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ANALYSIS

Learning-by-Doing vs. Learning by Researching in a model of climate change policy analysis

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Abstract

Most of the predictions and conclusions in the climate change literature have been made and drawn on the basis of theoretical analyses and quantitative models that assume exogenous technological change. How do these predictions and conclusions change if we endogenize technical progress? In this paper we consider two different drivers of technological change–Research and Development (R&D) and Learning-by-Doing (LbD)–and we embed them into the popular Nordhaus and Yang's RICE model. We then use the corresponding two model versions to simulate different policy scenarios and compare the results focusing on consumption, physical capital, emissions abatement rates, and R&D expenditures. Our findings suggest that R&D-driven and LbD-driven technologies lead to quite similar dynamic patterns of the relevant variables we analyze. However, the greater flexibility enjoyed by agents who are able to optimally choose R&D expenditures seems to imply more welfare relative to the LbD case.

Keywords: Climate policy; Environmental modeling; Integrated assessment; Technical change

JEL classification: H0; H2; H3

1. Introduction

That current rates of greenhouse gas emissions cannot be sustained in the long run is by now an undisputed fact. Current production modes, with their associated levels of fossil fuel consumption, cannot proceed at present rates.

No one really believes or is ready to accept, however, that the solution of the climate change problem consists of reducing the pace of economic growth. Instead, it is believed that changes in technology will bring about the longed decoupling of economic growth from generation of polluting emissions. There is a difference in attitude in this respect, though. Some maintain a faithful view that

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technological change, having a life of its own, will automatically solve the problem. Others express the conviction that the process of technological change by and large responds to impulses and incentives, and it has therefore to be fostered by appropriate policy actions.

The above remarks are reflected in climate models, the main quantitative tools designed either to depict long run energy and pollution scenarios or to assist in climate change policy analysis. Indeed, these models have traditionally accounted for the presence of technical change, albeit usually evolving in an exogenous fashion. More recently, models have been proposed where the technology changes endogenously and/or its change is induced by deliberate choices of agents and government intervention.[1] However, these contributions have mainly focused on the role of Research and Development (R&D) as a source of changing technology, thus neglecting the time-honored concept of Learning-by-Doing (LbD) as the basis for technological change.[2] A research question therefore naturally arises: how do consequences and implications of R&D-driven technological change compare to those generated by a Learning-by-Doing mechanism within the conceptual framework of a model of integrated assessment? The goal of this paper is try to provide an answer to this question.

The strategy we follow is to take a popular model–RICE, proposed by Nordhaus and Yang (1996)–and modify it so as to incorporate both a formulation of a R&D-driven technology and a specification centered upon LbD. While the former extension of the RICE model has been already undertaken elsewhere,[3] the implementation of the latter mechanism is new and is described here. No numerical complete climate–economy model that we know features both a R&D-driven and a LbD-based process of endogenous technical change.

Our way to formalize the process of LbD, and the way we follow, is by assuming that there is a LbD-driven stock of knowledge which enters the output production technology as one of the production factors and, at the same time, affects the relationship linking production to emissions. This approach is in line with the one originally proposed by Goulder and Mathai (2000). In their article these authors explored the importance of policy induced technological change for the design of carbon abatement policies. In their model a social planner aims to minimize the present value of the abatement costs in order to achieve a given emission target. These costs depend, besides the abatement level itself, also upon a stock of knowledge. To capture how knowledge increases over time, Goulder and Mathai consider two formulations: R&D and experience. The later takes the form of cumulated abatement done in the past. The authors then compare R&D-based and LbD-based knowledge accumulation focusing on optimal abatement and emission tax trajectories under both a cost-effectiveness criterion (how to achieve a target most cheaply) and a benefit–cost criterion (what is the optimal level of abatement?). In particular, they find that, when knowledge is gained through R&D investments, the presence of an immediately improving technology justifies a delay in abatement efforts, while when LbD is the source of knowledge the impact on the timing of abatement turns out to be ambiguous.

In our work we retain Goulder and Mathai's central idea of a knowledge stock as a vehicle of induced technological change. Notice, however, that while in their work a social planner faces a constraint on carbon concentration (i.e. cumulated emissions) within a cost minimization framework, in our context welfare is maximized in each region by selecting optimal consumption and investment in physical and knowledge capital. Moreover, there are six different regions in our model which play a Nash game taking into account caps on emissions.

In the model considered here more knowledge will help firms to increase their productivity and, at the same time, reduce their negative impact on the environment. In one version the central planner in each country chooses the optimal R&D effort that, in turn, increases the stock of technological knowledge. The amount of R&D is therefore a policy variable envisaged by the model. As far as LbD is concerned,

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[1] See e.g. the special issue of *Resource and Energy Economics* edited by Carraro et al. (2003).

[2] Arrow (1962) is the seminal paper on this issue. Note that reference is made here to the so-called top-down models. In bottom-up energy system models LbD has been typically the key element for reducing the cost of adoption of new technologies.

[3] See Buonanno et al. (2000, 2001, 2003) and Castelnuovo et al. (2003a,b). The model has been employed to analyze relevant policy questions by Buchner et al. (2002a,b), and Bosello et al. (2003).

we use arguments originally made by Arrow (1962) in supposing that the accumulation of knowledge occurs not as a result of deliberate (R&D) efforts, but as a side effect of conventional economic activity. As such, LbD is a costless activity, a view shared also by Goulder and Mathai (2000) but not agreed upon by all environmental economists.

LbD has been introduced in climate models first in the bottom-up approach by Anderson and Bird (1992) and Messner (1995, 1997). Central in these dynamic energy simulation (“bottom-up”) models is the notion of “learning curve”, which reflects the observation that with greater “experience” (cumulative production), there is a pronounced tendency for a decline in the unit costs of novel technologies (such as photovoltaics and wind power), but there is no obvious decline in the unit costs of more conventional methods (such as supercritical coal and natural gas-combined cycle). The newer technologies tend to be higher in unit costs than the conventional ones. If investors base all their decisions on immediate costs, there would be little tendency to support the newer technologies that are currently more expensive. Their cumulative experience is too small, and they could be “locked out” permanently. This is the rationale for public intervention in the market. Leaning-by-Doing entails the acceptance of high near-term costs in return for an expected lowering of future costs.

To model LbD in a simple manner, we follow Romer (1996) and assume that learning occurs as a side effect of the accumulation of new physical capital. This entails a production function that exhibits increasing returns to capital. In order to maintain the analogy with the R&D-based version of the model we also allow for the emission–output ratio to depend upon cumulated capacity, i.e. the sum of past physical investment efforts. It should be apparent that these model specifications make explicit reference to the recently developed theory of endogenous growth that emphasizes the role of knowledge, of physical and human capital, R&D activities, and LbD.

