Impacts of RD&D on Carbon Mitigation Cost

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Abstract: We have introduced learning-by-searching (LBS) and learning investments (subsidies) for carbon-free technologies in MERGE5 to assess the impacts of RD&D investments on the costs of achieving different climate stabilization targets.

The paper is organized in two parts. First we describe the modeling of two-factor learning curves (TFLC), including subsidies in form of learning investment; indicators that capture the RD&D impacts in meeting policy objectives are used. We restrict our investigation to the introduction of two stylized backstop technologies: one for the electric and the other for the non-electric markets. In the second part, we apply the modified model, as developed in the first part, to analyze the impacts of endogenous and induced technological change on carbon-mitigation policy, and we contrast, through illustrative example, the resulting impacts with the situation without learning. We show that in the case where the carbon concentrations are stabilized to pre-specified levels, sales of advanced technology increase, and the marginal cost of carbon control together with the cost of mitigation decreases.

Although this report describes research in progress, we have carried this model sufficiently far to conclude that increased commitments (either private or public) to the development of new technologies to advance along their respective learning curves has a potential for substantial reductions in the cost of climate mitigation at a level necessary to reach safe concentrations of atmospheric carbon.

Keywords: Climate change policies; MERGE5; Inter-temporal general equilibrium model; Subsidies; Technological change; Stabilization Policies.

Introduction

The Paul Scherrer Institute (PSI), which is involved in the Swiss NCCR-Climate Program on "Climate Variability and Risk", uses Integrated Assessment Models (IAMs) to simulate policies to aid in climate-change mitigation. We report here selected results from a version of the MERGE model [1] that supports endogenous and induced technological learning.

Many efforts have been undertaken to model endogenous and induced technological change [2, 3, 4, 5, 8, 10, 12, 13, 14], but problems arise when RD&D spending is introduced as decisions variables in optimization models with perfect foresight. One typical problem encountered in the first studies applying optimization models like ERIS or MERGE-ETL [4, 5, 13], is a restricted level of R&D investments reported as needed to support new and advanced technologies. On the contrary, simulation models with adaptive expectations [9, 11, 12] do not indicate such behavior. Also quite a few endogenous growth models are addressing the question of R&D support for new technologies and the rest of the economy [8, 16, 17, 18, 19]. The study reported herein is another effort to evaluate the economic advantages of endogenous and induced learning *via* public and private RD&D spending in support of carbon-free generation technology. The method investigated herein prescribes early R&D support and learning investments in carbon-free systems to aid these technologies to follow learning curves. This dedicated RD&D spending influences developments during the demonstration and deployment phases and reduces the cost of new technologies. We assume that public RD&D spending of research institutes, together with the research investments of industries that act as global players, creates knowledge that can be compensated and appropriated *via* market diffusion and uptake of these new technological systems on the global level. We expect that the increased sales of these advanced systems introduced under a global carbon constraint will reduce the cost of stabilization policies by reducing the marginal cost of carbon control. Under such developments, non-carbon-emitting technologies are expected to help stabilize future energy prices.

This formulation of the MERGE model defines RD&D as a decision variable, and presents numerical examples which reveal the implications of RD&D directed in favor of carbon-mitigation policies to stabilize carbon concentrations (*e.g*., at 450 ppmv). Section 2 discusses the modeling framework and the assumptions on which costs, emissions, and learning characteristics of technologies that compete in the energy markets are based; this section also explains the formulation of the TFLC model, together with the introduction of subsidies in MERGE. We consider scenarios related to a stabilization of CO_2 concentrations in the atmosphere when including (or excluding) technological learning and other scenario drivers that stabilize the temperature change to levels that are below a pre-specified maximum level. Section 3 then reports on this numerical application, as well as describing impacts of modeling endogenous technological progress in the MERGE environment. Section 4 concludes with an elaboration of the importance of policies that favor/foster endogenous technological learning (ETL).

2. Modeling framework

2.1 MERGE

The **m**odel for **e**valuating **r**egional and **g**lobal **e**ffects (MERGE) is an integrated assessment model (IAM) that provides a framework for assessing climate-change management proposals. We apply the MERGE5 version described by Manne and Richels [1, 6], which already includes some generic technologies capable of learning-by-doing (LBD), but we introduce algorithms that model both learning-by-searching (LBS) and learning subsidies. The world modeled by MERGE is divided into nine geopolitical regions: Canada, Australia and New Zealand (CANZ); China; eastern Europe and the former Soviet Union (EEFSU); India; Japan; Mexico, and OPEC (MOPEC); western Europe (WEUR); the United States of America (USA); and the rest of the world (ROW).

An ETA-MACRO model describes each of these nine regions. The ETA-MACRO model is itself a link of two submodels: ETA and MACRO. The ETA component is a 'bottom-up' engineering model; it describes the energy-supply sector of a given region, including the production of non-electric energy (fossil fuels, synthetic fuels, and renewables) as well as the generation of electricity. The ETA-MACRO model captures price-dependent substitutions of energy forms (*e.g*., switching to low-carbon fossil fuels) and energy technologies (*e.g*., the use of renewable-energy power plants instead of fossil-fuel systems) to achieve specified CO_2 reduction targets.

