4]

Against this background, this paper explores the question of how to induce technological change that enhances the efficiency of existing energy technologies and/or makes new carbon-free technologies available. Various types of public policies may influence the rate and direction of technological change, including carbon pricing, R&D policies and subsidies to the deployment of existing technologies (for recent OECD discussion of these policies and their interactions, see Duval, 2008). These are explored here, with the view to assessing the effects of alternative policy mixes on future GHG emission paths and/or on the costs of achieving given GHG concentration stabilisation targets. The analysis is carried out with the WITCH model, an energy/economy/climate model developed by the climate change modelling group at

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2. This would reduce not only future abatement costs but also their sensitivity to emission-reduction objectives, thereby providing some hedging against the risk of a larger than expected need for action against climate change (Stern, 2007, Chapter16). This is because broadening the portfolio of low-cost options would flatten the slope of the marginal abatement curve, thereby limiting the cost of unexpected shifts in required (optimal) abatement levels due e.g. to unexpected shifts in climate damages.

3. In power generation, R&D spending as a share of total turnover was about eight times lower than in the manufacturing sector as a whole (OECD Roundtable on Sustainable Development, 2006). This is consistent with disaggregated sectoral analysis for the United States (Alic *et al.* 2003).

4. For example, based on learning rate assumptions across a wide range of technologies and in the absence of any carbon price, IEA (2008) puts cumulative (undiscounted) deployment costs of low-carbon technologies consistent with a 50% cut in world emissions by 2050 at about $US7 trillion. These costs are computed in the absence of a carbon price and would, therefore, be smaller in the presence of such a price.

Fondazione Eni Enrico Mattei (FEEM), which has been used extensively for climate policy analysis.[5] The main conclusions from this work, which feed into broader, recent OECD work on the economics of climate change and future policy options (Burniaux *et al.* 2008), are:

- A carbon price has sizeable effects on R&D and technology deployment. For instance, the WITCH model's (inter-temporally optimal) world carbon price path to stabilise long-run CO_2 concentration at 450 ppm and overall GHG concentration at about 550 ppm CO_2eq[6] is estimated to induce a four-fold increase in energy R&D expenditure and investment in deployment of renewable power generation by 2050, compared with the baseline scenario. These effects increase over time and/or as concentration targets become more stringent, reflecting a higher CO_2 price. In fact, because marginal abatement costs rise disproportionately with emission reductions, investment in technology also increases disproportionately with the stringency of the emission reduction objective.

- Expectations of future carbon prices and, therefore, the credibility of future climate policy commitments, matter a great deal for today's investment in low-carbon R&D and technology deployment. For instance, under similar carbon price levels, R&D investment is found to be noticeably higher under a 550 ppm CO_2eq GHG (450 ppm CO_2 only) concentration stabilisation objective than under a 650 ppm CO_2eq (550 ppm CO_2 only) scenario, reflecting higher expected future increases in carbon prices.

- In the absence of major technological breakthroughs, induced technological change associated with higher R&D investment and technology deployment may have only modest effects on policy costs, especially under less stringent GHG concentration stabilisation objectives. This is mainly for two reasons. First, decreasing marginal impacts of R&D on energy efficiency and fading learning effects in renewable energies ultimately limit the gains to be reaped from induced technological change. Second, in the electricity sector, low-carbon options already exist today, including nuclear energy and carbon capture and storage (CCS). Both are projected to account for an increasing share of the future energy mix under a rising carbon price. If, for technological, political or safety reasons the penetration of nuclear energy and CCS were constrained, investments in R&D and renewable power generation would be increased, but at the same time overall mitigation costs would rise significantly as some of the few widely deployable abatement opportunities would be lost. This suggests that exploiting all currently available technological options may be more important than boosting R&D on energy efficiency in minimising the costs of climate change mitigation.

- By contrast, R&D focusing on major technological breakthroughs could significantly reduce future mitigation costs and would give a far greater role to induced technological change in containing such costs. Under a 550 ppm CO_2eq (450 ppm CO_2 only) concentration stabilisation scenario with world carbon pricing and R&D targeted at two carbon-free backstop technologies in the electricity and non-electricity sectors, mitigation costs in 2050 are halved – from about 4% of world GDP to under 2% – compared with a "no-backstop" scenario, and the pay-off from these innovative technologies becomes increasingly large in the second half of the century. The non-electricity backstop technology contributes most to such reduction in long-term mitigation

5 See, for example, Bosetti, Carraro *et al.* (2007a). A list of applications and papers can be found at www.feem-web.it/witch.

6. This is the optimal world carbon price path under the non-cooperative solution of the model when a 450 ppm long-run CO2 concentration stabilisation target is imposed. Emissions of non-CO_2 gases are not covered by the WITCH model and are thus excluded from the simulations, However, stabilisation of CO2 concentration at 450 ppm roughly corresponds to stabilisation of overall GHG concentration at 550 ppm. See below for details.

costs. This reflects the fact that in the absence of backstops, the electricity sector can count on a wider array of low-carbon abatement options (nuclear power and CCS, wind and solar) than the non-electricity sector.

- However, lower long-term mitigation costs come at the price of higher medium-run costs. This reflects the large and sustained increase in R&D investment needed to develop the two backstop technologies, which in the simulations push energy R&D spending as a share of GDP above its previous historical peak of the mid-1980s.

- Even assuming R&D could achieve major technological breakthroughs, a strong price signal is still needed to spur the necessary investments. The optimal carbon price path in the "backstops" scenario is virtually unchanged from its level in the "no backstop" case until 2020, falling significantly below the latter only at a later stage, as the innovative technologies account for a rising share of the energy mix.

- WITCH simulations suggest that a global R&D fund to subsidise R&D and/or low-carbon technology deployment could further reduce mitigation costs if it came on top of a carbon price. However, the optimal size of such a fund, and its effects, are found to be typically small. This partly reflects the assumption in WITCH that social returns are almost entirely appropriated by each region, resulting in rather small international spillovers. Further research on the existence, nature and magnitude of international spillovers is warranted.

- Finally, while raising world R&D spending over and above the increase induced by a carbon price can reduce mitigation costs, R&D *alone* is not an effective option to address climate change. Even under optimistic assumptions, no global R&D policy of any size – even if implausibly large, *e.g.* 1 percentage point of world GDP, representing a 30-fold increase with respect to current levels – appears to be able on its own to stabilise carbon concentrations during this century. For instance, under a global R&D fund that would gradually bring world energy-related R&D spending back to its early-1980s peak level, CO_2 concentration is found to rise continuously, reaching over 650 ppm (corresponding to over 750 ppm CO_2eq all gases included) by the end of the century. This reflects the lags required for any breakthrough technologies to penetrate the market and, more fundamentally, the difficulty of out-performing fossil fuel-based energy production if the external costs of GHG emissions are not priced into traditional technologies. Qualitatively similar findings hold for a global policy to subsidise the deployment of existing technologies.

The remainder of this paper is organised as follows. Section 2 presents the structure of the WITCH model and describes the specification of technological improvements, namely R&D and "learning by doing". Section 3 explores the impact of carbon pricing on R&D, technology diffusion and mitigation policy costs. Section 4 introduces the possibility for R&D to develop and diffuse two breakthrough carbon-free backstop technologies in the electricity and non-electricity sectors, and reassesses the results from Section 3 in that context. Section 5 analyses the extent to which a global R&D policy could contribute to climate change mitigation and to reduce mitigation costs, either as a complement to carbon pricing or as a stand-alone policy, and with and without the possibility to develop breakthrough carbon-free backstop technologies. Comparable analysis is also carried out in that section, assuming the global fund subsidises the deployment of existing low-carbon technologies, rather than R&D in energy efficiency or backstop technologies. Despite wide recognition of the importance of technological development for climate change control and for the costs of any stabilisation policies, significant uncertainty remains on the appropriate way of modelling technological change and parameterisation of the models. Against this background, Section 6 provides some elements of sensitivity analysis of the main results to key technological parameters for both existing and new technologies.

2. The World Induced Technical Change Hybrid (WITCH) model

Full details on the WITCH model can be found in Bosetti, Massetti *et al.* (2007), as well as in Bosetti, Carraro *et al.* (2006). The description below focuses on the overall model structure, the specification of endogenous technical change processes and the extensions introduced as part of this paper to explore specific R&D policies.

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 CO_2 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 CO_2 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*. Advances in carbon mitigation technologies are described by both diffusion and innovation processes. "Learning by doing" (LbD) and "Learning by researching" (R&D) processes are explicitly modelled and enable to identify the "optimal"[7] 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 co-operative 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) be 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.

Endogenous Technical Change (ETC) in the WITCH model

In the basic version of WITCH, technical change is endogenous and is driven both by LbD and by public energy R&D investments.[8] 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.

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

7 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.

8 Due to data availability constraints only public R&D is used to calibrate the current version of WITCH. However, public R&D is assumed to respond in a qualitatively similar way as private R&D to climate change mitigation policies.

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:

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

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.

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. 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 (Jones, 1995) and empirically supported by Popp (Popp, 2002) for energy-efficient innovations in the United States:

$$HE(n,t+1)\ =\ aI_{R\&D}(n,t)^b HE(n,t)^c + HE(n,t)(1-\delta_{R\&D}) \tag{3}$$

Where $\delta_{R\&D}$ is the depreciation rate of knowledge, and b and c are both between 0 and 1 so that there are diminishing returns to R&D both at any given time and across time periods. Reflecting the high social returns from energy R&D, it is assumed that the return on energy R&D investment is 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:

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

where 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). This way of capturing innovation market failures was also suggested by Nordhaus (2003).

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-searching" (LbS) in existing low carbon technologies (wind and solar electricity, electricity from integrated gasifier combined cycle (IGCC) plants with carbon capture and storage (CCS)), and the possibility of developing breakthrough, zero-carbon technologies (so-called "backstops") for both the electricity and non-electricity sectors.

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 (see below).[9]

Bearing this caveat in mind, the investment cost in a technology tec is assumed to be driven both by LbS (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 $CC_{tec,t}$:

$$\frac{P_{tec,T}}{P_{tec,0}} = \left(\frac{R\&D_{tec,T-2}}{R\&D_{tec,0}}\right)^{-e} * \left(\frac{CC_{tec,T}}{CC_{tec,0}}\right)^{-d} \tag{5}$$

where the *R&D stock* accumulates with the perpetual inventory method 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 ($-d$) 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 d, e, lr and lrs can be expressed as follows:

9 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 (see below).

$$1 - lr = 2^{-d} \text{ and } 1 - lrs = 2^{-e} \quad (6)$$

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.

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 1.

Table 1. Learning ratios for diffusion (lr) and innovation (lrs) processes across selected studies and technologies

Technology	Author	lr	lrs
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%*

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.[10]

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 infrastructure 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.

Spillovers in knowledge and experience

In addition to the international LbD spillovers mentioned above, WITCH also features international spillovers in knowledge for energy efficiency improvements. The amount of spillovers entering each world region is assumed to depend both on a pool of freely available world knowledge and on the ability of each country to benefit from it. In turn, this absorption capacity depends on the domestic knowledge stock, which is built up through domestic R&D according to a standard perpetual capital accumulation rule. The region then combines knowledge acquired from abroad with the domestic knowledge stock to produce new technologies at home. For details, see Bosetti, Carraro *et al.* (2007b).

3. Impact of carbon pricing on induced technological change and mitigation policy costs in the basic WITCH model

This section proceeds in two steps. It starts by exploring the impact of carbon pricing on induced technological change (ITC), which in the basic WITCH model – *i.e.* the WITCH model without backstop technologies – occurs through energy efficiency gains – which in turn result from higher energy R&D investments – and technology diffusion. The impact of ITC for mitigation policy costs is then assessed.

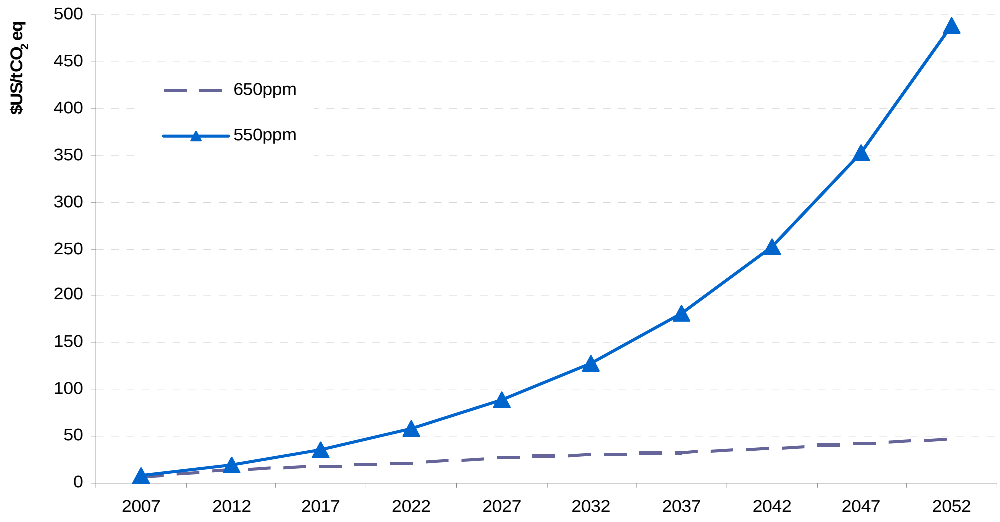
Carbon pricing and induced technological change

The impact of carbon pricing on ITC is assessed under two long-run CO_2 concentration targets, namely 450 ppm and 550 ppm, corresponding to about 550 ppm and 650 ppm all gases included, respectively – all figures and tables in this paper primarily refer to overall concentration including all gases. More precisely, two world carbon price paths consistent with such targets – in fact, the intertemporally optimal carbon price paths – are considered, and their implications for energy R&D, energy efficiency and the diffusion of existing renewable energy are assessed. Given the non-linearity of marginal abatement costs as a function

10 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.