With the two versions of the modified RICE model just briefly described we perform numerical simulations in order to assess qualitative differences in the reaction of variables such as consumption, physical capital, domestic abatement rates, and R&D expenditures to a change of the policy scenario that takes place under either a R&D or a LbD formulation.[4] More specifically, we compare the simulation evidence obtained under endogenous versus exogenous environmental technical change in order to understand if the driver of endogenous technological improvement matters. Our results suggest that these differences are far from being marked from a qualitative viewpoint. However, the greater flexibility enjoyed by agents when able to control R&D expenditures seems to imply a larger welfare gain moving from exogenous to endogenous environmental technical change.

The structure of the paper goes as follows. In Section 2 a sketch of model is offered, starting from the original RICE formulation leading up to our two alternative formulations. We also describe how the model accounts for international emission trading and our parameter calibration choices. In order to quantify the effects of introducing endogenous environmental technical change either via R&D or via LbD, Section 3 presents results of some illustrative simulation runs under alternative environmental policy scenarios, coherent with the implementation of the Kyoto Protocol.[5] First, the impact of imposing an emission target without allowing for trade is studied. Then, emission trading is considered, with exchange taking place amongst Annex B countries. A few final remarks together with directions for further research close the paper.

2. Modelling endogenous technical change

As stated above, the climate–economy model we employ is an extension of the benchmark RICE model due to Nordhaus and Yang (1996). This is a model of intertemporal optimal economic growth

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[4] Notice that, in principle, one might want to study this issue from an analytical perspective. Unfortunately, a closed form solution for the policy functions of our growth model could be obtained only under very restrictive assumptions. A way to by-pass the analytical difficulties would be to log-linearize the model around its steady state, but this would make our conclusions valid only if the economy oscillated in a neighbourhood of it. This is the reason why we decided to compute the numerical solution of the model.

[5] These simulation exercises are not meant to be realistic, given the recent developments in international climate negotiation. We use the Kyoto Protocol for our simulations because the content of that agreement is well understood.

coupled with a climate module. In it a policy game is played by the six regions (U.S.A., Japan, Europe, Former Soviet Union, China, and the Rest-of-the-World) in which the world is divided. In each region a social planner chooses the optimal level of two instruments: fixed investments and rate of emission control (abatement). An additional instrument, the amount of permits, which each country wants to buy or sell, is available when a Kyoto-cum-trading scenario is considered. We now show how the original model is enriched in order to take R&D and LbD into account. Note that, in order to conserve on space, we only display the equations of the model that are relevant for our purposes; those common to the original RICE model are contained in an Appendix.

2.1. The model without endogenous environmental technological change

As a starting point we consider the specification of the model in which knowledge affects only factor productivity. In the case accumulation of knowledge is brought about by R&D spending and the corresponding stock is a factor of production, which enters a country production technology along with physical capital and labor.[6] Knowledge in this case enhances the rate of productivity (see Griliches, 1979, 1984) and the original RICE production function is modified as follows:

$$Q(n,t) = A(n,t)K_{\mathrm{R}}(n,t)^{\beta_n^{\mathrm{R}}}\left[L(n,t)^{\gamma}K_{\mathrm{F}}(n,t)^{1-\gamma}\right] \tag{1a}$$

where Q is output (gross of climate change effects), A the exogenous level of technology and K_{R}, L and K_{F} are respectively the inputs from knowledge capital, labor (that evolves exogenously over time) and physical capital (n and t index time and country respectively). The stock of knowledge accumulates according to:

$$K_{\mathrm{R}}(n,t+1) = \mathrm{R\&D}(n,t) + (1-\delta_{\mathrm{R}})K_{\mathrm{R}}(n,t) \tag{2}$$

where R&D are expenditures in Research and Development and δ_{R} is the rate of knowledge depreciation. Finally, R&D spending is included in the fundamental identity of sources and uses:

$$Y(n,t) = C(n,t) + I(n,t) + \mathrm{R\&D}(n,t) \tag{3a}$$

where C is consumption, I gross fixed capital formation and Y is output net of climate change effects. It is seen that R&D is an additional instrument whose optimal value can be chosen by each region's planner.

In the case of Learning-by-Doing Eq. (1a) has to be amended in a manner that enables a rise in productivity due to physical capital (installed capacity), without the contribution of K_{R} in the production function. This idea can be formalized by simply modifying the Cobb–Douglas coefficients, so that returns to scale result to be increasing, owing to the augmented capital–output elasticity. Eq. (1a) is therefore modified as follows:

$$\begin{aligned} Q(n,t) &= A(n,t)\left[L(n,t)^{1-\gamma}K_{\mathrm{F}}(n,t)^{\gamma}\right]K_{\mathrm{F}}(n,t)^{\beta^{\mathrm{L}}} \\ &= A(n,t)\left[L(n,t)^{1-\gamma}K_{\mathrm{F}}(n,t)^{\gamma+\beta^{\mathrm{L}}}\right] \end{aligned} \tag{1b}$$

where β^{L} can be referred to as the Learning-by-Doing coefficient.

Under LbD Eq. (2) is absent from this version of the model and Eq. (3a) reverts back to its original formulation in the RICE model:

$$Y(n,t) = C(n,t) + I(n,t) \tag{3b}$$

This implies that, under the LbD approach, knowledge creation does not place any claim on resources, *ceteris paribus.*

2.2. Accounting for endogenous environmental technical change

As stated in the Introduction, we are especially interested in a model in which, besides affecting factor productivity, knowledge influences also the emissions–output ratio. This case is referred to as

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[6] A major limitation of the original RICE model is the absence of energy as a factor of production. Emissions are linked directly to the amount of output produced, rather than to the amount of energy consumed. While we are very conscious of this limitation, we did not go so far as to modify the basic structure of the RICE model. It would be however interesting to check the robustness of our results once energy is included as a factor of production in a model like the one in this paper. This is one of our next research tasks.