MACRO is a 'top-down' macro-economic growth model, that balances the non-energy part of the economy of a given region using a nested constant-elasticity-of-substitution (CES) production function. The MACRO model also captures autonomous (*e.g*., price-independent) effects and macro-economic feedbacks between the energy sector and the rest of the economy, such as the impacts of higher energy prices (*e.g*., resulting from CO_2 control) on economic activities. Finally, inclusion of a climate and damage model makes MERGE an Integrated Assessment Model. MERGE accounts for market damages, (through production losses), and non-market damages (through losses in global welfare).

The mathematical formulation of regional ETA-MACRO submodels translates into a convex, non-linear, optimization problem, where the economic equilibrium is determined by a single optimization. More precisely, the model maximizes a welfare function defined as the net present value of the logarithm of regional consumption adjusted for the non-market damages. Included in the wealth of each MERGE region are initial endowments in fossil fuels, renewables, and CO_2 emission permits.

MERGE links the regional ETA-MACRO submodels, and aggregates the regional welfare functions, adjusted for the non-market damages, into a global welfare function using appropriate Negishi weights (REF). The regional submodels are further linked by international trade of oil, gas, synthetic fuels, industrial-energy-intensive products, CO_2 permits, and an aggregate good expressed in a monetary unit (the 'numéraire' good) that represents all other (non-energy) traded goods. A global constraint then ensures that international trade of these commodities is balanced.

Regional technological learning with global spillovers, climate-change impacts and the associated market and non-market damages further enhance the regional links and interactions. A fixed set of Negishi weights defines a so-called Negishi welfare problem, the solving of which corresponds to the maximizing of the global welfare function. MERGE updates iteratively the Negishi weights in solving sequentially the corresponding Negishi welfare problem. The interactive update of the Negishi weights is conducted until a Pareto-optimal equilibrium is found.

2.2. Technology Description

Technological learning describes how the specific cost of a given technology is reduced through the accumulation of knowledge with respect to that technology. This learning process evolves either from manufacturing and operation of the technology (LBD) or research-and-development (LBS) expenditures allocated to that technology. A learning curve relates the specific cost incurred by a given technology to one or more factors describing the accumulation of knowledge in that technology. In MERGE, these factors are taken as the cumulative power generation in the one-factor learning curve, and the cumulative R&D expenditures in the two-factor learning curve.

Earlier versions of the MERGE model did not consider endogenous technological learning (ETL). Instead, energy technologies have exogenous characteristics imposed as trends over time. In this version specifically, generation cost are assumed to decline over time (at a rate 0.5% *per annum*) as a result of autonomous (non-price-driven) technological progress. Furthermore, specific components of the energy technologies are treated as generic; for instance, high-cost (ADV-HC) and low-cost (ADV-LC) carbon-free power plants, or plants producing low-cost, non-electric energy from renewables (RNEW) are identified.

A number of ETL systems for electric and non-electric technologies have been introduced into MERGE [2, 3, 4, 6, 7]. Table 1 lists the technologies modeled in MERGE, with, the first generic learning technology corresponding to power generation and the second technology referring to a non-electric energy system.

Table 1. Technologies used in MERGE5 and naming conventions

Electric	**technologies**	Introduction date	Gen. Cost mills/kWh	Carbon Emissions kg C/kWh
HYDRO	Hydroelectric, and other renewables	Existing	40.	0.0
NUC	Remaining initial nuclear	Existing	50.	0.0
GAS-R	Remaining initial gas fired	Existing	35.7	0.1443
OIL-R	Remaining initial oil fired	Existing	37.8	0.2094
COAL-R	Remaining initial coal fired	Existing	20.3	0.2533
GAS-N	Advanced combined cycle (AGC)	2000	30.3	0.0935
GAS-A	Gas-Fuel Cell with removal	2020	47.7	0.0
COAL-N	Pulverized Coal	2000	40.6	0.1955
COAL-A	Coal-FC with CO2 recovery	2020	55.9	0.0068
IGCC	IGCC with CO2 removal	2020	62	0.024
ADV-HC	Carbon-free technologies, high cost	Existing	95	0.0
LBDE*	Generic back-stop with LBD	2010	95	0.0
Non-Electric	**technologies**		US$/GJ	tons C/GJ
CLDU	Coal direct use	Existing	2.5	0.0241
OIL1-OIL10	Oil categories	Existing	3-5.25	0.0199
GAS1-GAS10	Gas categories	Existing	2-4.25	0.0137
SYNF	Synthetic fuels	Existing	8.33	0.04
RNEW	Renewables	Existing	6.	0.0
NEB -HC	Renewables Back-stop, high cost.	Existing	14.	0.0
LBDN*	Generic back-stop with LBD	2010	14.	0.0

*) The two technologies with LBD become available in 2005 once sufficient RD&D investments will be made, otherwise are not available at all. Also, their penetration rates increases and their production cost is assumed to reduced due to RD&D spending.