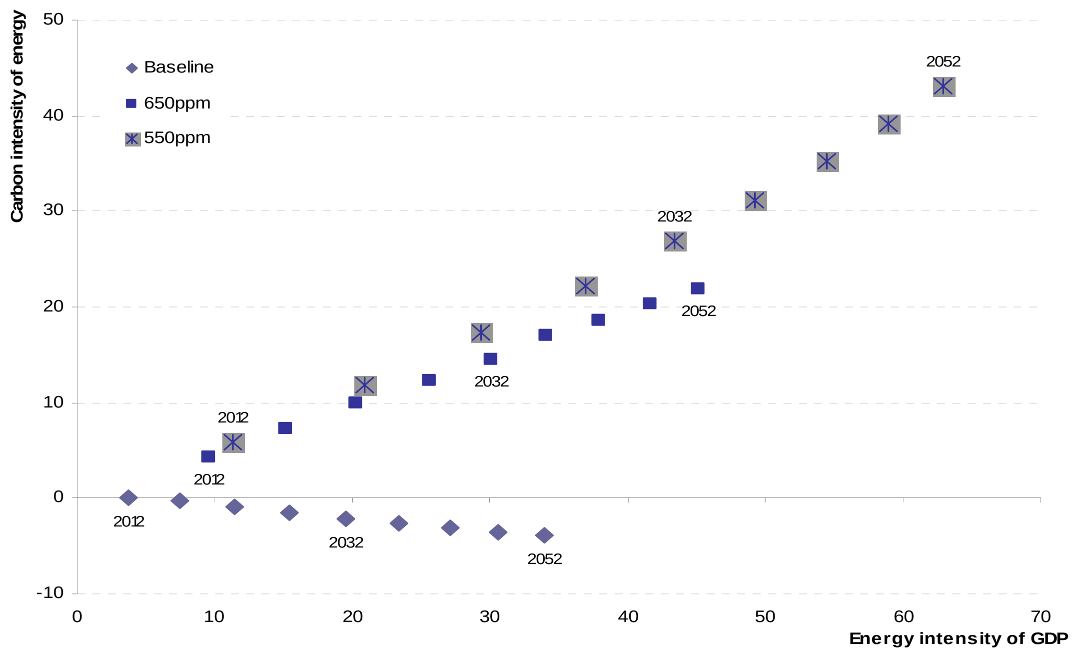
of concentration targets, there are increasing differences over time across carbon prices under these two scenarios (Figure 1).

Figure 1. Carbon price paths under 550 ppm and 650 ppm GHG concentration scenarios



The emission reductions required in the two scenarios imply both energy savings and energy decarbonisation (Figure 2).

Figure 2. World energy intensity and carbon intensity trajectories under alternative carbon price paths



Over the simulation period, world energy intensity is estimated to fall by 65% and 50% under the 550 ppm and 650 ppm GHG concentration scenarios, respectively. The carbon intensity of energy falls by about 45% and 25% respectively, in sharp contrast with its projected stagnation under the baseline scenario. Energy decarbonisation is achieved mainly in the power sector, where alternative technologies (wind and solar, CCS) are available. The share of low-carbon electricity in world power generation today is about 35% and it is projected to stay roughly constant in the baseline as the positive impact of increased penetration of renewables is offset by the rising importance of coal. By contrast, under the 550 ppm and 650 ppm GHG concentration scenarios, electricity would be significantly decarbonised, with the share of low-carbon technologies in the world electricity mix rising to about 90% and 70% by mid-century, respectively.

The impact of carbon pricing on investment choices is found to be significant, in particular for the 550 ppm GHG concentration scenario. Investments in wind and solar power generation are multiplied by about four and two relative to baseline by mid-century under the 550 ppm and 650 ppm scenarios, respectively (Figure 3, top panel). There are mutual feedback effects between investments in, and the cost of, these technologies through LbD, with investment costs of renewables declining by about 16% and 8% respectively under both scenarios by 2050, over and above the decrease already embedded in the baseline scenario (Figure 3, bottom panel). A strong carbon price signal also induces large investments in other low-carbon technologies, such as nuclear and coal with CCS. Nuclear power becomes especially competitive when carbon is priced, so that additional capacity would be built up at a slightly higher pace than in the 1980s, the period of the maximum expansion of nuclear power (Figure 4, top panel). CCS is also estimated to be deployed on a large scale under both 550 ppm and 650 ppm GHG concentration scenarios, with annual sequestration rising rapidly starting from 2025 to reach over 6 Gt CO_2eq by 2050 (Figure 4, bottom panel).

Carbon pricing is found not only to boost the deployment of renewable technologies, nuclear and CCS, but also to stimulate investments in energy efficiency enhancing R&D (Figure 5). However, differences with respect to baseline are significant only under a 550 ppm GHG concentration scenario. This reflects at least three factors:

- WITCH being a forward-looking model, for a *given* carbon price today, higher *expected* carbon prices in a 550 ppm GHG concentration scenario have large impacts on R&D spending, compared with a less stringent 650 ppm scenario. This effect magnifies the impact of carbon pricing on R&D expenditures.

- Technologies such as nuclear power and CCS are very responsive to carbon pricing. As a result, these abatement opportunities are exploited heavily under moderate carbon price scenarios – although some innovation might be eventually needed for large scale of deployment, while energy-efficiency R&D spending increases mainly when carbon prices get higher.

- The bulk of world emission cuts under moderate carbon price scenarios are undertaken in developing countries, where cheaper abatement opportunities can be exploited without much need for innovation.

Figure 3. Investment in and cost of wind and solar power generation under alternative carbon price paths

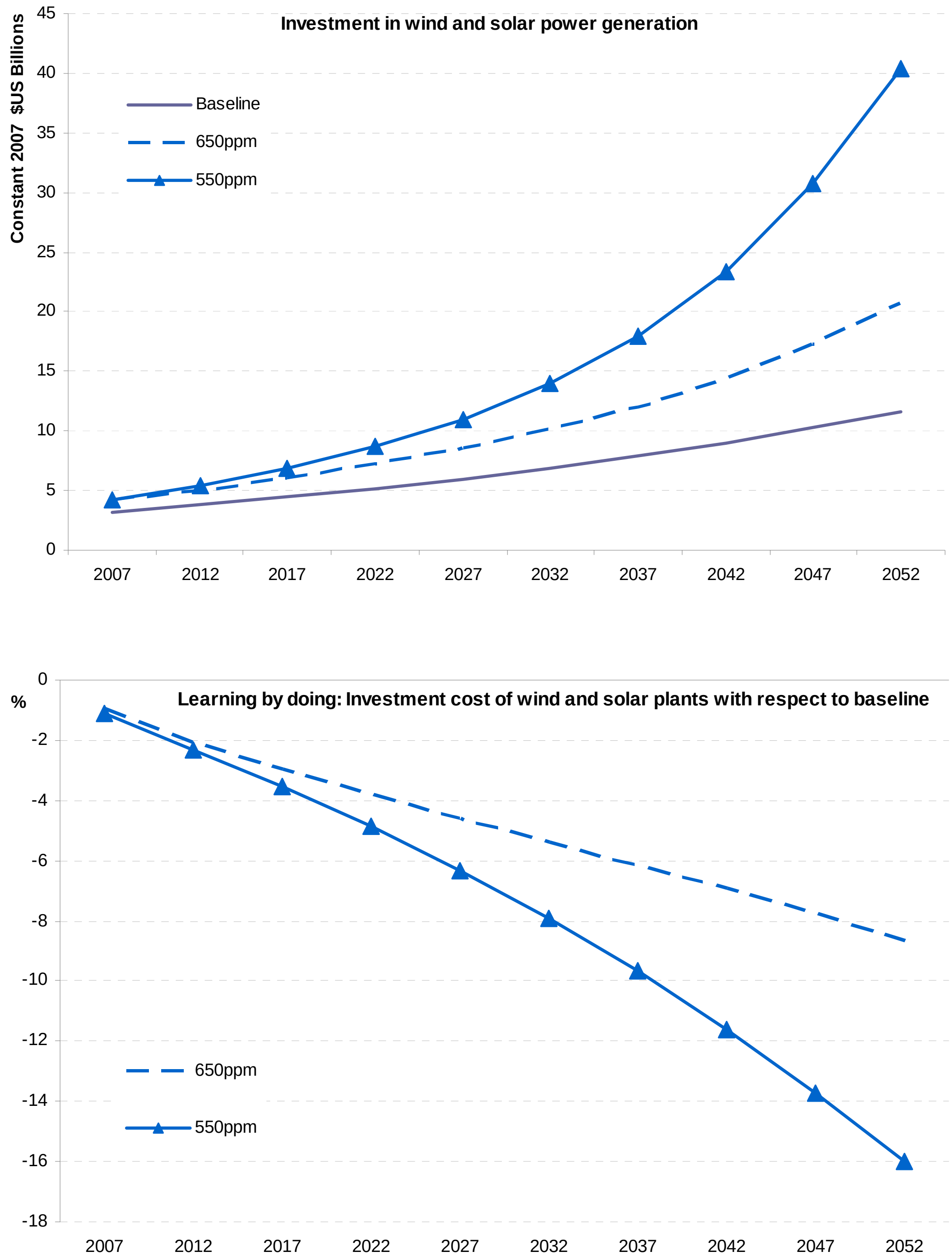
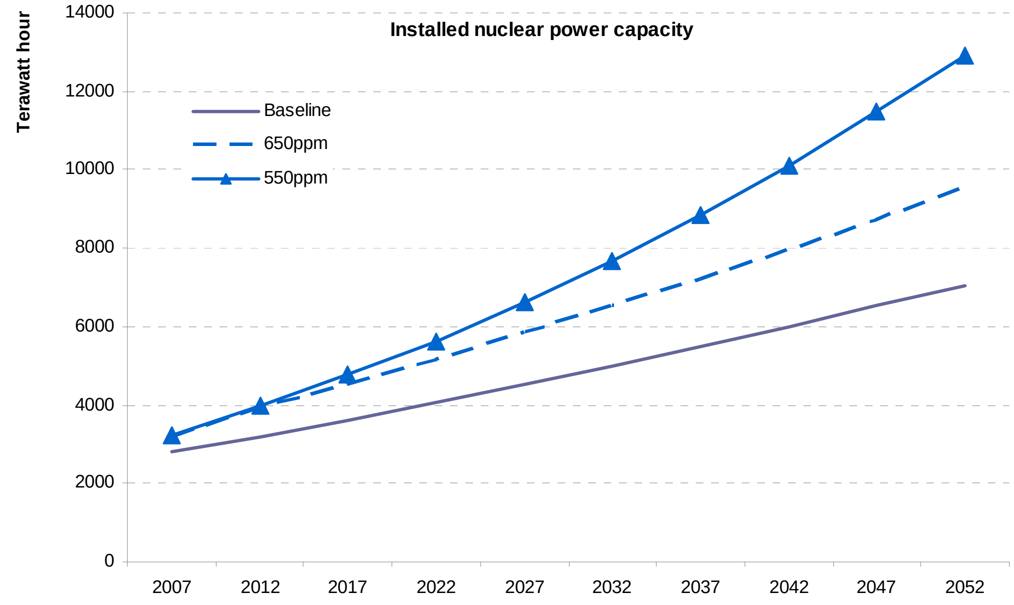


Figure 4. Installed nuclear power capacity and carbon sequestered under alternative carbon price paths



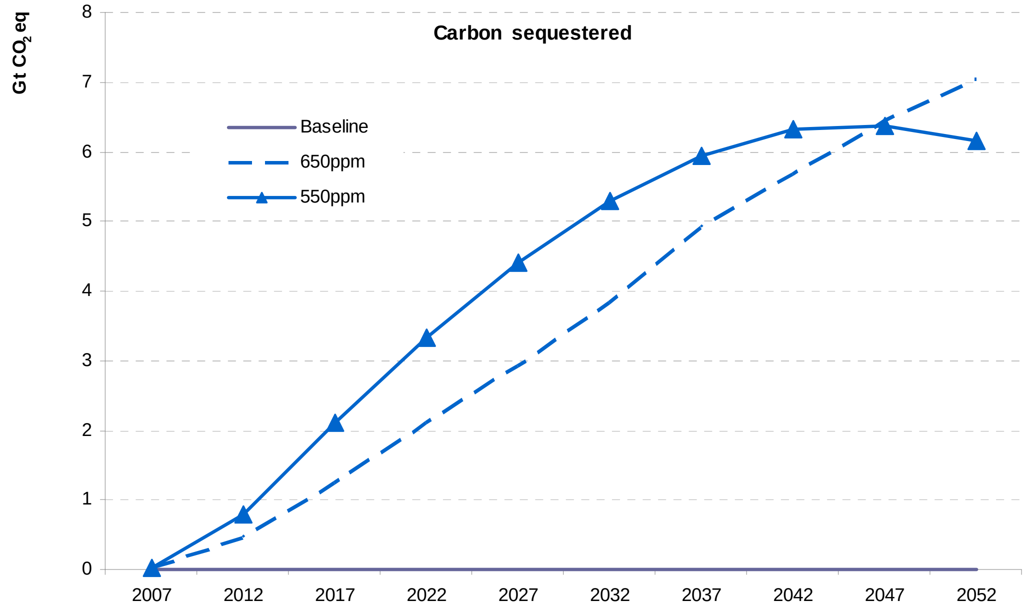
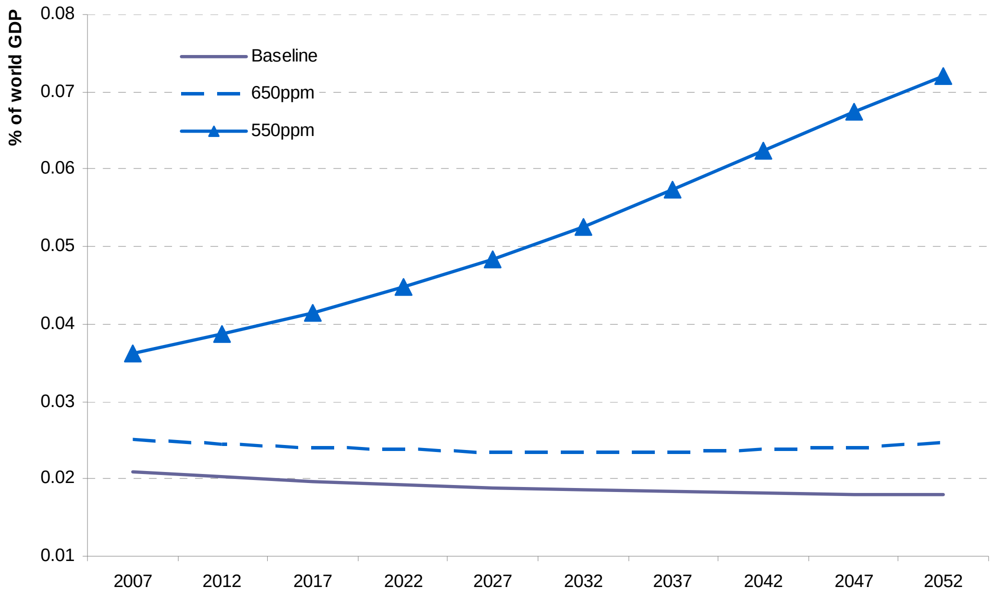