'endogenous environmental technical change'. Under the R&D approach, it is assumed that the stock of knowledge, besides being a factor of production, also serves the purpose of reducing, *ceteris paribus*, the level of carbon emissions. Thus, R&D efforts prompt both environmental and non-environmental technical progress. More precisely, consider the RICE emissions–output relationship, whose original version is as follows:

$$E(n,t) = [1-\mu(n,t)]\sigma(n,t)Q(n,t), \quad 0 \leq \mu(n,t) \leq 1 \tag{4}$$

where μ is the domestic abatement rate and σ is the exogenously given emissions–output ratio.[7] Accounting for endogenous environmental technical change, Eq. (4) is modified as follows:

$$E(n,t) = \left[\sigma_n + \chi_n^{\mathrm{R}} \exp\left(-\alpha_n^{\mathrm{R}} K_{\mathrm{R}}(n,t)\right)\right] \times [1-\mu(n,t)]Q(n,t) \tag{4a}$$

where α_n^{R} is the region-specific elasticity through which knowledge reduces the emission–output ratio, χ_n^{R} is a scaling coefficient, and σ_n is the value to which the emission–output ratio tends asymptotically as the stock of knowledge increases without limit. In this formulation, R&D contributes to output productivity on the one hand, and affects the emissions–output ratio, and therefore the overall level of pollution emissions, on the other hand.[8]

With a LbD-based knowledge accumulation, Eq. (4a) is simply replaced by the following:

$$E(n,t) = \left[\sigma_n + \chi_n^{\mathrm{L}} \exp\left(-\alpha_n^{\mathrm{L}} K_{\mathrm{F}}(n,t)\right)\right] \times [1-\mu(n,t)]Q(n,t) \tag{4b}$$

where we substitute knowledge capital with physical capital. Hence, physical capital covers the role that knowledge capital has in the R&D approach, i.e. K_{F} contributes to output productivity on the one hand, and affects the emissions–output ratio, and therefore the overall level of pollution emissions, on the other hand.[9]

2.3. Parameter calibration

As for parameter calibration and data requirements for the newly introduced variables, we proceed as follows (see also Buonanno et al., 2003). Firstly, coefficients already present in the original RICE model are left unchanged.[10] Next, when the R&D-driven stock of knowledge is considered as an input of the production function (see Eq. (1a)), for each region we calibrate the coefficient β_n^{R} so as to obtain in the year 2000 a value of the R&D–output ratio equal to the 1990 one. R&D figures for 1990 are taken from Coe and Helpman (1995), while the 1990 stock of knowledge for the USA, Japan, and Europe comes from Helpman's Web page.[11] For the remaining three macro-regions 1990 values of the knowledge stock are constructed by taking the average ratio between knowledge and physical capital of the three industrialised regions and multiplying it by the 1990 physical capital stock of the other regions as given in the RICE model. The regional parameters α_n^{R} and χ_n^{R} in Eq. (4a) are OLS estimated using time series of the emissions–output ratio and of the stock of knowledge (the sample runs from years 1990 to 2120, i.e. it consists of ten years of data). The data for the former variable are those used by Nordhaus and Yang (1996), while those for the latter variable are recovered from a BaU simulation conducted using the original emissions–

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[7] Notice that we use the expression 'emissions–output ratio' to indicate the time-varying, idiosyncratic coefficient $\sigma(n,t)$. To be precise, as Eq. (4) suggests, σ is the ratio between emissions and "abated" output.

[8] We are well aware of the fact that introducing a single type of R&D investment that serves two purposes is unsatisfactory. Unfortunately, lack of suitable data for environmental and non-environmental R&D for six world regions forces us to calibrate our model on the basis of data concerning a single R&D aggregate.

[9] Also with the Learning-by-Doing formulation, lack of reliable data prevents us from distinguishing between possible different sources of experience (say, non-environmental sources and environmental ones). Notice in addition that an alternative way to account for Learning-by-Doing would be to proxy it with cumulated abatement as the engine of environmental knowledge. This alternative modelization is left for further research.

[10] Although this choice might appear a bit puzzling, it should be noted that our goal is to perform a comparative analysis across scenarios which are all based on the 'technical change hypothesis'. To that end we need to parameterize the model in a 'plausible' way. From this point of view we do not see any need to face the difficult task of changing the original parameter values of Nordhaus and Yang (1996)'s model.

[11] Helpman's Web page is at the URL http://post.economics.harvard.edu/faculty/helpman/data.html.

Table 1
Coefficients of the ETC-RICE model

	α_n^{R}	χ_n^{R}	α_n^{L}	χ_n^{L}	σ_n	β_n^{R}	β^{L}	$\delta_{\mathrm{R,K}}$	K_{R} $(n,1990)$
USA	0.195440	0.019369	0.042667	0.023259	0.00971	0.04355	0.025	0.05	1.24200
Japan	0.522430	0.005270	0.122960	0.008230	0.00600	0.04550	0.025	0.05	0.27773
Europe	0.296490	0.007659	0.045242	0.009928	0.00699	0.03180	0.025	0.05	0.75526
China	0.618650	0.112771	0.024206	0.110836	0.00904	0.01080	0.025	0.05	0.03145
FSU	1.197400	0.095579	0.080718	0.095531	0.00935	0.01660	0.025	0.05	0.07269
ROW	0.072926	0.022409	0.002510	0.022241	0.00845	0.00927	0.025	0.05	0.39343

The stock of knowledge is expressed in trillions of 1990 U.S. dollars.

output ratio $\sigma(n,t)$ of the RICE 96 model.[12] The asymptotic values σ_n are computed by simulating the pattern of the exogenous emissions–output ratio in the original Nordhaus and Yang (1996)'s RICE model for 1000 periods: the values of the last period are then taken as asymptotes. Finally, the rate of knowledge depreciation is set at 5%, following a suggestion contained in Griliches (1979).

When Learning-by-Doing is the source of experience in the model, we do not calibrate the capital–output elasticity β. Short of empirical evidence to bear on this specific aspect, we arbitrarily set the value of that elasticity to be equal to 1/10 of the capital–output elasticity as in Nordhaus and Yang (1996)' s RICE model, i.e. $\beta^{\mathrm{L}}=0.025$. Technically speaking, we do so because of the impossibility of replicating the original BaU scenario without setting that elasticity equal to zero. Hence, in this way we are basically augmenting the physical capital productivity in order to capture the LbD effect.[13] Once imposed the value β to the elasticity parameter, we simulate a BaU scenario with an exogenous emissions–output ratio in order to collect the time series for the physical capital. We then OLS estimate the parameters α_n^{L} and χ_n^{L} in Eq. (4b) using the same time series of the emissions–output ratio as in the former OLS regressions, but replacing the stock of knowledge with the stock of physical capital (the sample still runs from years 1990 to 2120). Table 1 collects all the new coefficients and initial values introduced in the RICE 96 model.

3. Endogenous environmental technical change: optimal reaction to different environmental policies

In order to quantify the effects of introducing endogenous environmental technical change first via R&D and then via LbD, some resource allocation choices in different environmental policy scenarios, coherent with the implementation of the Kyoto Protocol, are considered. As stated above, the impact of imposing an emission target without allowing for trade is initially studied. Then, emission trading is considered, with exchange taking place amongst Annex B countries (Et-A1 scenario). For each optimization run, time paths of the following control variables (abatement, fixed investment, R&D expenditures, net demand for permits) are obtained and their impacts on the endogenous variables (emissions, GNP, consumption, and so on) over the period 2000–2050 (the well-known "Kyoto forever" scenario) computed. In what follows, we will focus mainly on the following control variables: consumption, fixed investment, domestic abatement and R&D expenditures. In our analysis we refer to "average differences", the differences being computed by considering the extent to which the optimal values taken on by the variables of interest in the "Kyoto" and "Et-A1" scenarios exceed those recorded under the Business-As-Usual hypothesis. In particular, in our analysis we select for presentation the control variables consumption of the *numeraire* good, physical capital, domestic abatement rate, and (where present) R&D expenditures. For ease of presentation we only display average figures over the simulation period 2010–2050. Moreover, we restrict our investigations to Annex B countries, assembled as in the original RICE Model, leaving out countries that do not have any commitment in the Kyoto Protocol.

