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Accounting for Uncertainty Affecting Technical Change in an Economic-Climate Model

Summary

The key role of technological change in the decline of energy and carbon intensities of aggregate economic activities is widely recognized. This has focused attention on the issue of developing endogenous models for the evolution of technological change. With a few exceptions this is done using a deterministic framework, even though technological change is a dynamic process which is uncertain by nature. Indeed, the two main vectors through which technological change may be conceptualized, learning through R&D investments and learning-by-doing, both evolve and cumulate in a stochastic manner. How misleading are climate strategies designed without accounting for such uncertainty? The main idea underlying the present piece of research is to assess and discuss the effect of endogenizing this uncertainty on optimal R&D investment trajectories and carbon emission abatement strategies. In order to do so, we use an implicit stochastic programming version of the FEEM-RICE model, first described in Bosetti, Carraro and Galeotti, (2005). The comparative advantage of taking a stochastic programming approach is estimated using as benchmarks the expected-value approach and the worst-case scenario approach. It appears that, accounting for uncertainty and irreversibility would affect both the optimal level of investment in R&D –which should be higher– and emission reductions –which should be contained in the early periods. Indeed, waiting and investing in R&D appears to be the most cost-effective hedging strategy.

Keywords: Stochastic Programming, Uncertainty and Learning, Endogenous Technical Change

JEL Classification: D62, D63, H23, Q29

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1. Introduction

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As underlined in a recent work by Manne *et al*. (2004) and according to the International Energy Agency, investment in energy R&D declined by approximately 50% worldwide between 1980 and 1999.¹ However, considering the recent boost in the price of oil, the widespread concern over the issue of energy security and the comeback (return) of the Kyoto Protocol, it now seems quite reasonable to expect a growing interest in the issue of energy technological change, R&D spending and its idiosyncrasies.

One of the two recognized main driving forces of technological evolution is the investment in research and development of new technologies, disembodied technological change in Grubler and Gritsevskyi (1996). The second vector of technological change is the accumulation of experience deriving from the change in hardware and actual implementation, the so-called learning-by-doing or embodied technological change.

In general, the decision-making processes involved in this type of investment are significantly influenced by uncertainty. This is due to the fact that research may fail to produce the desired results, because of technological-engineering barriers or because the new technology may turn out to be economically inconvenient. Economic unfeasibility often can be related to the lock-in structure of these investments with no flexibility and ways out (e.g., option to abandon the project if it is not profitable). Or, the new technology may immediately appear to be unattractive for final users (as in the case of technologies requiring huge initial efforts). In addition to this, learning is strongly affected by uncertainty on future policy. In the specific case of energy technological progress, the uncertain shape of future climate policy regimes is a decisive factor. Indeed, the definition of a strict stabilisation target or of a global carbon tax would imply faster hardware turnover, which in turn would imply faster learning rates.

¹ In a recent publication of the PEW Center on ITC and climate policy (2004), Larry Goulder shows how in the US Energy technology R&D expenditures started decreasing dramatically much earlier, namely in the late seventies, and they represent nowadays one fifth of what they were then.

Finally, the actual role played by technological change in energy and carbon intensities is also uncertain. This might be because of lock-in lock-out effects and because of the evolution in cluster of technologies, in one word because of the inertia which is in the nature of these dynamic phenomena, see Grubb (1996) for a detailed discussion. Also, political or social issues may be relevant, because they may strongly affect adoption rates - or else pure fate - which has historically proven to have a great deal of responsibility².

The purpose of this paper is to investigate the effect of uncertainty on short-term R&D investments and abatement strategies and its role in the transition towards more energy-efficient economies and less carbon-rich energy sources. First, sensitivity analysis is performed on crucial parameters to test for model stability and relative importance of different sources of uncertainty. The analysis is performed on the parameter accounting for crowding out of other investments due to investment in energy R&D (modeled here as in Popp, 2004); on the parameters controlling for the effect of endogenous technical change on the carbon and energy intensities; and on the effective learning accumulation parameters controlling for the rate of accumulation into a stock of effective knowledge/experience of the two learning processes.