Figure 5. World investment in energy efficiency improving R&D under alternative carbon price paths

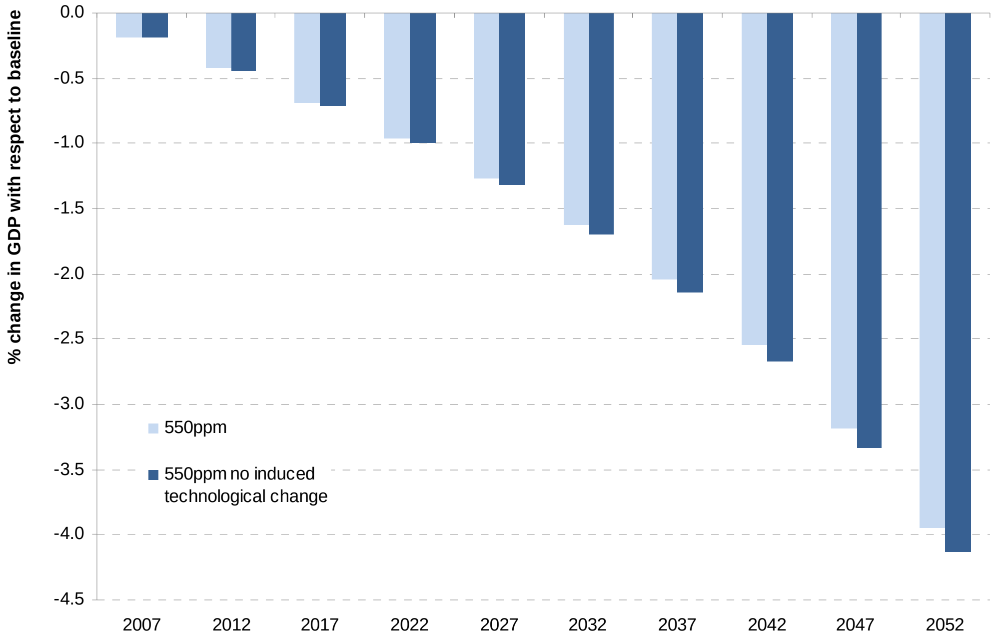


Impact of induced technological change on mitigation policy costs

Despite a sizeable impact of carbon price signals on innovation and deployment of low-carbon technologies, endogenising technological change and diffusion does not appear to make a large difference for mitigation policy costs in the basic version of WITCH. This can be inferred from a policy simulation in which a world carbon price path consistent with a 550 ppm GHG concentration target is implemented,[11] but regions are assumed not to have the possibility to expand their investment in energy efficiency R&D beyond baseline levels, and the deployment of wind and solar energy technologies does not lead to investment costs reduction through LbD effects. Under such a scenario, policy costs are estimated to rise only marginally compared with a 550 ppm GHG concentration scenario with ITC, from 3.9% to about 4.15% of world GDP in 2050 (Figure 6).

11 More precisely, a world cap-and-trade system is assumed to be implemented, with equal per capita allocation of allowances. Sensitivity analysis shows – as would be expected – that the allocation rule has mostly distributional effects and does not fundamentally affect the analysis of mitigation policy costs at the world level.

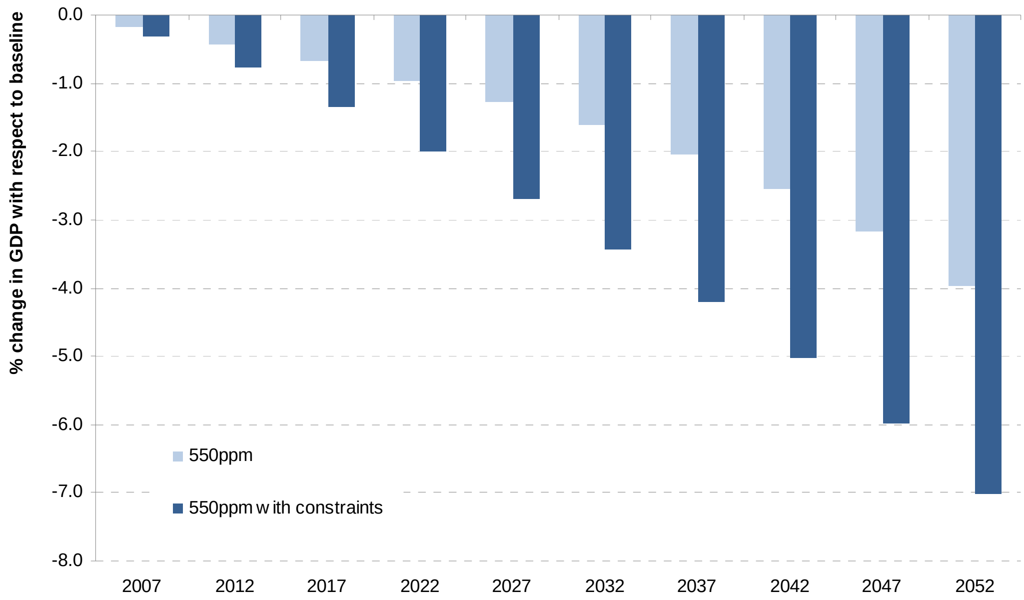
Figure 6. Projected world GDP costs under a 550 ppm GHG concentration scenario in the basic WITCH model, with and without induced technological change



Impact of technology availability on mitigation policy costs

The main factor behind the low impact of induced technological change on mitigation policy costs is that improving the technological and/or economic efficiency of the current portfolio of low-carbon options appears to matter far less than the breadth of that portfolio. In other words, mitigation policy costs can be reduced to a greater extent by widening the range of technological options available at competitive prices than through improvements in existing technologies. As will be discussed below, exploiting current technologies may also be more important than improving them. While this conclusion will come out forcefully when introducing new backstop technologies in the next section, it can also be shown by computing the impact on mitigation policy costs of constraints on the availability of existing technologies. Concretely, an illustrative world carbon price scenario consistent with a 550 ppm GHG concentration target is run where: *i)* nuclear energy is assumed to be constrained at current generation levels, *e.g.* for political or safety reasons; *ii)* CCS is not allowed, *e.g.* because it does not become competitive at market prices; and *iii)* wind and solar power generation provide at most 35% of total electricity, due *e.g.* to constraints on their deployment on a large-scale. Under such constraints, mitigation policy costs rise drastically, from 3.9% to over 7% of world GDP in 2050 (Figure 7).

Figure 7. Projected world GDP costs under a 550 ppm GHG concentration scenario in the basic WITCH model, with and without constraints on nuclear energy and carbon capture and storage



4. Major technological breakthroughs and the impact of carbon pricing on induced technological change and mitigation policy costs

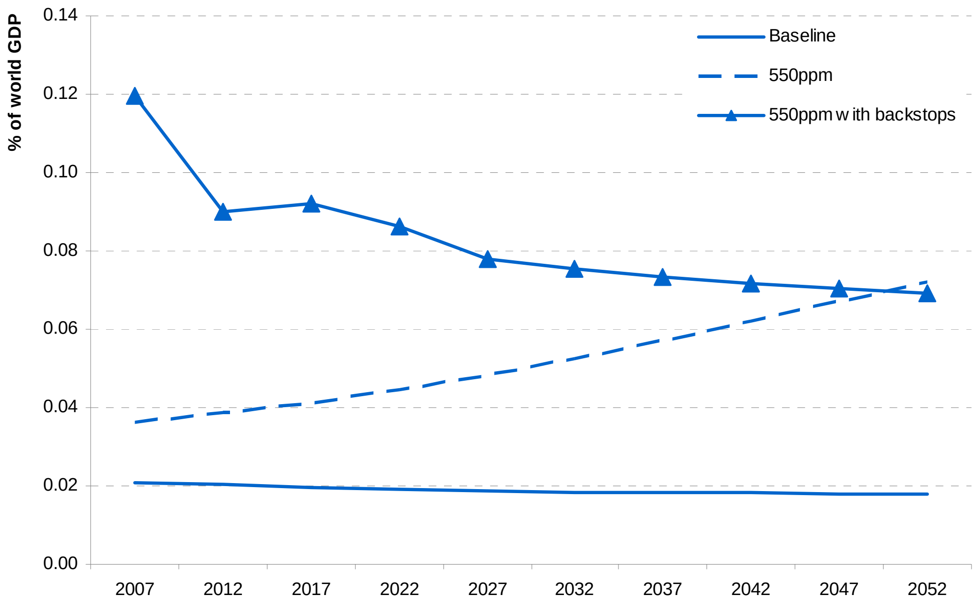
One major limitation of the previous analysis is that it implicitly focuses on incremental R&D aimed at improving energy efficiency and the diffusion of existing low-carbon technologies. In practice, mitigation policy may also aim at raising financing for the development and deployment of major new low-carbon technologies that would, in the long run, replace existing technologies on a wide scale. The mitigation cost implications of possible future development and diffusion of such backstop technologies are explored below for a 550 ppm GHG concentration stabilisation scenario. Again, the analysis proceeds in two steps. It starts by exploring the effects of carbon pricing on ITC, which now arises not only from energy efficiency gains and technology diffusion, but also from the emergence of backstops – through dedicated R&D and deployment. In a second step, the impact of ITC on mitigation policy costs is assessed.

Insofar as one motivation for developing backstop technologies in the electricity sector would be the existence of limitations to the deployment of already existing technologies, nuclear power installed capacity is assumed to be constrained at present levels throughout most of the analysis. Indeed, in the absence of such constraints there would be little need for developing breakthrough technologies in the electricity sector, at least in the context of the WITCH model. Also, the simulations presented below assumed that all agents have perfect knowledge about future backstop availability. An alternative, and an area for future work, would be to consider the stochastic programming version of the model in order to account for the uncertainty surrounding the emergence of backstops. This would allow assessing the impact of such uncertainty on optimal investment decisions in R&D and technology deployment.

Impact of backstop technologies on R&D and the energy technology mix

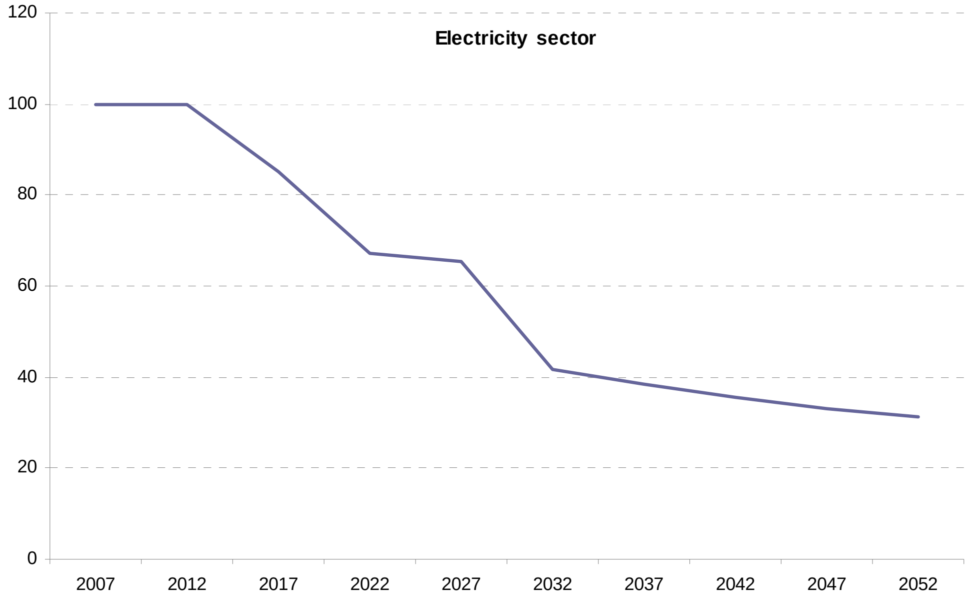
Unlike in most of the literature, backstop technologies are not assumed here to become available without dedicated investments. More realistically, they become available in the future only if adequate R&D investment costs are previously incurred. As a result, under a world carbon price scenario consistent with a 550 ppm GHG concentration target, the possible future availability of backstop technologies in the electricity and non-electricity sectors is estimated to substantially increase global energy R&D investments over the coming decades (Figure 8). This is especially the case when the (current and future) carbon pricing policy is announced and implemented, with energy R&D expenditures rising to about 0.12% of global GDP, above their peak level of 0.08% of GDP in 1980. The shape of the R&D spending path reflects the nature of investment in breakthrough technologies. These are characterised by very high marginal returns at the beginning, which then decline gradually as the R&D stock is built up and the potential for further cost declines through additional R&D investments fades out – especially once the technology becomes available and economically competitive. The cost of the backstop technologies follows an inverted S-shaped path (Figure 9). R&D activities bring costs down rapidly in the early phases, when backstops remain very expensive. After 2030-2040, further cost declines occur mainly through LbD, as the technologies are deployed.[12]