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[12] More specifically, for each region we regress $\ln[\sigma(n,t)-\sigma_n]$ against an intercept and $-K_{\mathrm{R}}(n,t)$. The antilog of the intercept provides an estimate of χ_n, while the slope coefficient produces an estimate of α_n.

[13] A sensitivity analysis was performed on the value of the 'learning-by-doing' coefficient: the working paper version of this study (Castelnuovo et al., 2003a,b) reports on that.

3.1. R&D-based technological change

Consider first the case in which the environmental technology evolves exogenously. With respect to the BaU scenario, and conditioning on the domestic abatement rate, the imposition of an emission ceiling is equivalent to having a ceiling on production, as highlighted by Eq. (4). This leads all Annex B countries to experience a welfare loss, since the average level of consumption unambiguously decreases, as shown in Fig. 1 (top panel). This is due to the reduction of physical capital stock by about 2–3% relative to the BaU scenario, as Fig. 2 suggests. Domestic abatement rates are inevitably enhanced when constraints on emissions are imposed, as evident in Fig. 3. Notice that, in this framework, R&D expenditures have a positive effect on the inputs' productivity only. Hence, it is not surprising to observe a lower average level of R&D expenditures after the imposition of the emission caps (Fig. 4).

Indeed, there seem to be some important deviations when allowing for the endogenous environmental technical change to be part of our analysis. In fact, in this latter case agents find it profitable to *raise* their R&D expenditures when upper bounds on emissions are activated (Fig. 4, bottom panel); they do so in order to improve their environmental technology, so as to be allowed to grow more (i.e. to reduce capital accumulation *less* than in the exogenous environmental technological change case after the imposition of the Kyoto constraints) and finally to consume more (Figs. 1 and 2). Not surprisingly, given the positive influence of the stock of R&D-driven knowledge on the environmental technology, agents' R&D expendi-

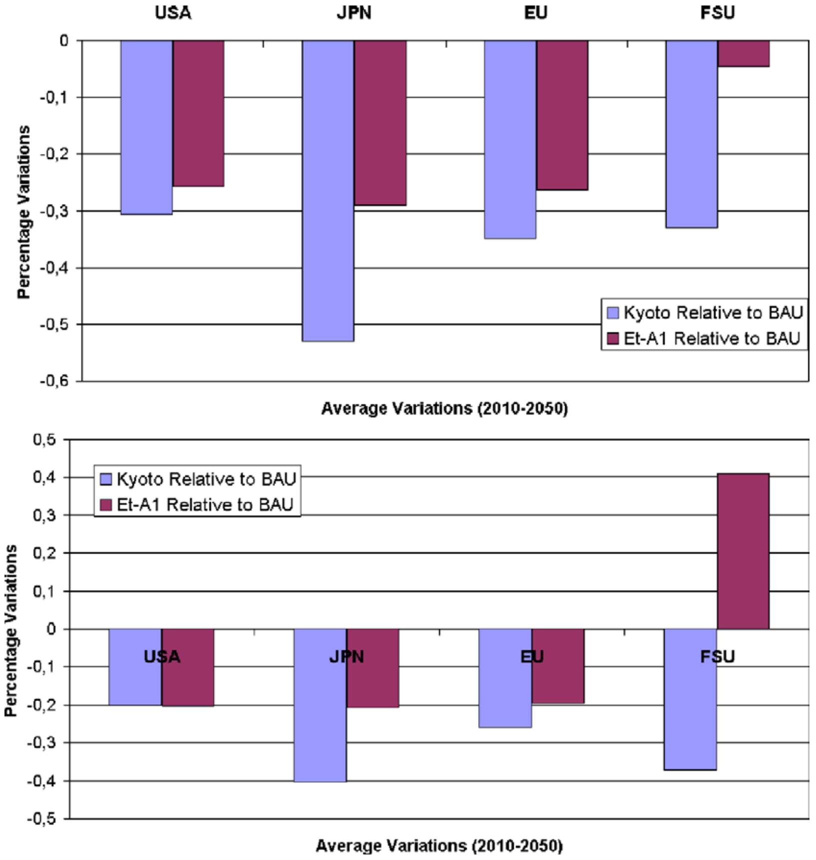

Fig. 1. Consumption level: variations across scenarios with R&D-driven knowledge stock and exogenous environmental technology (top panel). Consumption level: variations across scenarios with R&D-driven knowledge stock and endogenous environmental technology (bottom panel).

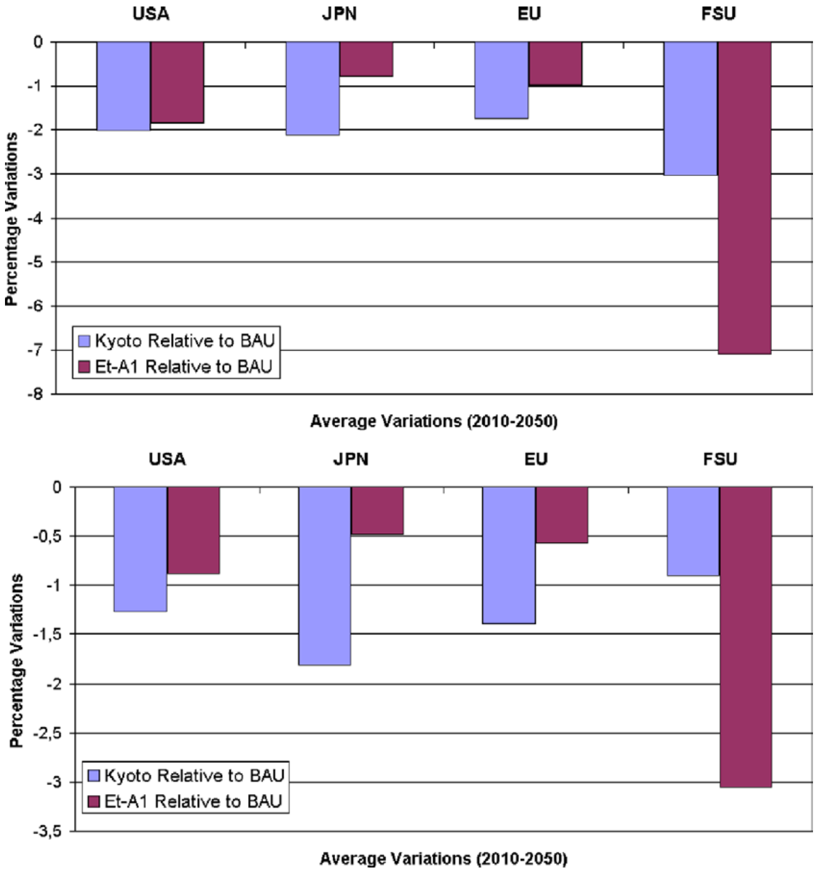

Fig. 2. Physical capital: variations across scenarios with R&D-driven knowledge stock and exogenous environmental technology (top panel). Physical capital: variations across scenarios with R&D-driven knowledge stock and endogenous environmental technology (bottom panel).

tures turn out being *complementary* to the domestic abatement action, while when the environmental technology is exogenous they are s*ubstitutes* (due to the fact that R&D expenditures raise production and, as a by product, pollution). To summarize, when agents can shape their emissions–output ratio, they are able to exploit this additional possibility to increase their welfare.