Although it is generally acceptable that LBD is commonly experienced in industrial dynamics, estimates of progress rates based on econometric analyses are uncertain and difficult to obtain, while the extrapolation of the estimated values into the future is speculative. We have assumed for LBD that a 20% cost reduction is incurred for each doubling in production, and a 15% cost reduction for each doubling in the knowledge stock. Also, a barrier is introduced to represent a maximum possible reduction of generating cost of (*e.g.*, 50 mills per kWh for electric backstop systems and 6 US$/GJ for the non-electric backstops). Electric-generation backstop technologies consist of renewable sources, like wind, solar PV and biomass, new nuclear concepts, and advanced-coal systems with carbon sequestration. Non-electric energy-generation/carrier backstops are identified with the use of methanol or hydrogen fuels, while the primary-energy sources for these non-electric energy carriers are either biomass or renewable electricity or nuclear energy (*i.e.*, a carbon-free non-exhaustible energy form). All technologies and the non-learning costs associated with these backstop systems are assumed to be encompassed in an autonomous cost reduction at a rate of 0.5% per annum.

2.3 *The Two Factor Learning Curve (TFLC)*

The section describes the inclusion of endogenous technological learning in MERGE5, using the TFLC formula (*e.g.*, with Learning -by- Doing and Learning -by- Searching components [9, 11, 12]). In the two-factor learning curve, the cumulative production (output) is used as a proxy for the accumulation of experience that affects the specific investment cost of a given technology. Similarly, the knowledge stock, defined as the accumulation of a depreciated

R&D spending, is used to determine cost reductions attendant LBS processes. The learning curve for the generation cost $GC_{k,t}$ (in US$ per MWh for electric or US$ per GJ for non-electric) of a technology *k* is then defined as:

$$GC_{k,t} = a \cdot CP_{k,t}^{-b} \cdot \mathrm{KS}_{\mathrm{k,t}}^{\mathrm{-c}} \tag{1}$$

with the knowledge stock $KS_{k,t}$ estimated as the depreciated sum of annual AR&D

$$KS_{k,t} = \mathrm{KS}_{\mathrm{k,t\text{-}1}} \cdot (1 - \mathrm{s}) + A\mathrm{R}\ \&\ \mathrm{D}_{\mathrm{k,t}} \cdot \mathrm{ypp}_{\mathrm{t}} \tag{2}$$

where s is the depreciation factor (e.g., 3 percent per year)

and *ypp* the number of years per period.

The parameter a can be calibrated by applying equation (1) for the initial point ($GC_{k,0}$, $KS_{k,0}, CP_{k,0}$) of the learning curve, and the parameters b and c are the learning indices. The latter define the speed of learning and are derived from the learning ratio. The learning ratio *lr* is the rate at which the generating cost declines each time the cumulative capacity doubles, while *lrs* is the rate at which the cost declines each time the knowledge stock doubles. The relation between b, *c*, *lr* and *lrs* can be expressed as follows:

$$\begin{aligned} 1 - \mathrm{lr} &= 2^{\mathrm{-b}} \\ 1 - \mathrm{lrs} &= 2^{\mathrm{-c}} \end{aligned} \tag{3}$$

The model assumes that both "learning" and "knowledge" diffuse to the entire world and create positive externalities. For the introduction of LBD and LBS options and learning investments (subsidies) into the model, a few new variables and equations are defined. The new variables refer to the annual research and development (AR&D) spending, the knowledge stock (KS) and the amount of subsidized production (SPE). The cumulative production of electricity (CP) is based on the annual generation of unsubsidized PE, and subsidized electricity, SPE.

$$\mathrm{CP}_{\mathrm{k,t}} = \mathrm{CP}_{\mathrm{k,t\text{-}1}} + (\mathrm{PE}_{\mathrm{k,t}} + SPE_{k,t}) \cdot ypp_t \tag{4}$$

The functional form of the learning curve is coded directly as a non-linear and non-convex formulation in MERGE5 according to equation (5), which is based on cumulative production and the knowledge stock relative to the starting year[1]. The CONOPT3[2] optimizer defines directly the global optimal solution in the case of a single LBD technology *per* market once the level of penetration is approximated based on the assumed annual expansion rates, and bounds are defined that exclude local optimum solutions [15].

$$\frac{GC_{k,t}}{GC_{k,0}} = \left(\frac{CP_{k,t}}{CP_{k,0}}\right)^{-b} \cdot \left(\frac{KS_{k,t}}{KS_{k,0}}\right)^{-c} \tag{5}$$

The economic production variable Y of MERGE must be re-formulated to take into account R&D spending and the subsidies in learning investments. We assume that knowledge creates positive externalities due to spillovers across different production firms. As the

[1] The initial annual energy R&D is 2 E-5 of the gross world product (GWP) equally divided for electric and non-electric backstop technologies. The assumed initial knowledge stock is 8 times the annual spending and the maximum annual growth rate in R&D is 5 percent. The depreciation rate of knowledge is 3% per year.