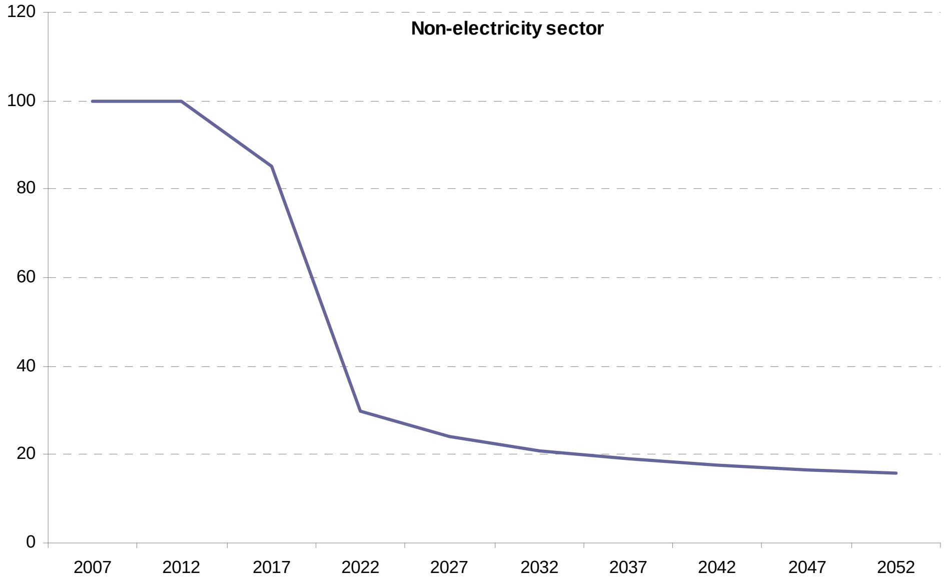
Figure 8. Projected energy R&D investments under a 550 ppm GHG concentration stabilisation scenario, with and without backstop technologies



12 Backstop technologies are also adopted at a later stage and to a lesser extent in developing regions.

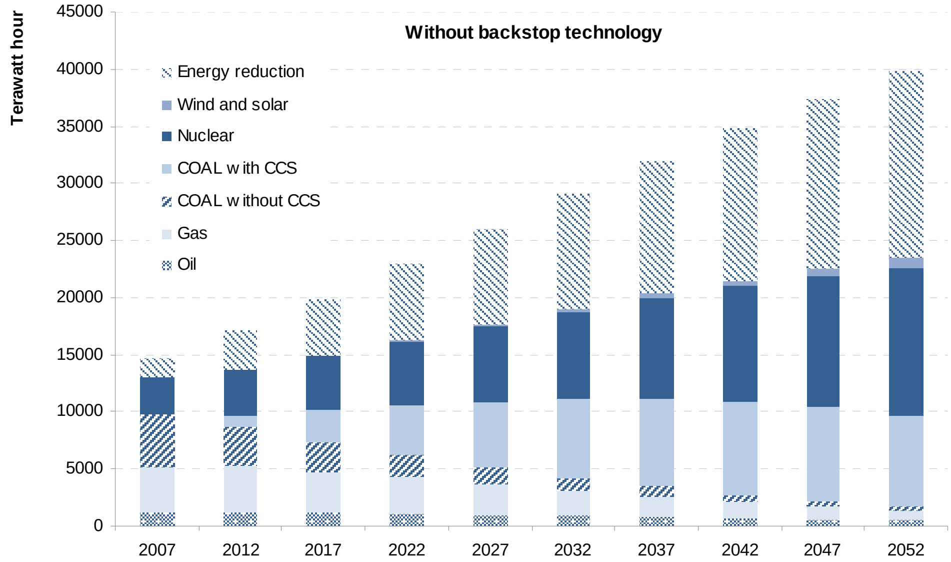
Figure 9. Simulated investment costs of the backstop technologies, 550 ppm GHG concentration stabilisation scenario (Index 2007=100)





The share of backstop technologies in the production of energy increases rapidly in the simulations. The backstop in the electricity sector substitutes for the large deployment of nuclear power capacity projected in the previous section in the absence of backstops (Figure 10), while the backstop in the non-electricity sector mainly relaxes the energy savings constraint that would otherwise be stringent (Figure 11).

Figure 10. Projected energy technology mix in the electricity sector under a 550 ppm GHG concentration stabilisation scenario, with and without electricity backstop technology



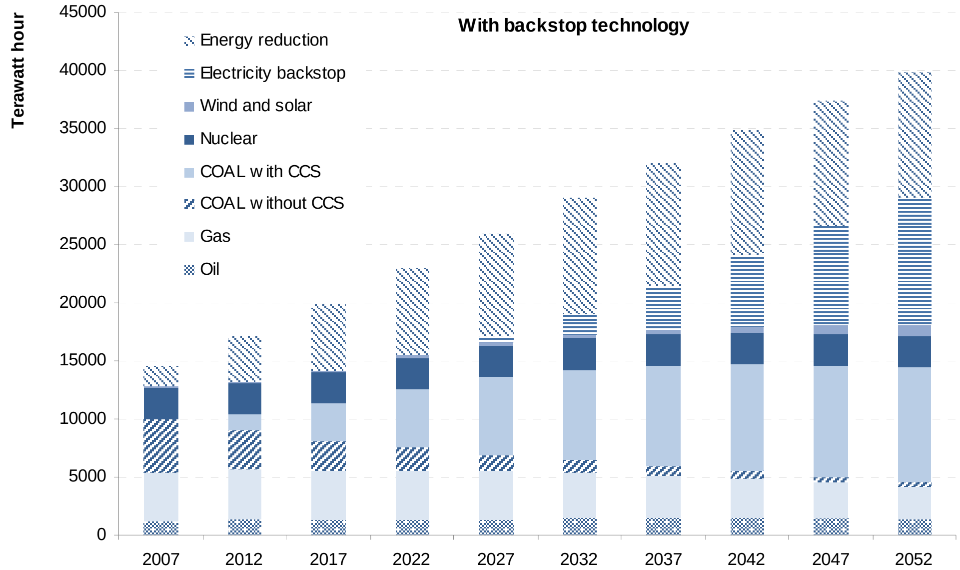
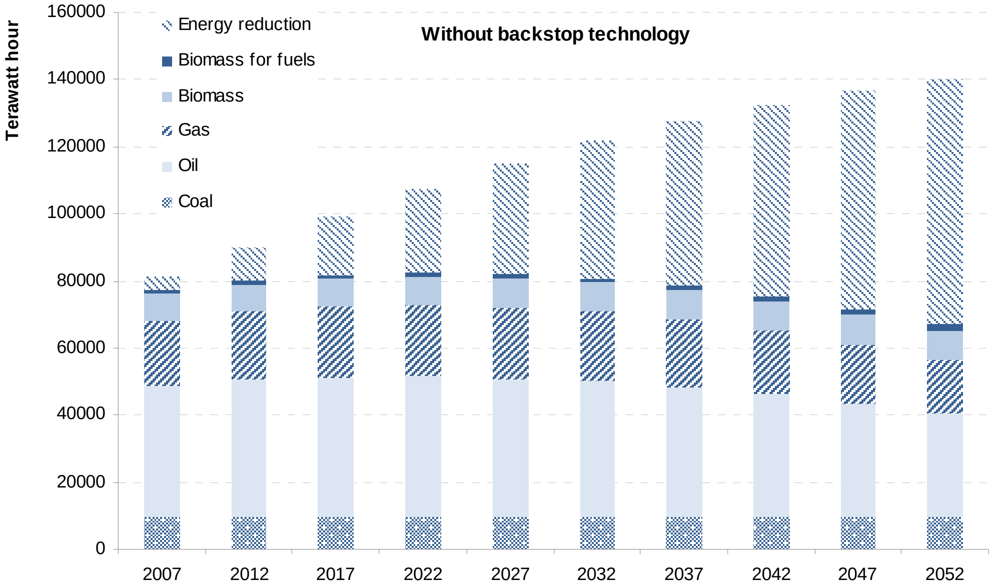
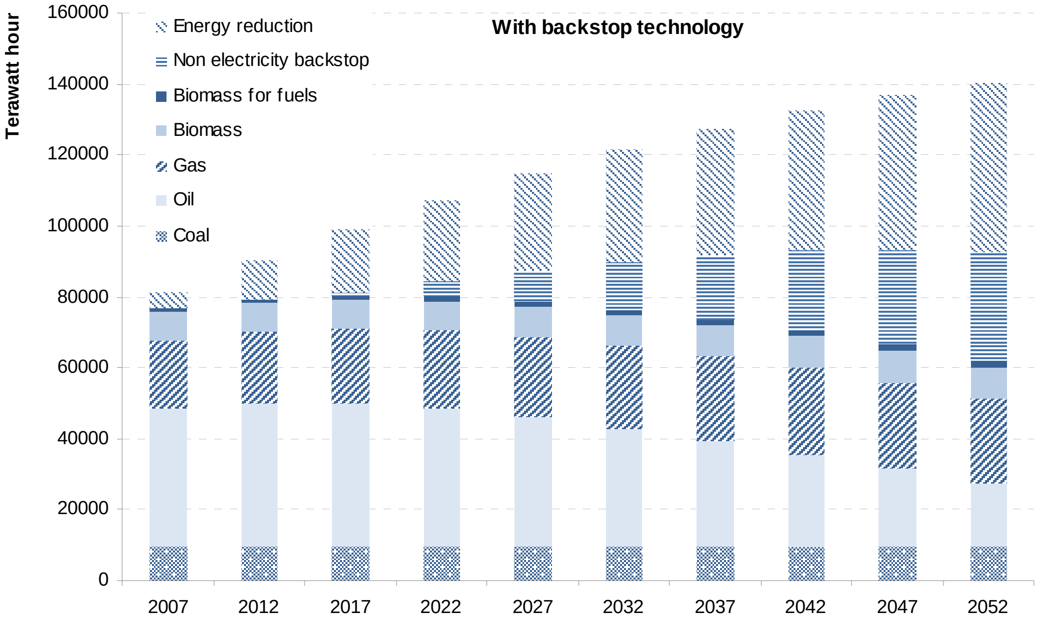


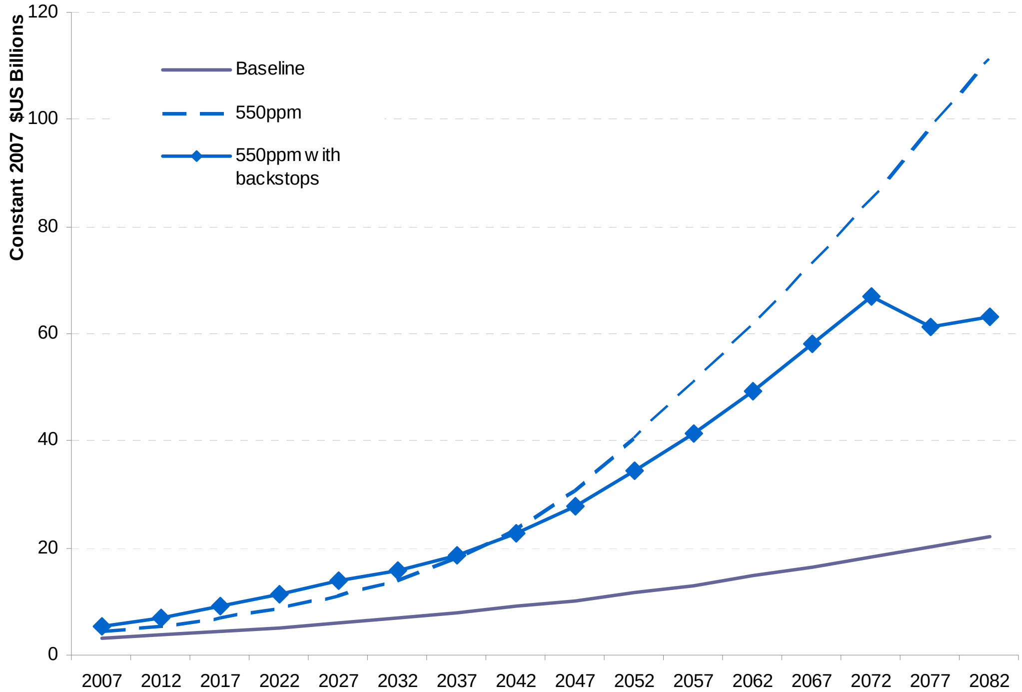
Figure 11. Projected energy technology mix in the non electricity sector under a 550 ppm GHG concentration stabilisation scenario, with and without non-electricity backstop technology





Compared with the previous section, where the 550 ppm GHG concentration target was to be achieved without the help backstops, R&D investments in backstop technologies are estimated to crowd out part of energy efficiency R&D. The electricity backstop technology also crowds out investments in wind and solar power generation.[13] This is mainly the case after mid-century, however, when the backstop technology becomes cost effective. In the first decades, investments in wind and solar are actually higher in the backstop case, reflecting the constraint imposed on nuclear power generation and the time lag needed for the electricity backstop to become competitive (Figure 12).

Figure 12. Investment in wind and solar power generation under a 550 ppm GHG concentration stabilisation scenario, with and without backstop technologies



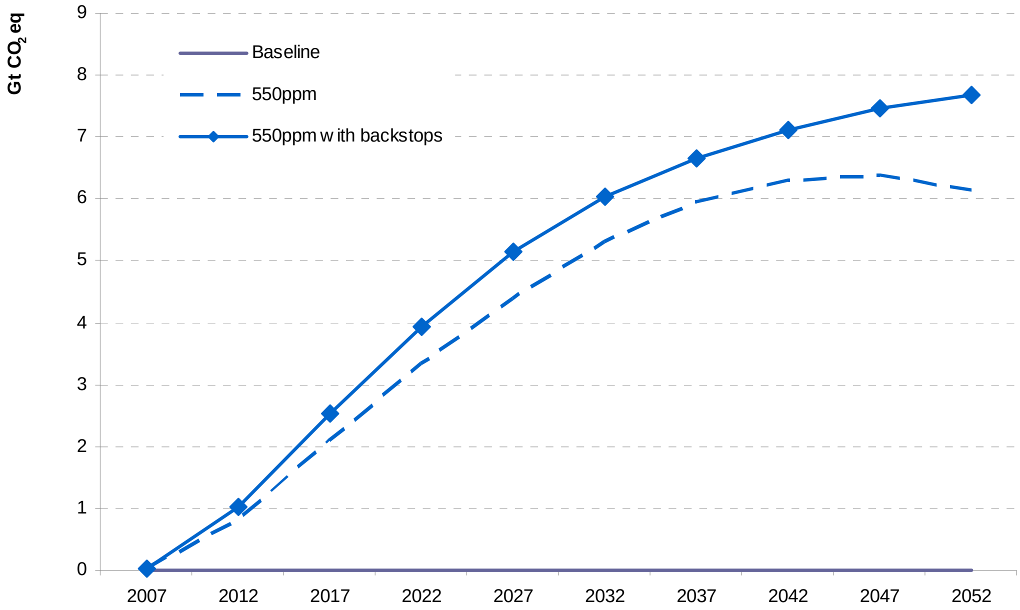
By contrast, the electricity backstop technology and CCS are found to be complementary. CCS remains an important mitigation measure throughout the century, although a saturation effect (at roughly 8 Gt CO_2eq) is embedded in the model, reflecting the exhaustibility of repository sites[14] (Figure 13). The drivers of this complementarity are the constraints on nuclear power generation and the existence of a carbon-free backstop technology in the non-electricity sector. This backstop technology relieves the electricity sector from the large mitigation burden that would otherwise limit CCS capacity in the long run, due to the imperfect capture rate of carbon.[15]

13 By definition, investments in nuclear power generation are also crowded out in the simulations.

14 Specifically, supply cost curves for carbon storage sites for each region are endogenous in the model.

15 In line with the technical estimates, the model assumes that 90% of the carbon is captured, while the remainder 10% is vented.