When emission trading between Annex B countries is permitted, we observe a generalized increase of consumption. This is hardly surprising, given that each region is endowed with an extra degree of freedom, i.e. the possibility to trading rights to pollute. Fig. 1 confirms this fact.

It is interesting to try to understand where these welfare-gains originate from. In fact, not all the change in consumption stems from an augmented production (caused by an increased average stock of capital). Indeed, the effects on the average variation of capital cannot be predicted a priori. Investment choices depend crucially on the role each country will have in the market: depending on the equilibrium price of emission permits, endogenously generated by the model, and on the basis of other information such as the domestic abatement cost, each country decides whether to act as a permits seller or buyer. In particular, in a very simplified view, a region will choose to be a seller when the marginal earnings from the emission permits market are higher than the marginal expenses needed in order to lower the emissions to the optimal point under the Kyoto ceiling. These expenses can be both direct (abatement costs) and indirect (less production, via lower average growth rate of capital, or more R&D). The opposite

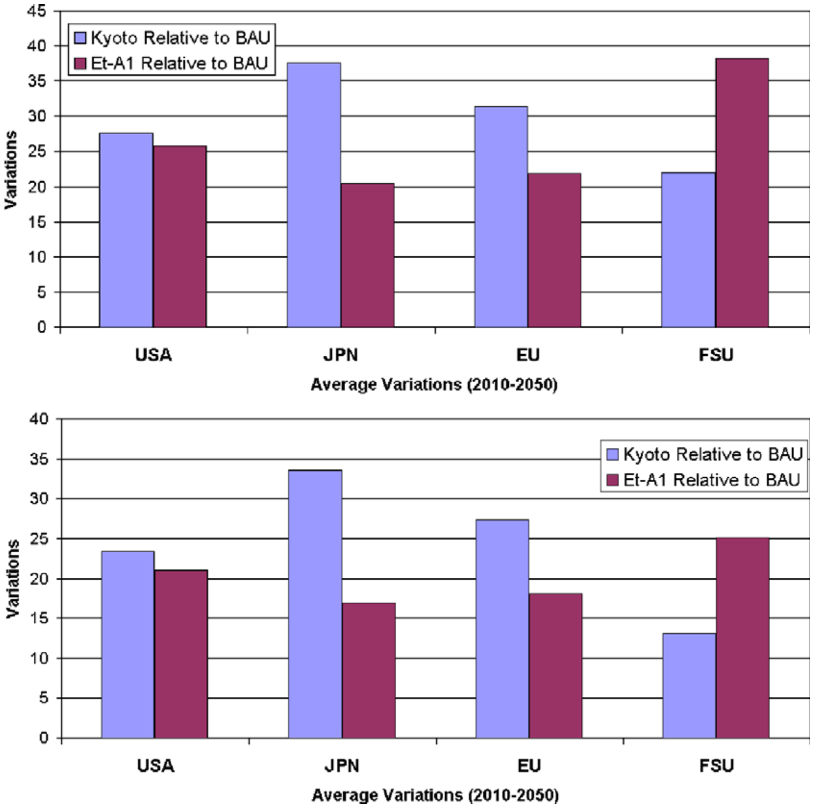

Fig. 3. Domestic abatement ration: variations across scenarios with R&D-driven knowledge stock and exogenous environmental technology (top panel). Domestic abatement rate: variations across scenarios with R&D-driven knowledge stock and endgenous environmental technology (bottom panel).

holds for buyers, i.e. costs for permits are lower than expenses to reduce emissions under Kyoto targets.

The considerations just made can explain why the Former Soviet Union (seller) *reduces* the optimal stock of capital more under trading, while USA, EU, and Japan (buyers) reduce it less (Fig. 2). This is possible given the 'relaxation' of the constraints on emissions they enjoy when purchasing a positive amount of permits. This brings buyers to a lower the emission control rate, since they may acquire on the market what they were previously obliged to obtain through domestic action. On the contrary, FSU (the unique seller) uses abatement and R&D expenditures as strategic variables; i.e., this country strongly raises them, in order to create a high number of emissions permits to be conveniently sold on the market.

With an endogenous emission–output ratio, the differences existing in the regions' optimal behaviour when moving from Kyoto to Et-A1 are qualitatively in line with what already observed. Quantitatively, the possibility of influencing the emissions–output ratio is welfare enhancing (this is true for all the regions, and in particular for FSU). All the changes noted in the previous paragraph and regarding physical capital, domestic abatement rate, and R&D expenditures appear to be of smaller magnitudes.

3.2. LbD-based technological change

Compared to the 'Learning by Researching' approach, the LbD version of the model presents one less choice variable, i.e. the control variables are now limited to consumption, domestic abatement, fixed investment and net demand for permits, since fixed capital replaces R&D expenditures in the role of knowledge accumulation. Thus, physical capital