[2] It takes around one hour to solve this version of MERGE with a 2.7-GHz machine up to the year 2100; and almost two hours are required in the case of a 2150 time horizon. Running times are significantly reduced (e.g., by 70%-95%), in the case of a warm start.

investments to technology development are not appropriated we also assume public support via subsidies in the early stage of technology implementation. The subsidies are such that backstop systems become competitive relative to the reference technology in the market and decreases with time following the cost reduction based on LBD and LBS.

$$Y_{rt} = C_{rt} + I_{rt} + EC_{rt} + DC_{rt} + NTX_{rt} + AR\&D_t - \sum_k SPE_{rkt} \cdot sdy_{k,0} \left(\frac{CP_{k,t}}{CP_{k,0}} \right)^{-b} \left(\frac{KS_{k,t}}{KS_{k,0}} \right)^{-c} \quad (6)$$

Thus, between the periods 2010-2040, part of the costs for the two-backstop technologies (*e.g.*, *sdy*) is either subsidized or is anyhow introduced in niche markets without charge. This cost consists of a maximum of 9 US$/GJ for the non-electric systems and 75 mills/kWh for the LBDE technology at the starting point of their introduction (*e.g.*, in the year 2010), and diminishes strongly as the generation costs follows the autonomous reduction rate and the learning curves[1]. Additionally, extra R&D spending is made available (*i.e.*, as a free variable within some expansion bounds) in the same periods to demonstrate technical feasibility, to reduce further the generation cost of carbon-free technology, and to accelerate their introduction. We also assume that the two learning technologies will be available in 2010 under sufficient RD&D support, while their penetration rates will increase (*e.g.*, to 13.5 % *per annum*; *i.e.*, well above the standard value of 11.5% applied in MERGE). Annualized RD&D investments reduce consumption, [*i.e.,* they are included in equation (6)] and are introduced only when enough benefits are generated to compensate for the cost of research and development. In other words, the induced benefits of the cost reduction for energy production should be greater than the discounted and cumulative cost of R&D. Finally, it is important to notice that the subsidized production (*i.e.*, SUPE or SUPN) contributes to the balance of electricity or of the primary-energy use, correspondingly[2]. As in the above formulation subsidies are always introduced in the market, we have restricted their penetration with an upper bound and let the model free to identify optimal AR&D levels to support backstop technology under different mitigation policies.

3 Case studies

3.1 The BaU cases

Several scenarios related to CO_2 emission control are presented as illustrations of the results generated by this version of MERGE. Apart from the business-as-usual (BaU) cases, where CO_2 emissions are not limited, we have considered the implications of stabilizing atmospheric carbon concentrations to 450 ppmv and a case with 2° Celsius as maximum temperature change. All three scenarios are assessed with and without ETL options. The baseline case is designated by BaU-N, where technological change is exogenous, whereas

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[1] Notice that the EC already includes the full cost of the LBDE and LBDN systems and therefore the subsidized cost is subtracted in equation (6).

[2] One could modify MERGE and formulate an endogenous growth model by adjusting the production function of the model assuming that R&D for energy-conservation will improve the energy productivity, together with the autonomous efficiency improvement of the energy sector, the technology specific learning, and the price effect. Similarly, the capital and labor productivity can be also indigenized assuming a productivity related knowledge stock. This MERGE formulation will drive R&D investments and innovations in the case of strong price changes and environmental constraints. The functional form of the production function shown below and the value of elasticities need statistical evaluation that will separate the contribution of autonomous efficiency improvements from the rest of the factors influencing energy intensity.

$$Y_{rt}^{\rho} = a_{rt} \cdot \left[\frac{KLS_t}{KLS_0} \right]^{-ra} \cdot K_{rt}^{\alpha\rho} \cdot L_{rt}^{(1-\alpha)\rho} + b_{rt} \cdot \left[\frac{ENS_t}{ENS_0} \right]^{-rb} \cdot E_{rt}^{\beta\rho} \cdot NE_{rt}^{(1-\beta)\rho} \quad (7)$$

BaU-L denotes the baseline case where LBD applies, and BaU-S designates the case where the TFLC and learning subsidies apply. The database for the baseline cases reflects the original data of MERGE5, while the stabilization cases consider policies to abate all greenhouse gases (GHGs) and adopt carbon sinks.

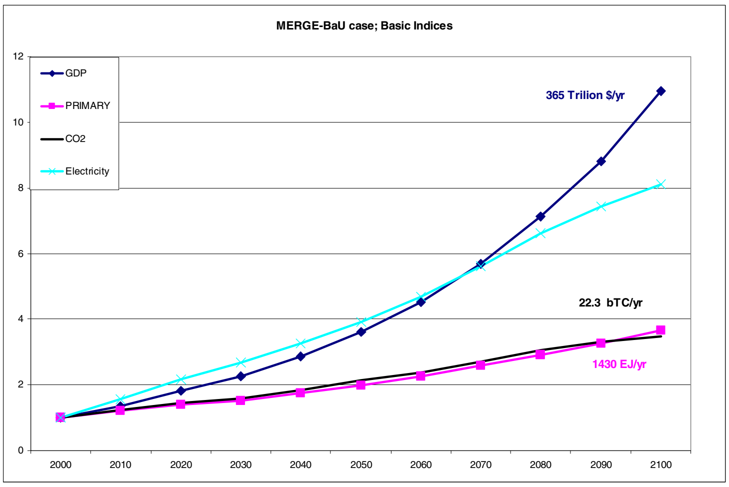

Fig. 1: *Basic indicators for the Reference case of MERGE5 w/o LBD relative to the starting year.*