Figure 13. Carbon sequestred under a 550 ppm GHG concentration stabilisation scenario, with and without backstop technologies



Impact of backstop technologies on carbon prices and mitigation policy costs

The possibility of investing in breakthrough technologies is estimated to greatly reduce the level and steepness of the carbon price path needed to meet the 550 ppm GHG concentration target (Figure 14). This is the case essentially at relatively distant horizons, however, as carbon prices behave in a roughly similar way with and without backstop technologies up to 2025. The latter point indicates that regardless of the possibility of developing breakthrough technologies in the electricity and non-electricity sectors, a strong carbon price signal is still needed over the next few decades in order to meet stringent emission reduction pathways at least cost. Finally, at distant horizons – especially beyond mid-century - the costs of meeting the 550 ppm GHG concentration target are significantly reduced by the availability of backstop technologies (Figure 15). However, this comes at the cost of higher GDP losses in the coming decades, due to the large increase in R&D effort needed to raise the productivity of the backstops.

Figure 14. Carbon price paths under a 550 ppm GHG concentration stabilisation scenario, with and without backstop technologies

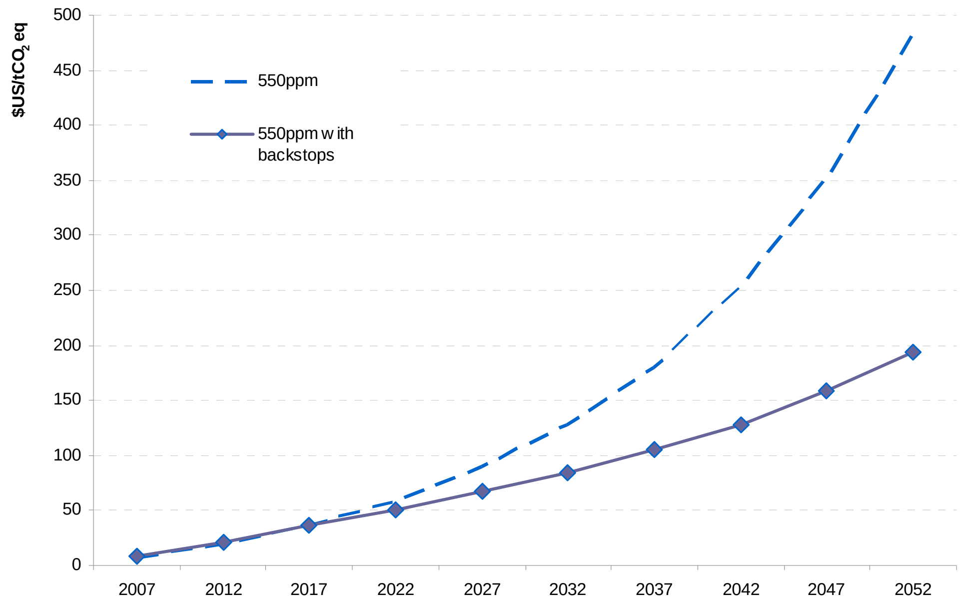
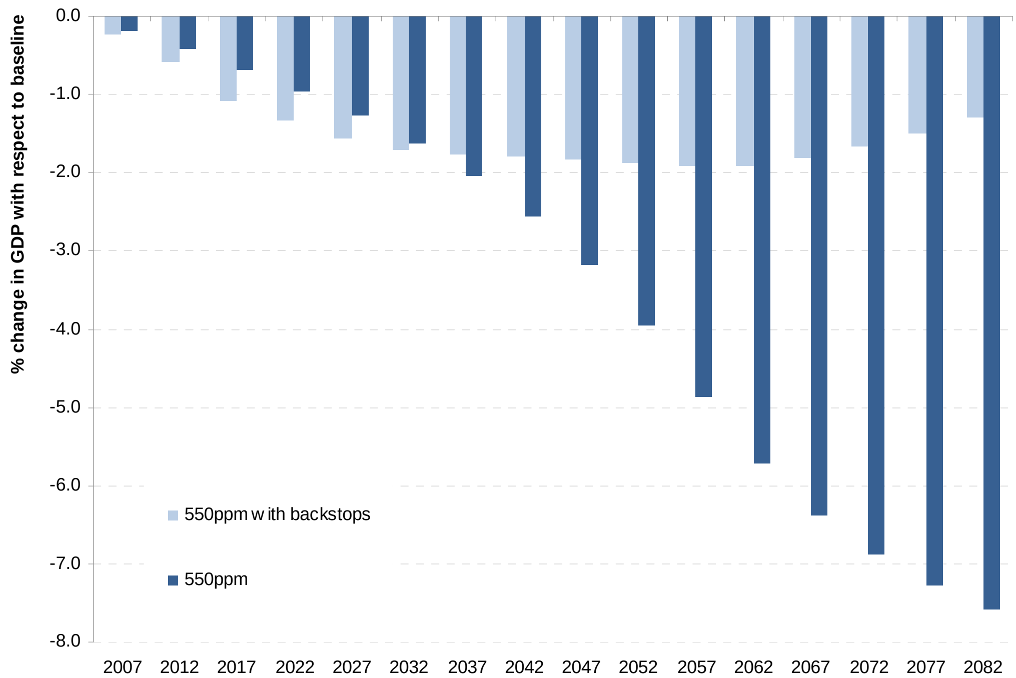
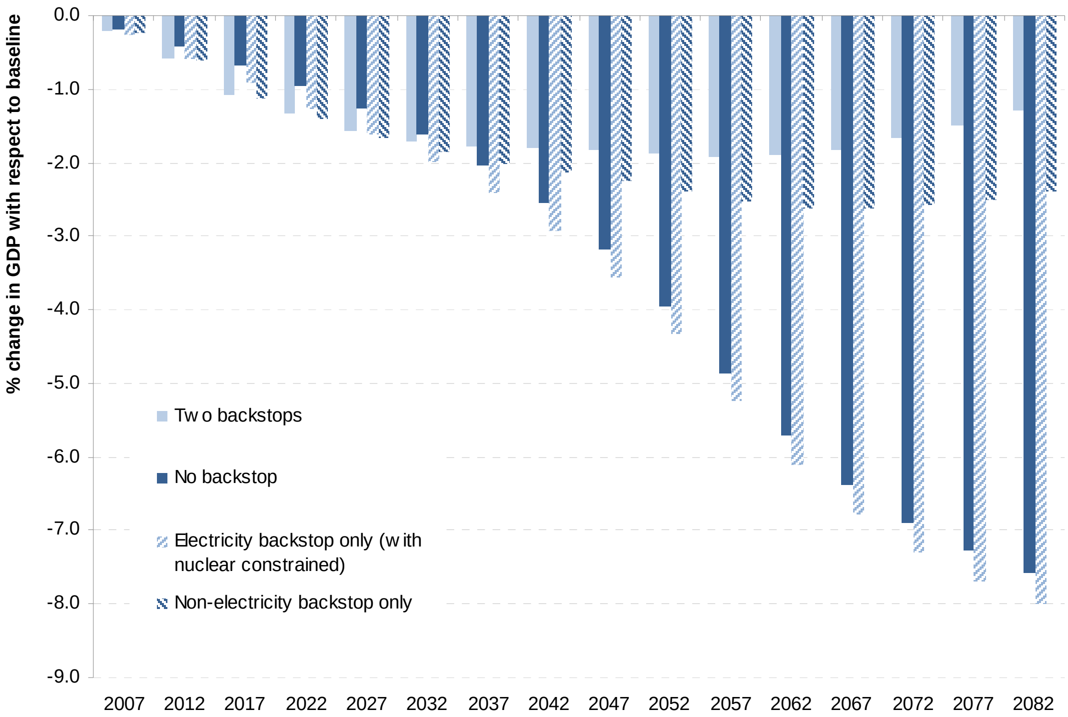


Figure 15. World GDP costs under a 550 ppm GHG concentration stabilisation scenario, with and without backstop technologies



The backstop technology in the non-electricity sector is found to matter more for mitigation costs than its electricity counterpart (Figure 16). In a simulation where only the electricity backstop is assumed to be available, the costs of meeting the 550 ppm GHG concentration target rise marginally, compared with a 550 ppm GHG concentration stabilisation scenario without backstops. This only partly reflects the assumed constraint on the expansion of nuclear power generation, since releasing that constraint would merely bring costs in line with a "no-backstops" scenario. By contrast, in a simulation where only the non-electricity backstop is assumed to be available, costs are drastically reduced, and in fact are not far above the estimated costs under a scenario where both backstops are available. These results highlight the importance of developing carbon-free technologies in the non-electricity sector, where the abatement potential of currently commercially available mitigation options is comparatively smaller than in the electricity sector.

Figure 16. World GDP costs under a 550 ppm GHG concentration stabilisation scenario, with electricity backstop and non-electricity backstop only



5. Impact of global R&D policies on future emissions and mitigation policy costs

R&D spillovers and the case for dedicated R&D policies

As discussed in the main text, a number of market imperfections are likely, in practice, to undermine R&D incentives. As a result, global R&D spending could remain below levels that would be optimal even if a world price were put on carbon. This issue cannot be thoroughly explored with the WITCH model since most of the relevant market imperfections are not featured in the model. In particular, there are no domestic

R&D spillovers, *i.e.* each region is assumed to fully appropriate domestic social returns to R&D. One issue that can be explored, however, is whether the existence of international – as opposed to domestic – R&D spillovers may justify an international R&D policy, *e.g.* in the form of a global fund that would finance R&D projects (see below). In the WITCH model, international R&D spillovers arise from the fact that energy-related knowledge capital – and therefore energy efficiency – is increased not only through domestic R&D but also *via* the absorption of international knowledge, where absorption capacity increases with the region's R&D capital stock (for details, see Bosetti, Carraro *et al.* 2007b).[16] However, the economics of international R&D spillovers is not entirely settled, and empirical evidence is scarce, making it difficult to model and quantify these effects. Therefore, any model-based analysis of international R&D spillovers and their implications for optimal international R&D policy should be interpreted with great care.

Bearing these concerns in mind, an illustrative global fund is considered, which is financed through a given share of each region's GDP, and provides a subsidy to each region – allocated on an equal per capita basis – that adds to their own expenditures on energy efficiency-improving R&D. This "additionality" constraint is imposed because otherwise the optimal reaction of each region to the subsidy would be to cut their own R&D expenditures, *i.e.* the R&D spending spurred by the subsidy would fully crowd out other domestic R&D investments.[17] The optimal size of the fund can then be approximated by the international knowledge spillover effect, computed as the difference between R&D under the cooperative and non-cooperative solutions of the model, *i.e.* as the difference between the energy efficiency R&D investments that would be undertaken if regions jointly maximised their welfare and the levels prevailing when countries act strategically and maximise their own welfare taking other regions' choices as given (Nash equilibrium).

In practice, however, the optimal size of a global R&D fund is found to be very small – amounting to just about $US5 billion by mid-century and $US20 billion by the end of the century, resulting in a negligible impact on policy costs. Allowing for R&D investment in backstop technologies – and assuming these also yield international spillovers – would yield an optimal fund of larger size, but it would not radically change the findings. This fundamentally reflects the limited range of R&D spillovers – especially at the domestic level – featured in the model.

The impact of combining R&D policies and carbon pricing on mitigation costs in a "no-backstops" world

Given the limited insights that can be drawn from considering an "optimal" global R&D fund, the analysis focuses instead on the effects of a fund of arbitrary, but yet plausible size. Concretely, a fund to subsidise a level of investment in energy efficiency R&D equivalent to the global public R&D expenditures of the 1980s – or around 0.08% of world GDP, starting at about $US40 billion today – is considered.

In a scenario where such an R&D fund is established in association with a global cap-and-trade scheme designed to achieve a 550 ppm GHG concentration target, public energy efficiency R&D increases significantly, reaching up to 0.11% of world GDP. However, compared with a carbon pricing (cap-and-trade) policy alone, the paths of energy intensity, carbon intensity of energy, the carbon price and GDP are only marginally affected. In particular, the need to finance the R&D fund initially increases GDP costs, and

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16 R&D investment in WITCH is a strategic variable, whose optimal value is computed by solving a dynamic game. Therefore, its (Nash) equilibrium value is subject to free-riding effects induced by international knowledge spillovers.