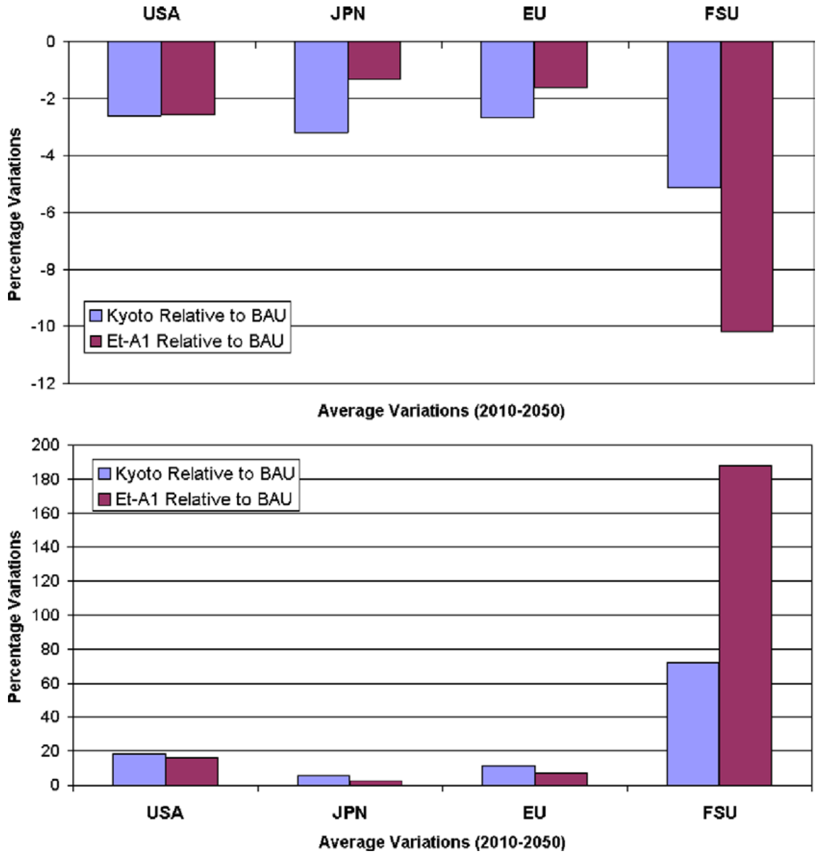

Fig. 4. R&D expenditures: variations across scenarios with R&D-driven knowledge stock and exogenous environmental technology (top panel). R&D expenditures: variations across scenarios with R&D-driven knowledge stock and endogenous environmental technology (bottom panel).

now plays the same role that knowledge capital had in the R&D approach. Notice that this fact has some implications. On the one hand, the physical capital's marginal returns are higher, so for a given amount of capital the overall production is now higher.[14] In this set up there is *not* any distinction between the input per se (physical capital) and the element, which enhances its productivity (knowledge). So, it is not possible to substitute welfare today (i.e. less consumption) with higher productivity of the input tomorrow (i.e. more knowledge *given the same amount of capital*). By contrast, this was feasible in the R&D-driven knowledge case. In our opinion, this distinction is important. In fact, it is true that R&D is a costly avenue to improve the stock of knowledge. However, it is also a different aggregate with respect to capital, so–at least in our analysis–it allows a more flexible management of the available resources with respect to the LbD case. If environmental technical change is endogenous, agents have to modify their amount of physical capital in order to improve the emissions–output ratio. This does not happen in the R&D case. Roughly put, in our set up LbD causes knowledge growth for free, but agents are a bit more constrained in their choices with respect to the R&D-driven knowledge case. These

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[14] There is an important assumption behind our way of accounting for LbD. When determining the optimal amount of resources to be invested in physical capital, agents are perfectly aware of the 'learning effect' triggered by capital accumulation. Hence, they fully understand that the marginal productivity of capital is enhanced by the learning effect and take it into account when determining their optimal decisions. Notice that in our analysis there is no room for within-region externalities or between-region spillovers: while little can be done with respect to the former, we intend to address the latter issue explicitly in future research.

considerations will be of help in interpreting the results we obtained.

Let us consider the case of an exogenous sigma. The imposition of an emission ceiling, without the possibility of trading emission permits, turns out to be a ceiling on production, so a ceiling on fixed capital, which leads to a decrease in consumption, as depicted in Fig. 5. Indeed, the reduction in physical capital seems to be slightly bigger than in the R&D-driven case (compare Figs. 2 and 6). This is justified by the fact that, in the BaU scenario, agents are not emissions-constrained, so that they decide to accumulate quite a lot of capital. When the Kyoto limits become part of the framework, the reduction of the physical capital has to be such that, even considering the high productivity of capital, the pollution stemming from the production activity does not exceed the environmental constraints; hence, the reduction is quantitatively important. Not surprisingly, agents abate domestically in order to comply with Kyoto; the increase in the domestic efforts is larger with the LbD hypothesis (compare Figs. 3 and 7).

How do things change when the environmental technical change is allowed for? Indeed, the welfare reduction is milder in this latter case. Indeed, the fact that the environmental technology is driven by the stock of physical capital does not seem to be too problematic. Notice the striking difference that exists between the physical capital variations recorded with an exogenous vs. an endogenous environmental technology. In the latter case, agents in general *augment* the amount of resources allocated to physical capital, because in this way they are both much more productive and environ-

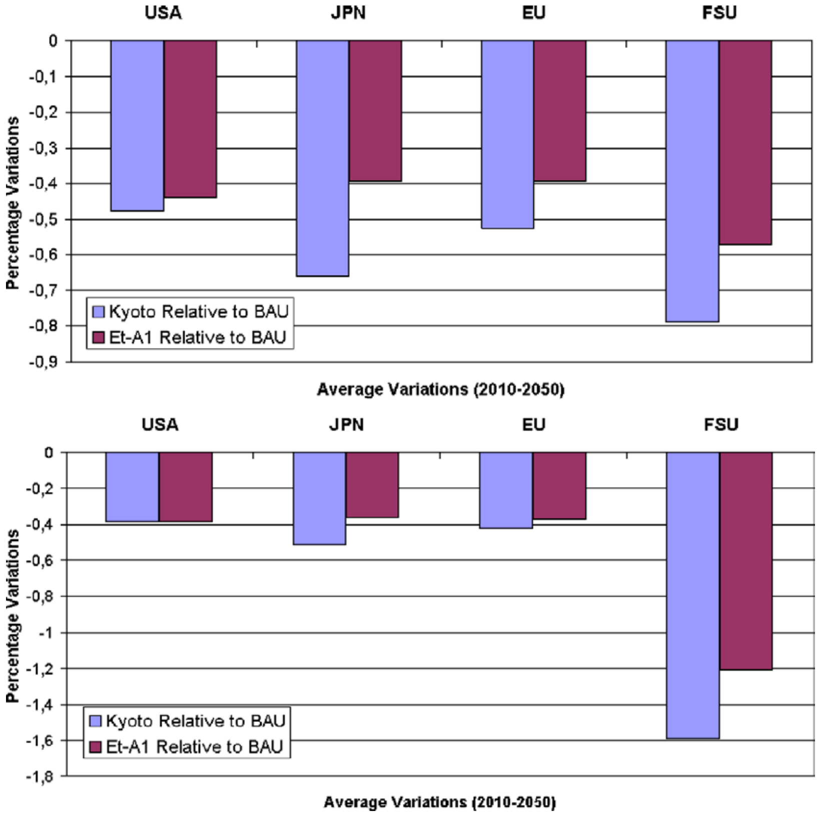

Fig. 5. Consumption level: variations across scenarios with LbD-driven knowledge stock (elasticity=0.025) and exogenous environmental technology (top panel). Consumption level: variations across scenarios with LbD-driven knowledge stock (elasticity=0.025) and endogenous environmental technology (bottom panel).