In the BaU-N case, the world GDP grows more than 11 times (*i.e.,* to US$365 trillion) between 2000 and 2100; but primary-energy supply and carbon emissions are strongly decoupled from economic growth and increase by only 3.8 times (i.e., to 1,430 EJ of primary energy per annum and 22.3 GtC/yr carbon emissions in 2100). In the BaU-N case, global CO_2 concentrations increase to 750 ppmv, while the global average temperature rise is 2.48° Celsius[1]. Most of the economic growth occurs in economies (currently) in transition and in developing countries. Regional differences in income, primary-energy intensity, and carbon intensity of GDP are decreasing over time. The currently less-developed countries assume a high economic growth such that they will produce 2/3 of the global GDP in the year 2100 *versus* 1/3 for OECD countries. It should be noted that the potential socio-economic growth underlying this scenario is exogenous as well as the autonomous efficiency improvement. As substitution for non-electric energy is based mainly on electricity use, there is a late decoupling between economic growth and electricity consumption.

Energy efficiency and decarbonization continue to contribute to improved energy, economic, and environmental indices. Policies that support technological learning result in a strong contribution of renewables in meeting non-electric-sector demands. This shift enhances the use of non-electric backstop technologies for which a learning rate of 20% cost reduction *per* doubling of production, and a 15% decrease *per* doubling of the knowledge stock has been assumed. For the BaU-S case, therefore, renewable-energy sources contribute 39%, coal 45%, nuclear 2% of the energy mix, with oil and gas contributing the remaining 14% compared to a 56% contribution for coal in the BaU-N scenario. Learning in the BaU-L case reduces

[1] Additional temperature change is expected after the year 2100 due to climate forcing that has already taken place before but it will take decades to materialize.

emissions to 20.4 GtC/yr[1] in the year 2100. The following section compares the stabilization of atmospheric carbon concentration and the maximum atmospheric temperature change.

3.2 Indicators

The study results presented herein, with the help of selected indicators, demonstrate the benefits of enhanced RD&D support of the two-backstop technologies. The indicators specify the gains induced from the global sales of these technologies, as well as the attendant reduction in the marginal costs of carbon control *per* US$ spent for RD&D, along with the improved environmental and resource performance associated with:

1) reference case (BaU)
2) stabilization of the average surface temperature below 2° Celsius (2DC)
3) stabilization of atmospheric concentrations of CO_2 to 450 ppmv (450)

Listed below is a range of indicators that are defined as "Sales" or "Tax-Revenue" *per* unit of RD&D spending for each scenario (*pre* represents the price per unit of electricity; *prn* the price for non-electric; *mc* the price of carbon; *em* the carbon emissions; *incst* the part of generating cost that subject to learning).

Sales: $$\sum_{t} (\mathrm{PE\_lbde}_{rt} \cdot \mathrm{pre}_{rt} + \mathrm{PN\_lbdn}_{rt} \cdot \mathrm{prn}_{rt}) \cdot \mathrm{ypp}_t e^{-\delta \cdot \mathrm{ypp}_t (t-1)t}$$

Tax-Revenue: $$\sum_{t} mc_{rt} \cdot em_{rt} \cdot ypp_t \cdot e^{-\delta \cdot ypp_t (t-1)t}$$

RD&D: $$\sum_{krt} \left[(arnd_{krt} + SUB_{rkt} \cdot incst_{k,0} \left(\frac{CP_{k,t}}{CP_{k,0}} \right)^{-b} \left(\frac{KS_{k,t}}{KS_{k,0}} \right)^{-c} \right] ypp_t \cdot e^{-\delta \cdot ypp_t (t-1)}$$

Other indicators related to global warming are based on, or related to, emissions, concentrations, and temperature change, the maximum rate of temperature change and the carbon price. For the use of depleteable resources, indicators are defined related to the Resource-to-Production ratio, R/P (yr), for oil and gas, as well as the maximum oil and gas price within a given scenario development. For economic indicators, the discounted GDP *per capita*, the discounted consumption *per capita*, the energy system costs, and finally the Negishi welfare function (*i.e.,* the discounted logarithm of consumption, as weighted across all world regions based on Negishi weights).

The following figures illustrate the impact of learning on the generating cost and other indicators for the electric and backstop technologies for the reference and the 450-ppmv cases. Obviously, the stronger the carbon constraint, the faster the penetration of carbon-free technologies into the market mixes, and the stronger the cost reduction while LBS is important during the first, introductory periods of the new technologies.

[1] The situation is different when learning has been assumed for all technologies resulting in a stronger introduction of advanced coal-power generation, new nuclear systems and GCC systems [7], a fact that demonstrates how uncertain are the developments in the second half of this century.