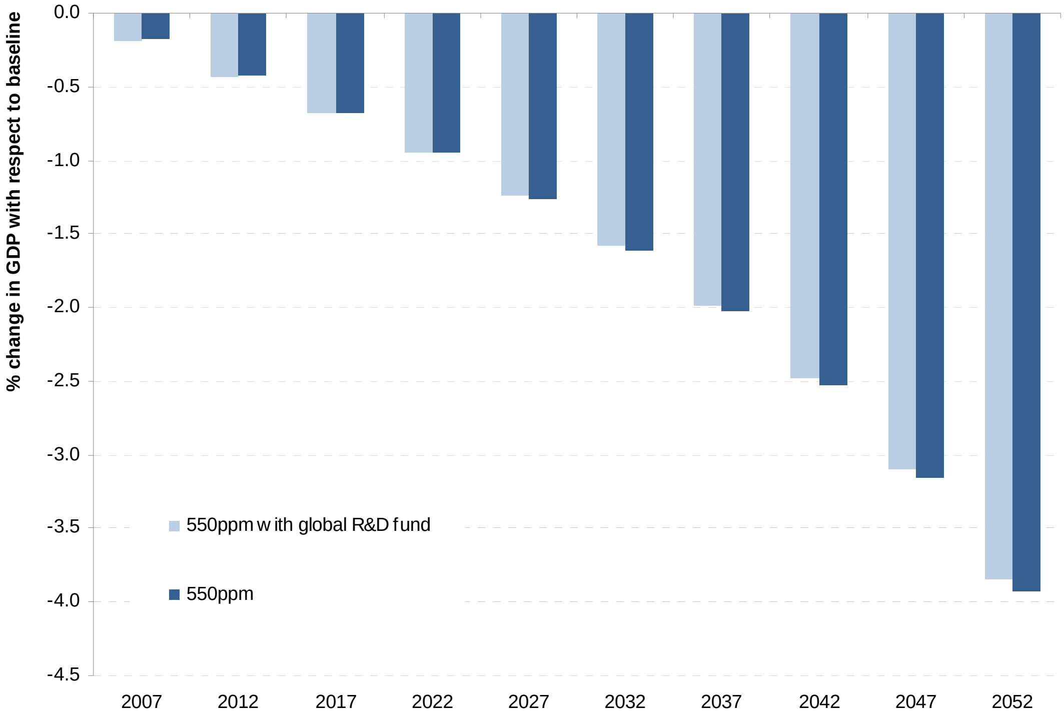
17 To implement the additionality constraint, a minimum level of energy efficiency R&D investment is imposed in all regions, equal to what would be Pareto optimal under a 550 ppm GHG concentration stabilisation scenario.

the reduction achieved subsequently (with respect to baseline) is found to be very small, from 3.9% to 3.8% of world GDP in 2050 (Figure 17) :

- A reduction in GDP costs is found because the fund corrects for the (international) knowledge externality by forcing regions – through the "additionality constraint" –to invest more than they would consider optimal if they acted alone. This more than offsets the loss in flexibility and costs incurred by each region as a result of these forced investments.

- The reduction in GDP costs is small, however, because carbon pricing alone already boosts R&D and energy efficiency substantially, so that additional R&D only has a marginal impact.

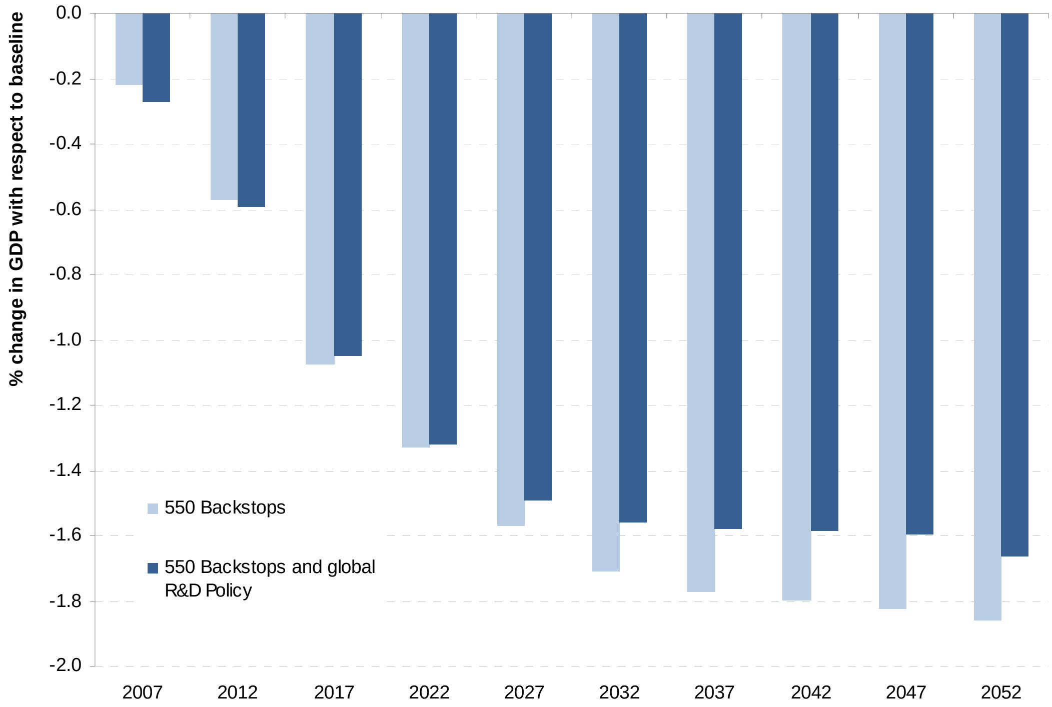
Figure 17. World GDP costs under a 550 ppm GHG concentration stabilisation scenario in the basic WITCH model, with and without energy efficiency improving R&D fund



The impact of combining R&D policies and carbon pricing on mitigation costs in the presence of backstop technologies

One major limitation of energy efficiency improving R&D is that it cannot help "decarbonise" the world economy. Against this background, the effects of a global R&D policy are reassessed here in the presence of breakthrough technologies, given that these would contribute to decarbonisation. Concretely, the version of WITCH including backstop technologies is used, and the international R&D fund is now assumed to finance R&D in such backstops. However, compared with a cap-and-trade policy alone, the fund is still found to have small effects on the world carbon price and GDP, although these are somewhat larger than in the case of an energy efficiency improving R&D fund (Figure 18). This is again essentially because carbon pricing alone would already substantially boost R&D in backstop technologies and because the international R&D spillovers to be internalised by the fund are limited.

Figure 18. World GDP costs under a 550 ppm GHG concentration stabilisation scenario in the presence of backstop technologies, with and without global fund dedicated to R&D in backstops

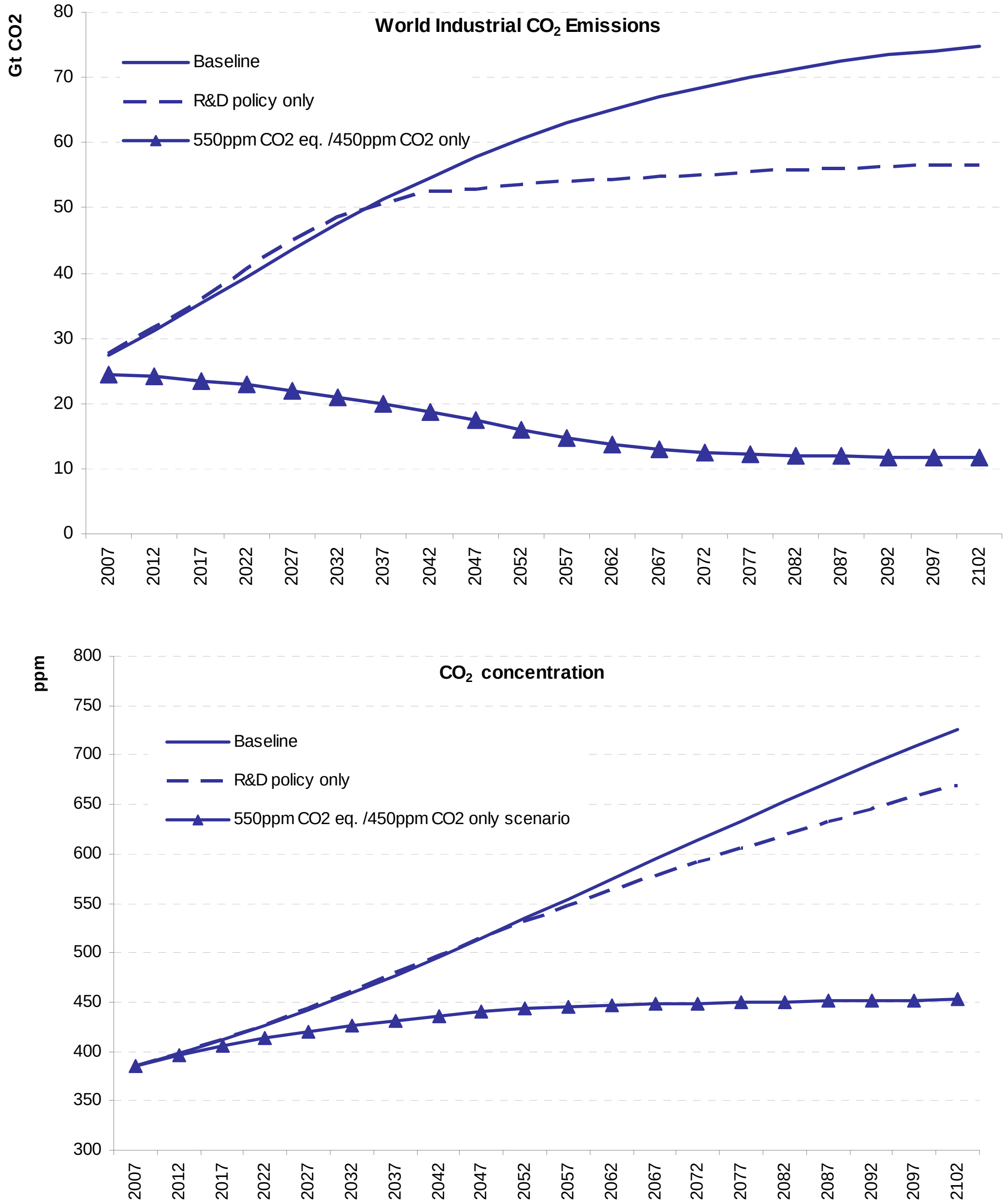


R&D as a stand-alone policy

One open issue is whether, and at what levels, global R&D spending alone could stabilise future greenhouse gas concentrations. Indeed, raising R&D expenditures may be politically easier than pricing carbon worldwide, at least in the short-run. Therefore, a global R&D fund of 0.08% of world GDP – corresponding to the peak level of public R&D investment efforts reached in the early 1980s – is assumed to be established in the absence of any carbon pricing policy. Also, in order for the fund to have the largest possible impact on future emissions, the two backstop technologies in the electricity and non-electricity sectors are assumed to be available. The fund subsidises investments in R&D for these backstops in all regions, based on an equal-per-capita subsidy allocation rule. Finally, the "additionality" constraint applies, *i.e.* R&D spending from the fund comes over and above the expenditures that would be made without it in a baseline scenario.

Even under these fairly optimistic assumptions, the R&D policy alone only succeeds in stabilising world CO_2 *emissions* by mid-century, reflecting the time needed for R&D spending to pay off (Figure 19, top panel). The effect on CO_2 concentration is minimal, due to the inertia in the climate system. CO_2-only concentration is projected to be close to baseline levels until mid-century, diverging afterwards but still reaching over 650 ppm by the end of the century (Figure 19, bottom panel). While the environmental effectiveness of the R&D policy is found to be very weak, it yields a GDP gain with respect to baseline of about 0.3 % of world GDP in 2050 and 2% in 2100, reflecting the internalisation of international knowledge spillovers.

Figure 19. Projected CO_2 emissions and concentration under a global R&D policy only



Setting a fund of larger size than considered here would not radically improve the environmental effectiveness of a stand-alone R&D policy. For instance, even an implausibly large global fund – equal to 1% of world GDP, representing a 30-fold increase with respect to current public energy R&D spending worldwide – is not found to stabilise CO_2 concentration during this century. This reflects mainly the loss of cheap abatement opportunities over the coming decades, *i.e.* during the transition period required for R&D to foster major breakthroughs, as well as declining marginal returns to R&D.

Technology deployment policies

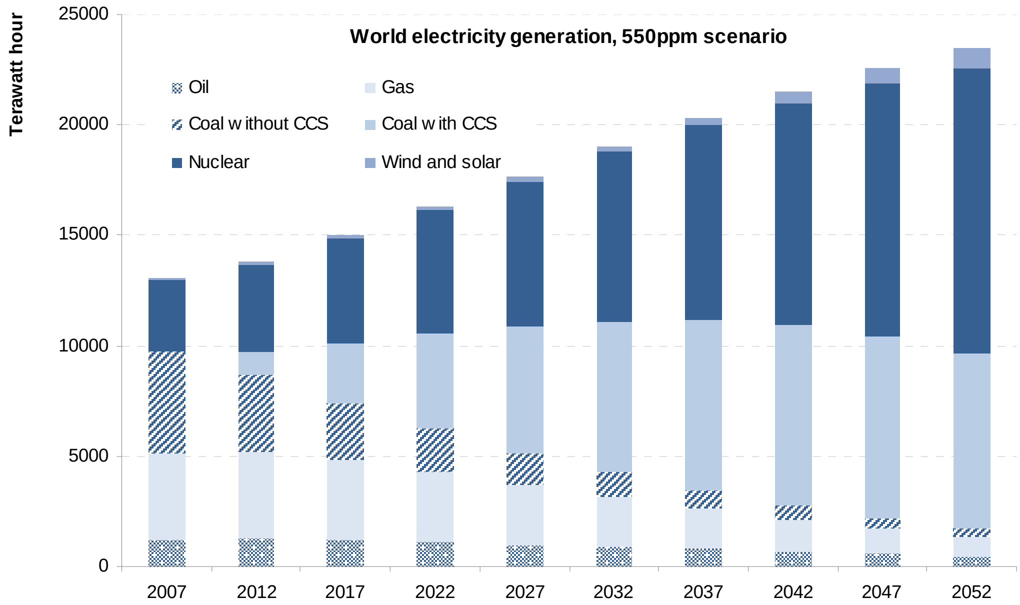
One limitation of R&D policies, especially as stand-alone policies, is that they take time to pay off. In this context, one open issue is whether a global fund to subsidise the deployment of already existing technologies may perform better. There is a theoretical case for such a policy in the WITCH model because the cost of existing low-carbon technologies (wind and solar power generation, CCS) falls with research and installed capacity at the world level, *i.e.* there are international knowledge and learning spillovers. However, this abstracts from the fact that domestic renewable energy subsidies are already high in many OECD countries, which substantially weakens the case for further policy action at the international level.