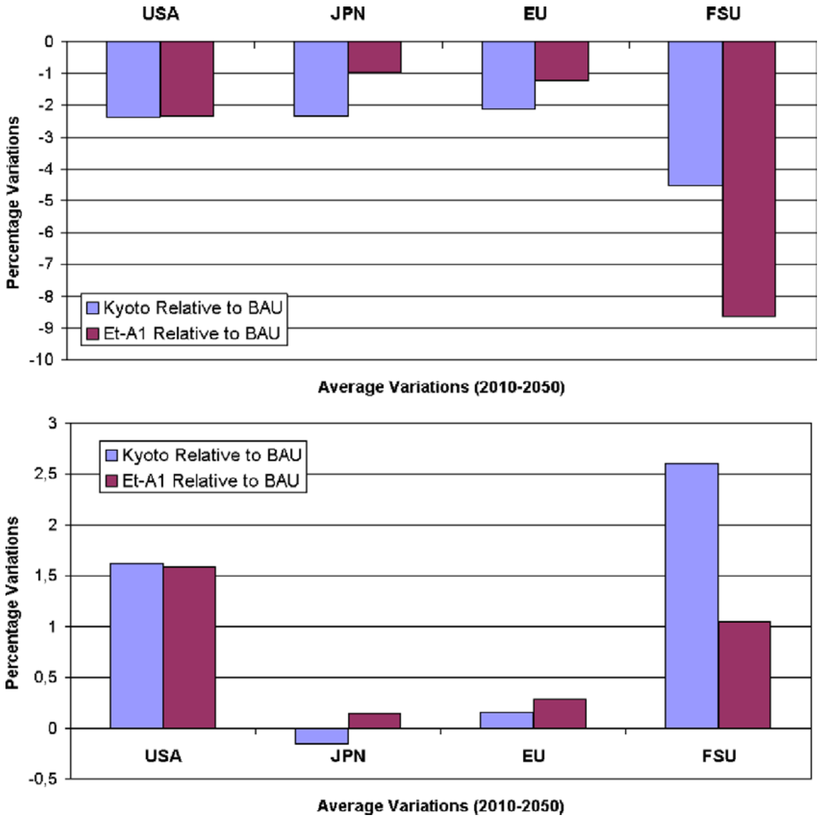

Fig. 6. Physical capital: variations across scenarios with LbD-driven knowledge stock (elasticity=0.025) and exogenous environmental technology (top panel). Physical capital: variations across scenarios with LbD-driven knowledge stock (elasticity=0.025) and endogenous environmental technology (bottom panel).

mentally efficient (i.e. a given amount of output causes a small flow of emissions). De facto, this is the situation in which agents are able to exploit all the large returns that can come from the LbD-driven knowledge, so there is a strong incentive to keep investing in physical capital. As far as the domestic abatement rate is concerned, we do not notice remarkable differences as opposed to the case with exogenous sigma.

When allowing for the emissions trading, what we observe is that the regions acting as purchasers on the permits market (i.e. USA, Japan, and Europe) slightly augment their capital accumulation, whilst the seller (namely, FSU) experiences a further reduction as far as this variable is concerned, since it finds it profitable to reduce emissions in order to enjoy the gains from trade stemming from the emissions market. Consistently, the purchasers reduce their domestic abatement efforts, while the sellers increase them optimally.

3.3. A comparison between the two approaches

As stated in the Introduction, one central aim of our analysis is to assess if significant qualitative differences exist when moving across scenarios under R&D vs. LbD specifications of technical change. Interestingly, our findings regarding the imposition of emissions constraints (with or without flexibility mechanism) are, qualitatively speaking, quite similar. In fact, in both formulations it is generally true that the costs of complying with the Kyoto limits are lower when the environmental technical change is shaped as an endogenous process. Moreover, aside from some exception (USA and FSU), imposing ceilings to emissions leads to a reduction in the stock of physical

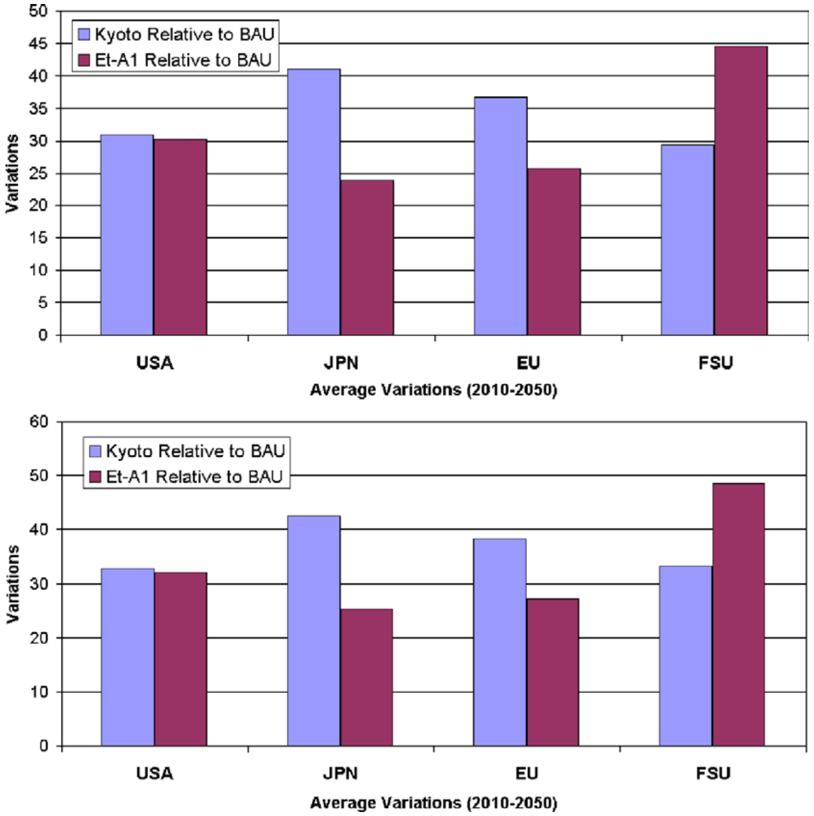

Fig. 7. Domestic abatement rate: variations across scenarios with LbD-driven knowledge stock (elasticity=0.025) and exogenous environmental technology (top panel). Domestic abatement rate: variations across scenarios with LbD-driven knowledge stock (elasticity=0.025) and endogenous technical change (bottom panel).

capital and an obvious increase of the domestic effort aimed at an environmental improvement. As expected, the flexibility mechanism (i.e. emissions trading) makes complying with the Kyoto Protocol less costly.