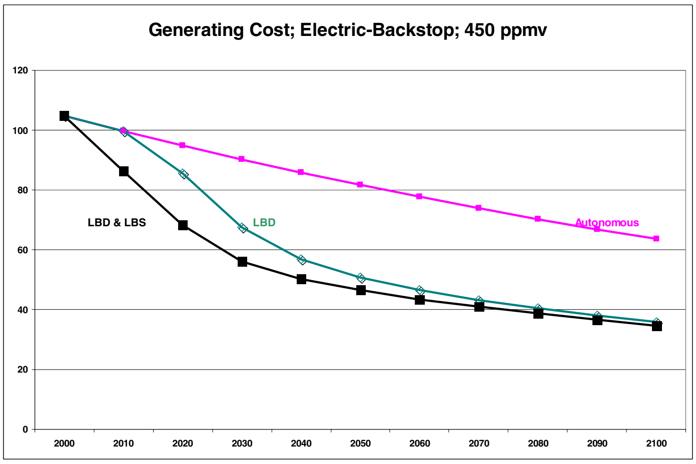

Fig. 2: *A significant cost reduction over time is shown when LBD applies. RD&D policies are important in the early stage of introducing a new technology.*

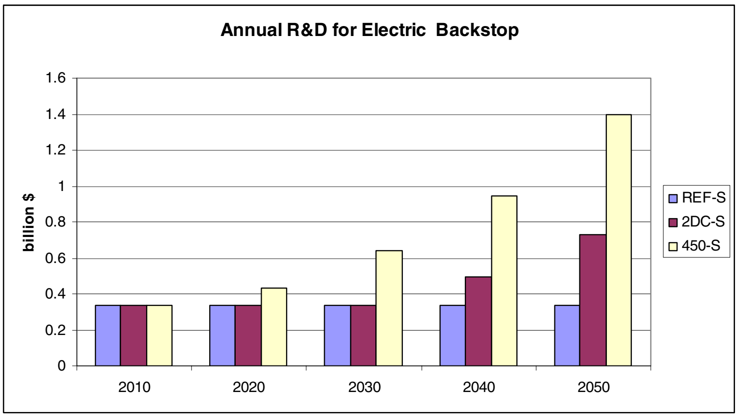

Fig. 3a: *Annual R&D spending for Electric Backstop technology as function of carbon mitigation policy. The importance of R&D becomes significant under the carbon stabilization constraints.*

Fig. 3a gives the annual R&D support for the period of 2010-2050 and for the three cases (*i.e.,* BaU-S, 2DC-S, and 450-S) where R&D acts as decision variable. The needed (R&D) support is at the lower bound in the reference case and increases significantly in the case of stabilizing CO_2 concentrations to 450 ppmv. The impact of R&D spending expressed as discounted and cumulative sales of backstop technology (Fig. 3b), increases with the need to mitigate climate change. As far as the other indicators are concerned, the most significant ones are those that refer to the maximum price of oil and of carbon emission rights (see Fig. 3c). Both maximal prices (for oil and carbon permits) are significantly reduced as a consequence of R&D support that accelerates the energy cost reductions as shown in Fig. 4.

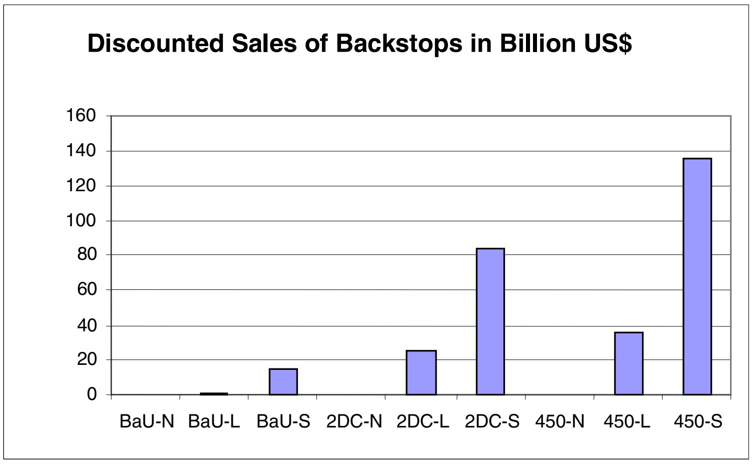

Fig. 3b: *Discounted and cumulative sales of backstop production in Billion US$ for different carbon stabilization policies. The induced R&D learning reduces cost but increases penetration of backstop technology.*

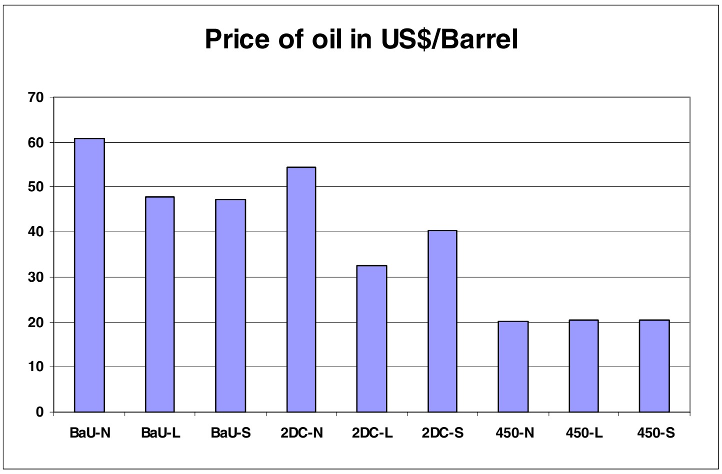

Fig. 3c: *Climate mitigation and RD&D policies reduce use of fossil fuels and the maximum oil price significantly.*