Following previous analysis undertaken to explore R&D policies, the fund is assumed to be equivalent to 0.08% of world GDP, and is analysed both as a complement to carbon pricing (cap-and-trade scheme under a 550 ppm GHG concentration stabilisation scenario) and as a stand-alone policy. Financial resources are assumed to be split equally between wind and solar technologies and CCS.[18] Compared with carbon pricing alone, setting up a technology deployment fund speeds up the decrease in costs and diffusion of existing low-carbon technologies, and as a result it significantly alters the energy mix (Figure 20). In particular, by 2050, wind and solar electricity represents a much larger share of world electricity production, while the penetration of CCS is essentially frontloaded but is not radically altered over a half-century horizon, reflecting the exhaustibility of repository sites. However, the impact on the world carbon price and mitigation policy costs is negligible. Reflecting the need to finance the subsidies, GDP costs with respect to baseline are initially increased, and they are only marginally reduced from 3.9% to 3.8% of world GDP in 2050 (Figure 21). This negligible impact is similar to that obtained above from a global R&D fund in the absence of backstop technologies.

When considered as a stand-alone policy, a global technology deployment subsidy is found to have a quicker impact on emissions than a global R&D fund, as would be expected (Figure 22, top panel). However, this effect gradually fades out, so that emissions resume their upward trend and concentration rises unchecked (Figure 22, bottom panel).

18 The fund is assumed to finance research in these existing technologies (LbS) rather than directly subsidise their deployment (LbD). The latter option would yield qualitatively similar, but even weaker effects than discussed below.

Figure 20. Projected energy technology mix in the electricity sector under a 550 ppm GHG concentration stabilisation scenario, with and without a global technology deployment fund



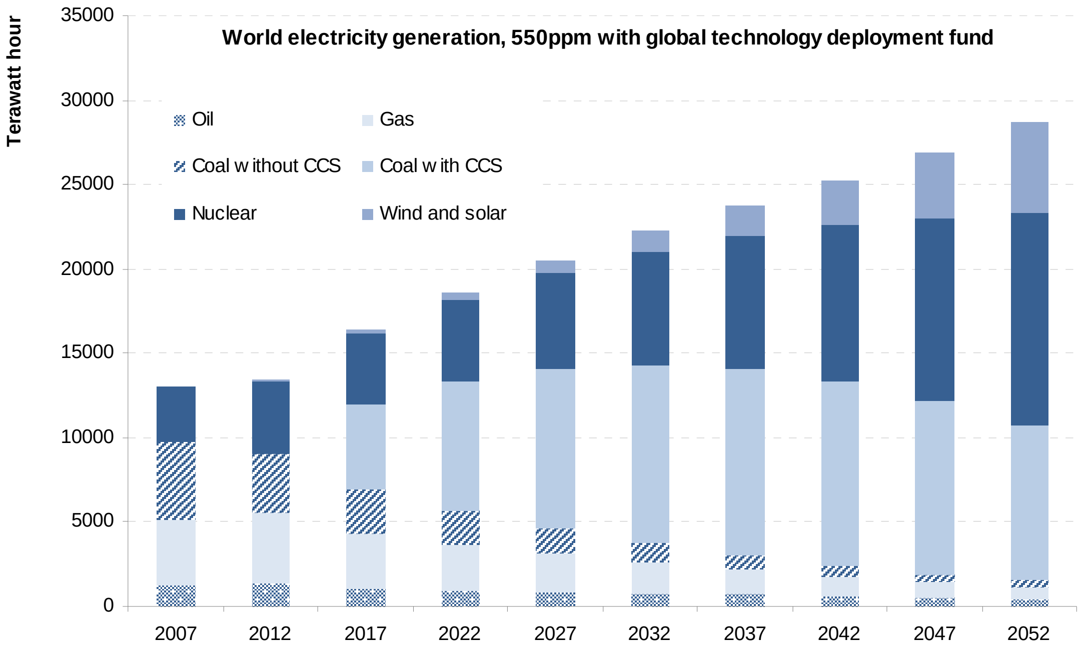
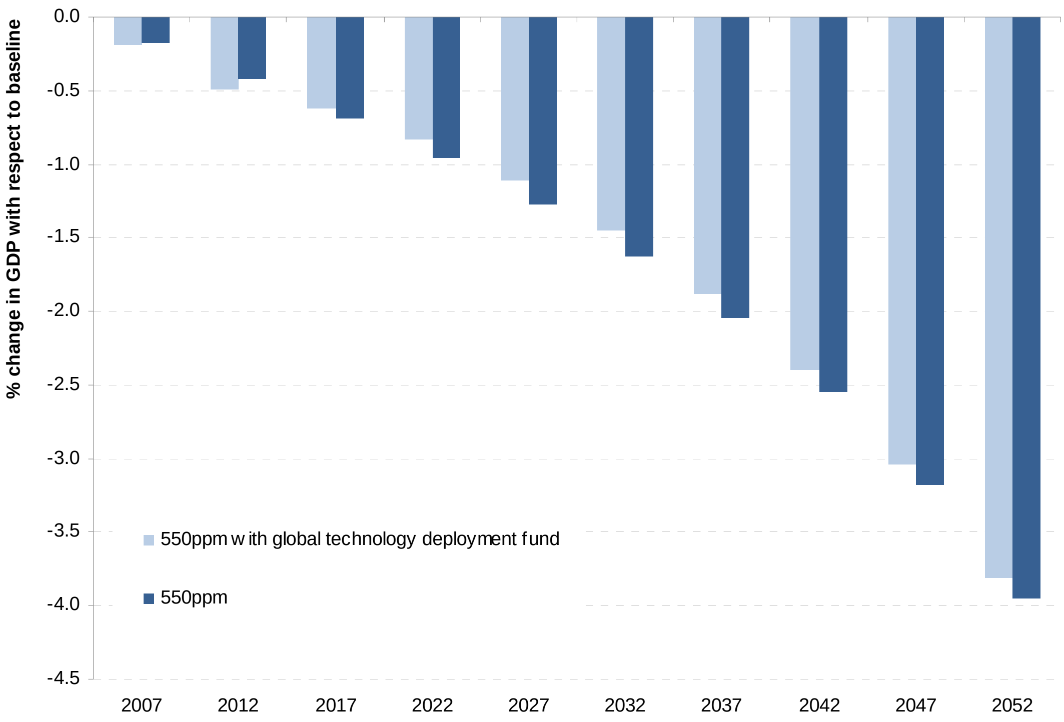


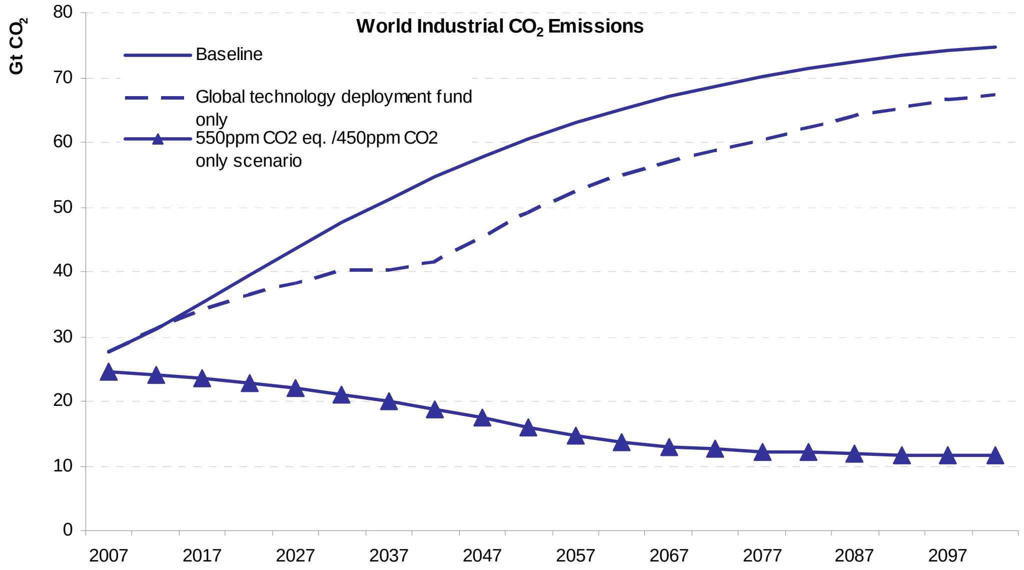
Figure 21. World GDP costs under a 550 ppm GHG concentration stabilisation scenario, with and without a global technology deployment fund

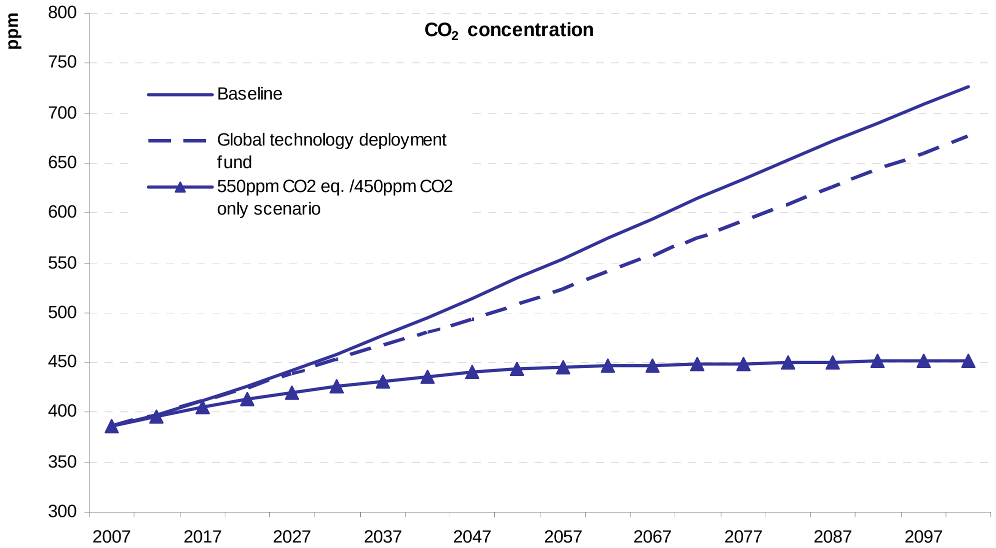


6. Sensitivity analysis

Existing uncertainty surrounding the appropriate way of modelling and calibrating the drivers of technological change calls for sensitivity analysis. Here, the robustness of the results is assessed by varying three key parameters for both existing and new technologies: *i)* LbD in renewable technologies; *ii)* the returns from R&D dedicated to energy efficiency; and *iii)* learning rates (progress ratios) and the speed of deployment of the backstop technologies. In each of these three cases, the parameters subject to sensitivity analysis are assumed to vary by +50% or -50% with respect to their central estimates, and 550 ppm GHG concentration stabilisation scenarios are run. The main finding is that only the specification of backstop technologies has a significant impact on projected carbon prices and mitigation policy costs.

Figure 22. Projected CO_2 emissions and concentration under a global technology deployment policy only



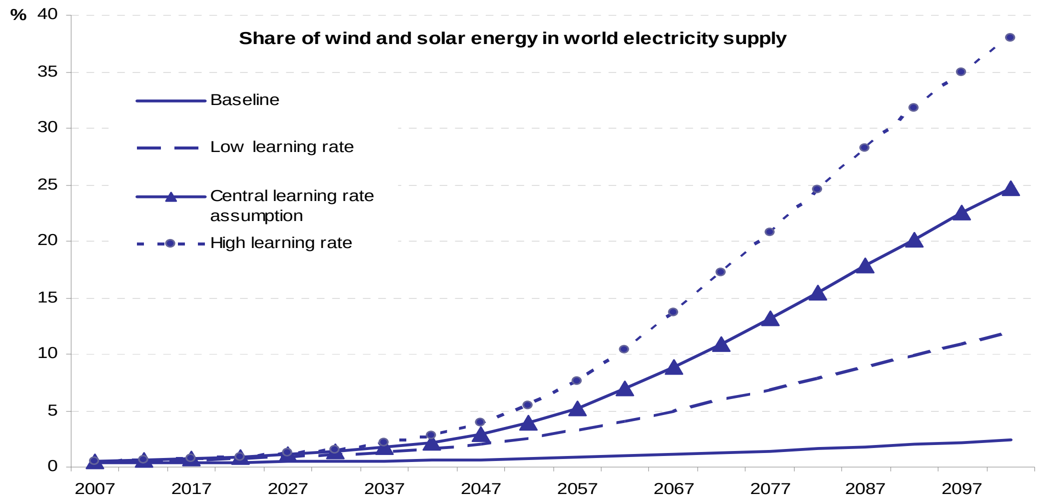


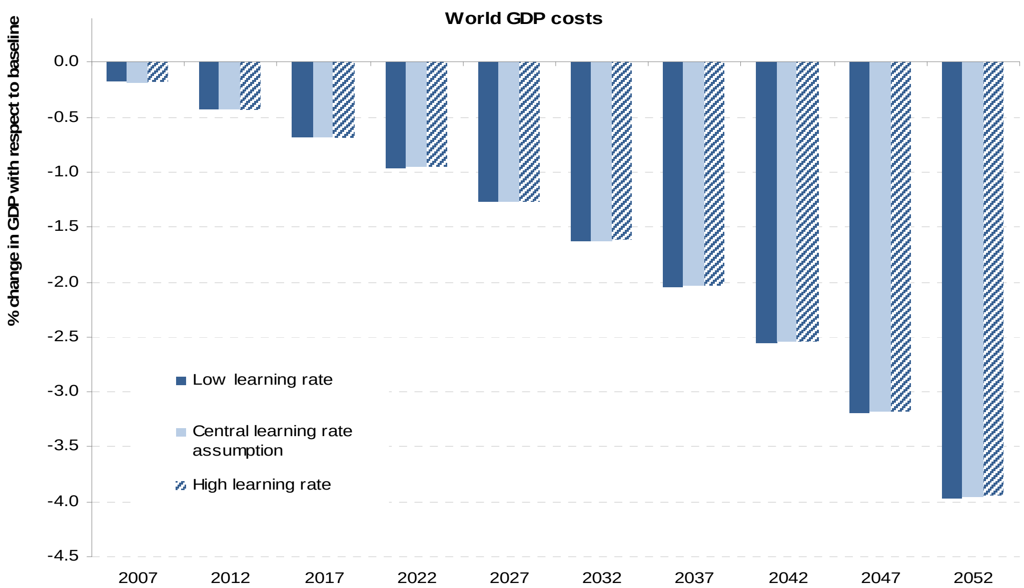
Learning by doing in wind and solar power generation

Despite vast empirical literature, considerable uncertainty remains regarding LbD for a wide range of technologies. In particular, learning rate estimates vary considerably for technologies used in the electricity sector, from about 1% to over 40%, around a central estimate of about 20% (Jamasab and Köhler, 2007; Kahouli-Brahmi, 2008). In the WITCH model, a learning rate of 13% – corresponding to a progress ratio of 0.2 – is considered for wind and solar technologies, a fairly conservative value in view of existing estimates (see for instance Junginger, Faaij *et al*. 2005; IEA, 2000). The sensitivity analysis considers two alternative cases where the progress ratio is 50% higher or lower (0.1 or 0.3), *i.e.* the learning rate is 19% or 7%.