Quantitatively speaking, some differences are worth underlining. First of all, the welfare losses seem to be more marked under LbD, both in the case of exogenous technical change and in the case of endogenous sigma. The intuition for this result is the following: when having to face the environmental constraints, under the R&D-driven hypothesis agents vary (also) the R&D expenditures levels in order to comply with Kyoto. This means that the (negative) impact of the environmental limits is optimally ‘distributed’ by the agents both on physical capital and on knowledge, which have in this case different elasticities with respect to output. Instead, in the LbD-driven knowledge framework, Kyoto’s implications in terms of reduced production affect uniquely physical capital; in other words, agents have one less degree of freedom, so it is not surprising that they obtain an inferior result in terms of welfare.

The key role of physical capital is confirmed by the fact that with an exogenous emission–output ratio the reduction of accumulated fixed investments is less pronounced under R&D; this is so because of the impossibility of improving the environmental technology by augmenting the stock of knowledge. Instead, when the emissions–output ratio is endogenous, capital plays the role of R&D, i.e. its reduction is less pronounced as opposed to the R&D-driven knowledge case because it causes the improvement of the environmental technology.

The fruitful interactions between R&D and domestic abatement rate imply that the latter is lower when agents may exploit the former; in other words, in presence of R&D agents undertake less domestic efforts as opposed to the LbD case, where those interactions are just not possible.

All the remarks just made also hold in the case of emissions trading, which renders less costly the compliance of the Kyoto protocol, without much affecting the relative importance of the agents' control variables.

4. Concluding remarks

Current modeling practices in the climate change literature are intensifying efforts at endogenizing the process of technological change. The bottom-up tradition has typically considered the notion of Learning-by-Doing, incorporated through learning curves associated with each technology considered. Top-down models have instead experimented more with R&D-based knowledge formation processes meant to capture the idea of an endogenously evolving technology. While there are a few recent attempts to allow for a role of R&D in the learning process specified by bottom-up models and to accommodate Learning-by-Doing in top-down models, it appears that no paper has yet studied both formulations within the same integrated assessment model.

In this paper we have extended Nordhaus and Yang (1996)'s RICE model to allow for, besides emission trading, endogenous technical change. A crucial role is attributed to the stock of knowledge, which accumulates either through deliberate, optimally selected, R&D activities, or through physical investment. In the latter case the stock of knowledge becomes equivalent to cumulative installed capacity. The model presented here specifies endogenous technical change (enhancing output production) along with or without endogenous environmental technical change (reducing emissions-to-output). In all cases the state of technology, both environmental and not, also evolves exogenously.

With these two versions of the model we ran a set a basic simulations under alternative regimes concerning emission trading within the context of the Kyoto Protocol.

Our results seem to support the conclusion that, although conceptually very different, R&D-driven and LbD-driven knowledge frameworks may lead to qualitatively similar findings. In particular, the possibility to affect the environmental technology does lower the costs of meeting the emissions caps, so enhancing the considered regions' welfare. However, our quantitative results lead us to believe that R&D, being a costly but additional control variable exploitable by optimizing agents, may provide the agents themselves with a better outcome as opposed to a pure LbD framework, in which knowledge accumulates for free but it may constrain agents to undertake optimal choices in a more "rigid" setup.

In this paper we did not study forms of hybrid knowledge formation, i.e. situations in which both R&D and LbD are jointly present. We guess that a hybrid knowledge formation could provide agents with a superior result, but empirical endeavors have to be undertaken before claiming so.

Of course much remains to be done in this line of research of which this paper is a step ahead. In particular it is necessary to overcome the limitations of the basic model used here. In this respect the obvious choice is to move to richer integrated assessment models, such as Nordhaus and Boyer (2000)'s more recent RICE version, with the endogenous technical change formulations of Nordhaus (2002) and Popp (2004). Within this new framework our next effort will be to allow for both R&D and LbD drivers of technical change *at the same time*.

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Appendix A. The remaining equations of the RICE model

In this appendix we reproduce the remaining equations that make up the whole model. These equations are reported here for the sake of completeness and are the same as the ones found in the original RICE model.

In each region there is a social planner who maximizes the following utility function:

$$\max_{\{C(n,t)\}} \sum_{t=1}^{T} \beta^{t-1} L(n,t) \log[C(n,t)/L(n,t)] \tag{A1}$$

where β is the discount factor, the other symbols having already been encountered. By assumption population equals the employed labor force. The discount factor is exogenously given (equal to 3%). The budget constraint is given by an equation like Eqs. (3a) and (3b) in the main text. The physical capital stock evolves as follows:

$$K(n,t+1) = (1-\delta_K)K(n,t) + I(n,t+1) \tag{A2}$$

where I is the level of investment in physical capital and δ is the rate of depreciation. The process is the same as that for R&D (see Eq. (2) in the main text).

Turning to the climate module of the model, the wedge existing between gross output Q and net output Y, justified by the negative effect exerted by the temperature level on the regions' utilities, is given by:

$$Y(n,t) = \Omega(n,t)Q(n,t) \tag{A3}$$

The term $\Omega(n,t)$ is a damage coefficient that explains the temperature effect on gross output. Its representation is the following:

$$\Omega(n,t) = \frac{1 - b_{1,n}\mu(n,t)^{b_2}}{1 + \theta_{1,n}[T(t)/2,5]^{\theta_2}} \tag{A4}$$

where μ is the domestic abatement rate controlled by each region, while T is the global atmospheric temperature (relative to pre-industrial level), and b_1, b_2, θ_1 and θ_2 are parameters.

Eqs. (4) (4a) (4b) in the text describe how emissions are generated by production activity and how they depend also on the domestic effort against pollution as well as the environmental technology that each region enjoys. Over time, emissions accumulate and form the stock of carbon concentration M:

$$M(t) = \gamma \sum_{n} E(n,t) + (1-\delta_M)M(t-1) \tag{A5}$$

where γ is the marginal atmospheric retention ratio of CO_2 emissions and δ_M is the rate of transfer of CO_2 from atmosphere to other reservoirs. The following step describes the relationship among the accumulation of greenhouse gases, the level of temperature, and climate change. The equations regulating the temperature level are:

$$\begin{aligned} T(t) = T(t-1) + \{&\tau_1[F(t) - \lambda T(t-1)] \\ &- \tau_2[T(t-1) - T^*(t-1)]\}/\tau_3 \end{aligned} \tag{A6}$$

$$T^*(t) = T^*(t-1) + [T_1(t-1) - T_2(t-1)]/\tau_4 \tag{A7}$$

$$F(t) = \eta \log[M(t)/M(0)]/\log(2) + O(t) \tag{A8}$$

where T^* is deep ocean temperature relative to pre-industrial level, F represents the radiative forcing from all greenhouse gas concentrations, τ_1, τ_2, τ_3, and τ_4 are parameters of the climate equation, λ is the feedback parameter in climate model (inverse to temperature-sensitivity coefficient), η is a parameter enhancing the carbon concentration impact on the radiative forcing, and O is an exogenously given force.

The base year is 1990 and the model is simulated in 10-year steps.

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