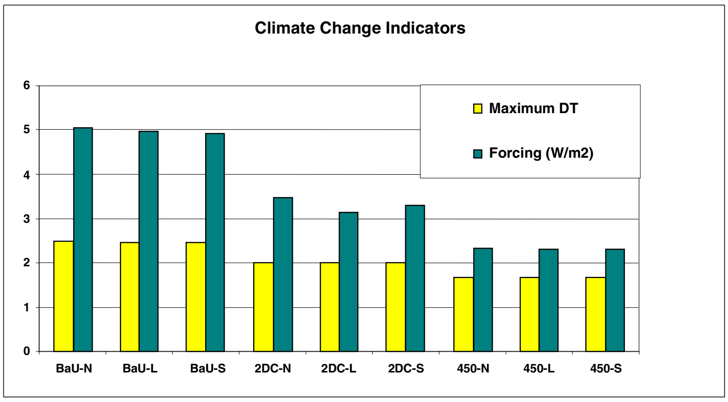

Fig. 3d: *Climate change indicators. The changes in forcing and the maximum surface temperature change (for the same policy target on mitigation) are less sensitive to RD&D.*

3.3 Stabilizing carbon concentrations

Economic considerations govern the transition to a low-carbon economy. Two of these considerations represent key options for the second half of this century: the exhaustion of oil and gas resources, and the significant cost reduction in carbon-free energy technologies. When RD&D policies are appropriately applied, that results in a significant reduction of energy generation cost and carbon control costs, as shown in Figs 2 and 5.

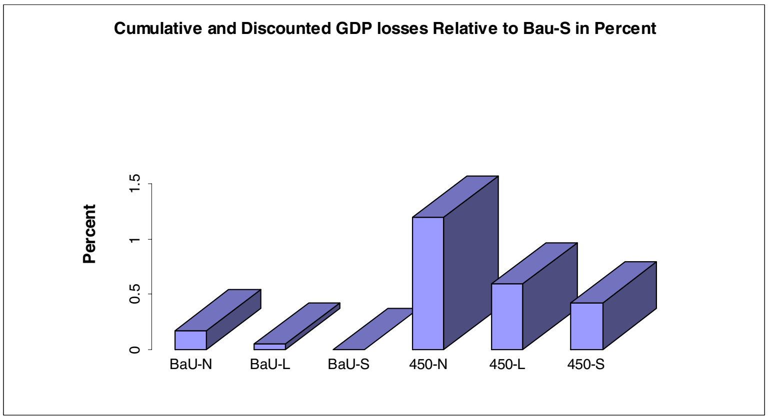

Fig. 4. *Cumulative and discounted GDP losses for the stabilization cases of carbon concentration, relative to the GDP of BaU-S. The cumulative and undiscounted GDP losses are significantly reduced in the case of LBD and LBS. For the 450-ppmv cases, the cumulative loss of 1.26% reduces first to 0.65 %, (e.g., in the LBD case) and then to 0.42% (e.g., in LBD & LBS case).*

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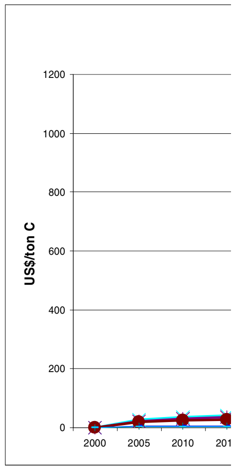

The scenarios where atmospheric CO_2 concentration is held to 450-ppmv assume that efficient strategies will be adopted worldwide and a full-scope transfer of "know-how" will take place. Under these circumstances, the following conclusions can be made: First, the cumulative GDP losses because of the introduction of carbon-stabilization constraints, in relation to the cumulative baseline-GDP production, are low: for example, below 1.1% in the base case, while with LBD and LBS favorable policies the GDP losses are less than 0.3% (Fig. 4). Secondly, the marginal costs related to carbon stabilization are also reduced to a fraction of the marginal cost without learning (Fig. 5), but remain significant for the case of the 450 ppmv atmospheric carbon limit.