A 550 ppm GHG concentration stabilisation scenario – achieved through a world cap-and-trade scheme, *i.e.* through a global carbon price – is then run under these two alternative assumptions. As would be expected, the uptake of renewable energy is sensitive to, and increases with the learning rate (Figure 23, top panel). However, in line with the above results, learning rate assumptions have negligible effects on mitigation policy costs (Figure 23, bottom panel).

Figure 23. Impact of alternative learning rate assumptions in wind and solar electricity on world electricity supply mix and mitigation policy costs



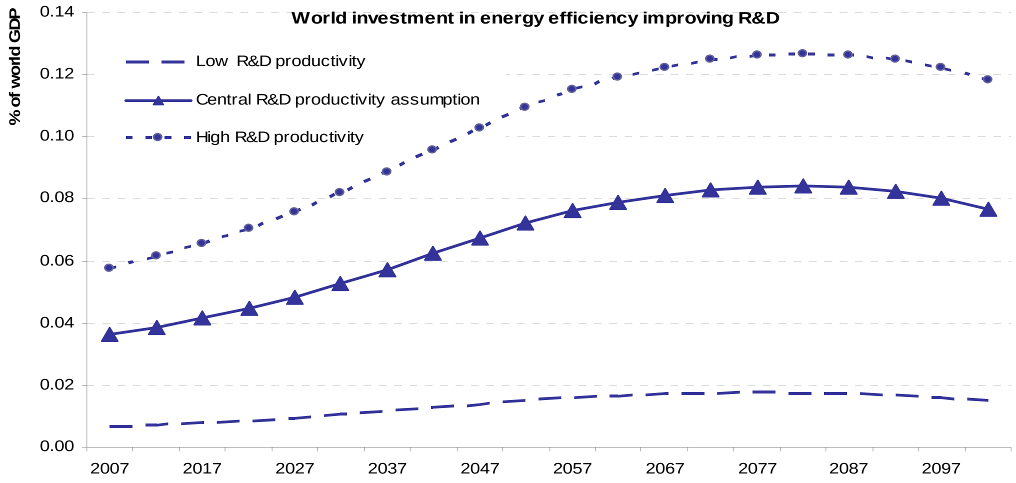


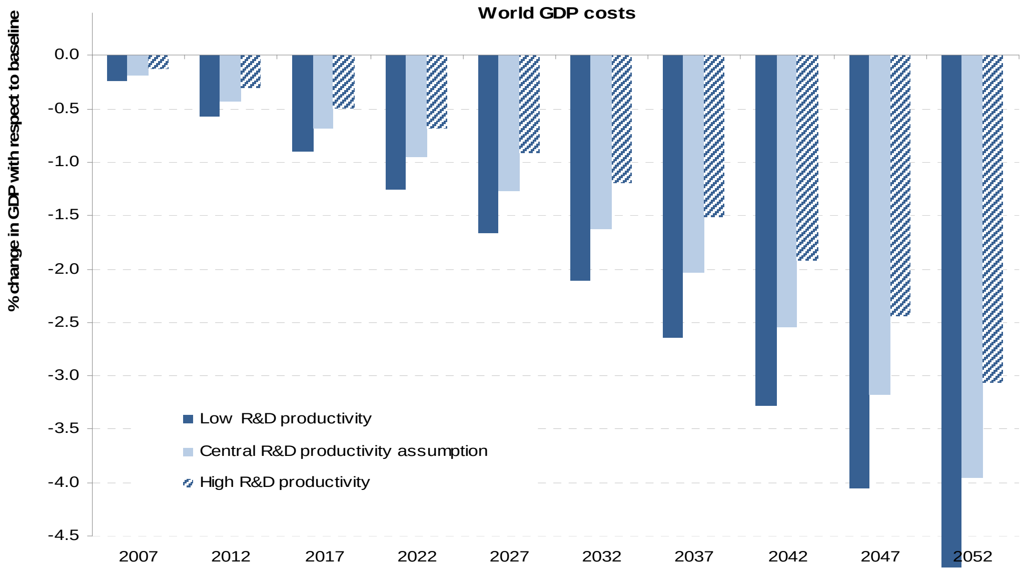
Returns from R&D dedicated to energy efficiency

Another important technology parameter in the model is the productivity of energy efficiency improving R&D, *i.e.* parameter *a* in equation (3) above. This parameter is allowed to vary by 50% around the central estimate of 0.3, *i.e.* $a = 0.3 \pm 0.15$.

A 550 ppm GHG concentration stabilisation scenario is then run under these two alternative assumptions. As would be expected, optimal investments in energy R&D are sensitive to, and increase with the productivity of R&D (Figure 24, top panel). However, and again in line with the above results, these productivity assumptions have negligible effects on mitigation policy costs (Figure 24, bottom panel).

Figure 24. Impact of alternative R&D productivity assumptions on world investment in energy efficiency improving R&D and mitigation policy costs

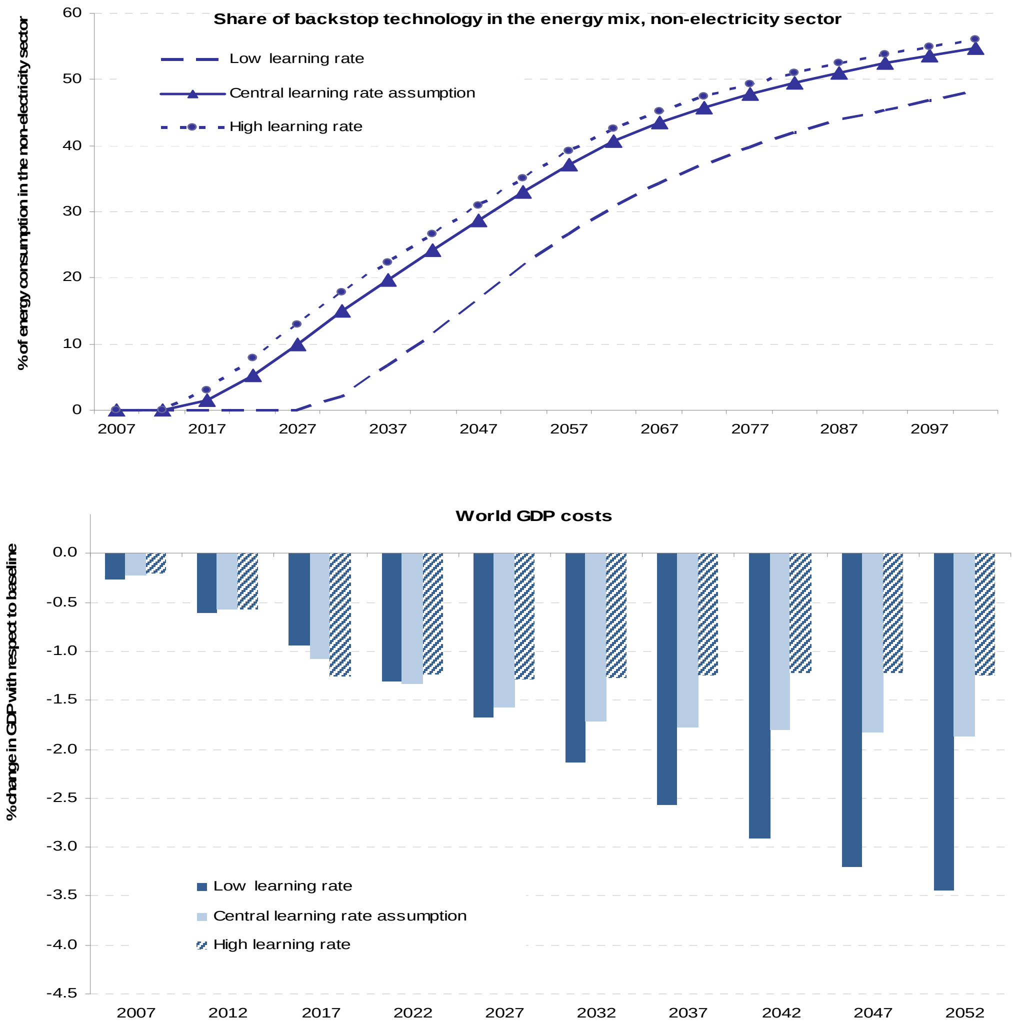




Specification of the backstop technologies

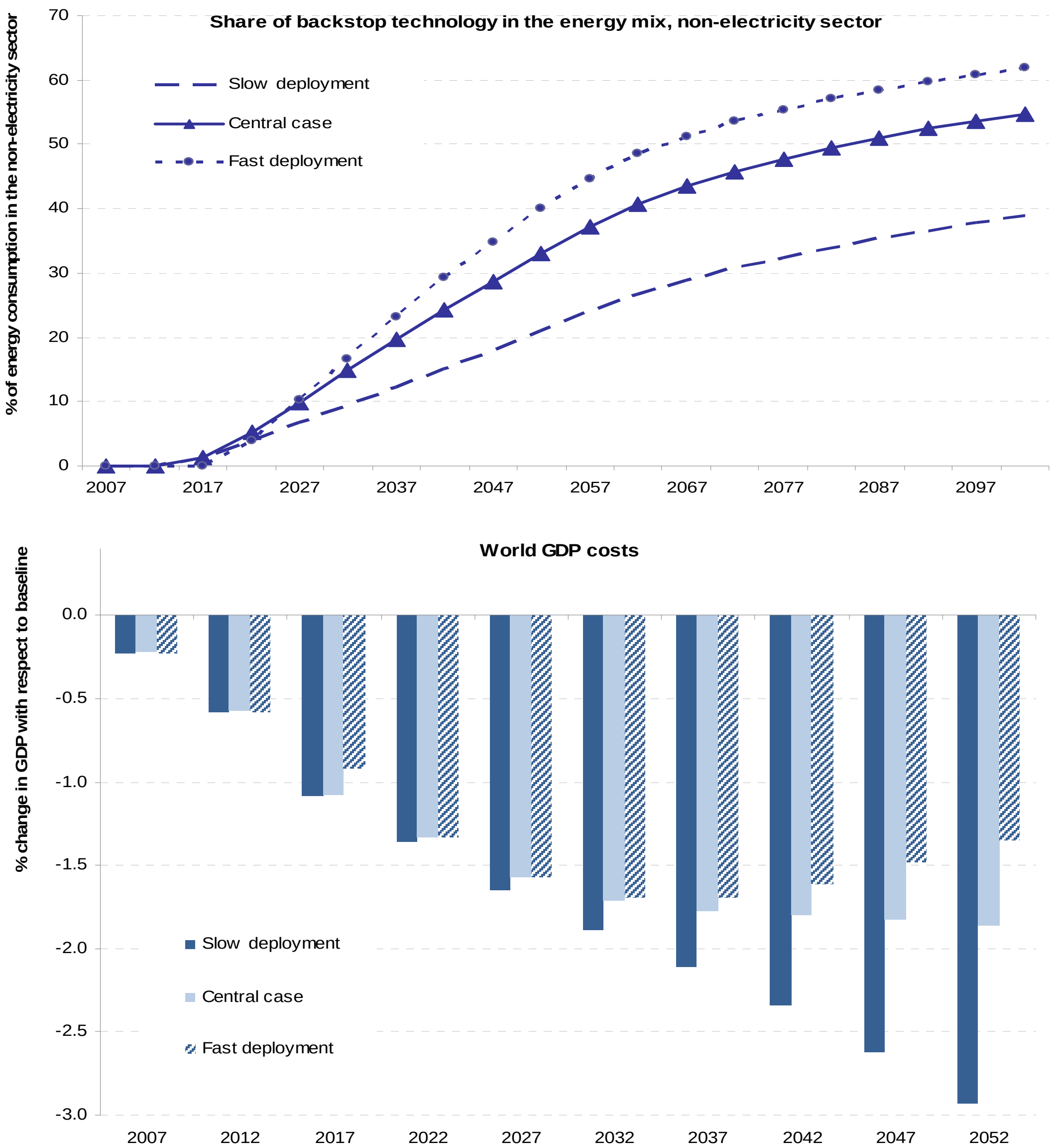
Although innovative future technologies are hard to specify by nature, one advantage of the backstop approach followed in this paper is to allow for model simplicity and tractable sensitivity analysis. In particular, the implications of alternative learning rates in research and deployment in the specification of "two-factor" learning curves can be explored. Here, both LbD and LbS processes are assumed to be either lower or higher than in the central case, by varying the corresponding progress ratios by +50% or -50% (see equations (5) and (6) in Section 2 above). Learning rate assumptions are found to have a sizeable impact on the competitiveness, and thereby on the market penetration of the backstop technologies under a 550 ppm GHG concentration stabilisation scenario (see Figure 25, top panel for the non- electricity sector). The impact of these assumptions is asymmetric, however, with higher learning rates having a limited impact due to limits on technology diffusion. This translates into large but asymmetric effects on GDP costs (Figure 25, lower panel). Under low learning rates, GDP costs increase significantly to 2.9% of world GDP in 2050, versus 1.9% only in the central case (and 3.9% in a "no backstop" central scenario, see Figure 6).

Figure 25. Impact of alternative learning rate assumptions in backstop technologies on their world market penetration and mitigation policy costs



The speed of deployment of the backstop technologies is another important driver of their future market penetration and impact on mitigation policy costs. Varying the relevant parameters by +50% or -50% has roughly similar effects as varying learning rates in research and deployment, albeit far less asymmetric (Figure 26). This confirms the fact that mitigation policy costs are far more sensitive to the technology assumptions driving the future development of backstop technologies than to those underlying learning processes in existing renewable energies or energy efficiency improving R&D.

Figure 26. Impact of alternative assumptions regarding the deployment speed of backstop technologies on their world market penetration and mitigation policy costs



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