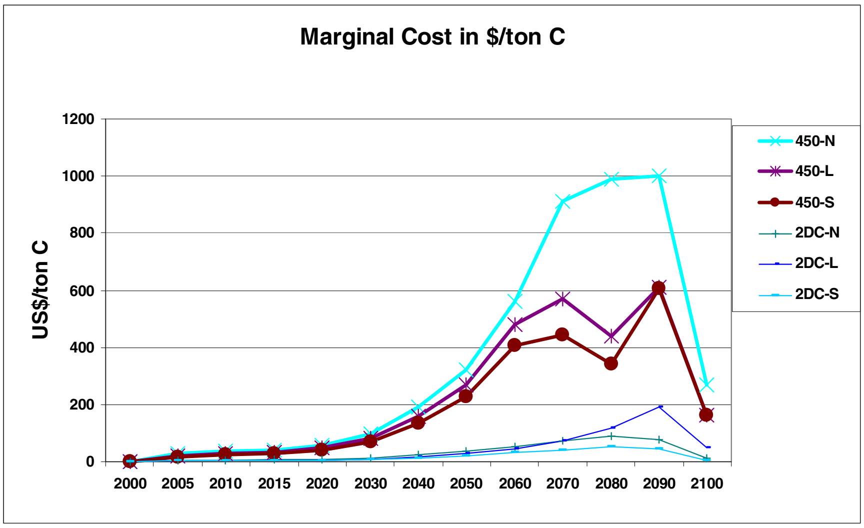

Fig. 5. *The marginal costs of carbon control are significantly reduced in the case of LBD and RD&D policies.*

Another way of expressing the importance of LBD is to graphically compare GDP losses as a function of time in a scenario when LBD is introduced, relative to the same constrained cases without LBD; this comparison relative to the BaU-N case is shown in Fig. 6. The importance of LBD increases with the severity of the constraint imposed.

All results emphasize the need to reduce the scientific uncertainty about climate change, to specify more appropriate stabilization targets, the options given to reduce the cost of carbon control *via* RD&D and to apply flexible strategies against the climate risk.

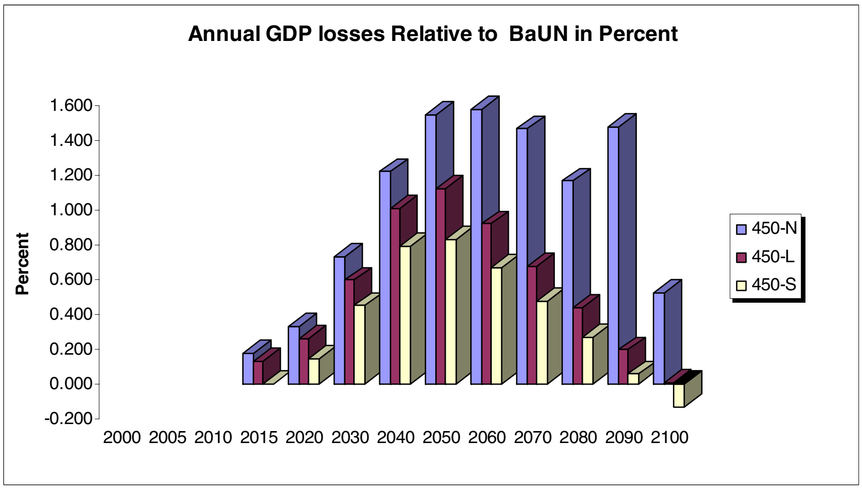

Fig. 6: *GDP reduction expressed as percentage change relative to the baseline case without LBD (450-N) versus the LBD (450-L) and RD&D (450-S) cases.*

4. Conclusions

Technological progress has and will continue to play a fundamental role in the evolution of energy systems; as such progress favors the transition toward more-efficient, economic, and cleaner energy technologies, rather than being driven by resource depletion *per se*. It is important, therefore, to incorporate the dynamics of technological change into energy system models. The work reported herein quantifies the impacts of RD&D spending on the development and promotion of carbon-free energy technologies that mitigate global warming. To quantify these impacts, the TFLC formulation has been introduced together with learning investments in favor of the two clusters of backstop technologies in MERGE5. Impacts have been quantified with the help of top-level economy-environmental indicators that describe the efficiency of RD&D in terms of key sustainability objectives.

To study the impacts of modeling endogenous technological change in MERGE, we have considered several scenarios related to CO_2 emissions and technological learning. Although our model shows that technological learning favors new advanced and back-stop systems, the newer model formulation does not significantly change the conclusions derived from the original MERGE model for the first half of this century; as fossil fuels (mainly coal and natural gas) will continue to retain a significant share of the global electricity and energy-supply markets in the next 50 years, while energy-related carbon emissions will continue to grow substantially. But, R&D spending is significantly increased in the first half of the century paving the way to reach carbon mitigation targets.

In the case where atmospheric carbon is stabilized at 450-ppmv, a significant development and market penetration of low-carbon generation options is required. Technological learning in these circumstances favors new advanced systems, represented collectively in the model as electric and non-electric backstop systems. Finally, the importance of technological progress for carbon control has been shown, as such progress allows low-cost carbon-reduction options to enter the generation mix and, hence, reduces GDP losses and minimizes the marginal cost of carbon control.

Although the above *interim* results are based on research in progress, we conclude that based on the level that knowledge and RD&D investments can be appropriated, increased commitments (either private or public) towards the development of new technologies, is a key strategy against global warming. By so appropriating, the carbon price could be reduced to maximum levels of around 400 US$ per ton of Carbon and the cumulative losses of GDP could be held below 0.5% relative to the reference case, in the case that carbon concentration in the atmosphere should be reduced to 450 ppmv.

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