Crucial variables appear to be extremely sensitive to the effective learning accumulation parameters. While other parameters are chosen in order to calibrate model baseline to the SRES B2 scenario³, effective learning factors are estimated for the base year using real data. We also assume that in subsequent periods, returns on R&D investments and cost savings due to experience will evolve stochastically. We also assume incremental learning concerning these effective R&D and LbD accumulation rates. As an example we consider two possible states of the world. One

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 2 A well known example is that of the QWERTY keyboard. "The first typewriters featured the awkward QWERTY keyboard, meant to slow typists down so as not to jam the then-primitive typing mechanism. But so many typists learned QWERTY, and passed it on to future typists, that it remains entrenched even though electronic word processing permits more ergonomic keyboard arrays. Just so, suggests Prof. Diamond, many of the "idiosyncrasies" that may bias some cultures against innovation may be due to accidents that arose for "trivial, temporary local reasons," and became fixed as "influential, long-lasting cultural features." Pure chance is thus assigned a place in the fate of cultures, but not the talents of the individuals who make them up." Squaring the Circle by Michael Levin, a review of Jared Diamond, Guns, Germs, and Steel: The Fates of Human Societies, W. W.Norton, 1997

 3 For a detailed discussion of the model calibration procedure the reader is referred to Bosetti, Carraro and Galeotti [2005].

characterized by an imminent technology breakthrough followed by a period of fast learning and fast decrease in the cost of the technology. The other characterized by technology stagnation, lockout of new technologies and delay in learning phenomena. What is the effect of this uncertainty on immediate strategies? Should the optimal reaction be a decrease in short-term optimal investment in knowledge? These questions are investigated both in a cost-benefit and a cost-minimization framework.

In order to perform such analysis, a stochastic version of the FEEM RICE model has been developed and solved for a scenario tree representing the combined uncertain evolution of the two learning rates.

The deterministic model, an extended version of Nordhaus and Boyer's RICE 99 (2000), is composed by a multi-region optimal economic growth module connected with a very simple climate module, which, in turn, feedbacks through damage function on the economic module. Moreover, as discussed in greater detail in Bosetti, Carraro and Galeotti (2005), the model has been extended in order to account for both learning-by-researching and learning-by-doing; the former vector of endogenous technical change is modelled through an R&D investment decision variable which cumulates deterministically through time; the latter is modelled as the stock of cumulated emissions reduction. The two inputs are aggregated to compose an index of technical progress which in turn affects both carbon and energy intensities.

This paper gives a twofold contribution. First it contributes to the climate policy debate, addressing crucial issues such as the optimality of delaying/anticipating R&D investment strategies and/or abatement efforts in the face of uncertainty affecting learning processes and future policy actions (what is the value of prior announcements of climate policies). Second, the paper contributes to the literature on modeling endogenous technical change, in the way R&D and LbD processes are modeled as incremental learning processes. To the best of the authors' knowledge it is the first application of a stochastic programming framework to the field, and as we will discuss, the methodology appears very well-suited to deal with a climate-economic model when endogenizing uncertainty.

The rest of the paper is structured in four sections, as follows. In the next section we briefly review literature on modeling uncertainty and endogenous technical change in climate-economic models. This is followed by a brief description of how the model is used for the simulation experiments. Section 4 discusses the stochastic formulation of the model and presents main results. Section 5 concludes.

2. Modeling Uncertainty in a Climate-Economic Model with Learning

When considering the role played by uncertainty, conceived both as parameter uncertainty and inherent stochasticity of involved processes, two policy-relevant effects arise pointing in opposite directions. We know that when facing irreversible decisions in the presence of uncertainty the possibility of waiting and learning has a positive value. However, the effect of this theoretic understanding is unclear (and strongly depends on probabilistic assumptions) when applied to the reality of climate change policy designing. If the effect of climate change irreversibility prevails, waiting will imply slowing down global emissions until clearer information concerning the potential damage becomes known; on the other hand, if irreversibility of immediate abatement action (and the relative costs) prevails, then an option value will be attached to the deferment of any abatement activity. In Nordhaus (1993) evidence is produced in favor of a greater concern for the first type of irreversibility, environmental irreversibility, while in Kolstad (1994) irreversibility of abatement sunk costs appears to have a crucial role. Furthermore, Peck and Teisberg (1993) found that none of these two sources of irreversibility has a definite role in shaping optimal abatement strategies.

On a similar line of ambiguity stands the debate on the issue of endogenizing technical change and its effect on climate policy: does technical change play in favor of postponing emission reductions until new discoveries will make it cheaper to abate, as argued by Wigley, Richels and Edmonds (1996)? Or does technological change represent an incentive to undertake at least some abatement in order to increase the stock of experience thus decreasing abatement costs, as discussed, among others, by Grubb (1996)? The answer generally depends on whether one believes learning-by-doing will prevail on the effect of R&D investments.

Within this controversy stands the present paper which delves into learning phenomena and how uncertainty affecting them is reflected on optimal climate policy decisions, in terms of timing and shaping abatement strategies and R&D investments.

In most cases climate-economic models are deterministic mainly for the sake of modeling and computation simplicity. However, the use of a set of deterministic equations in order to describe phenomena which are strongly affected by uncertainty often offers a poor representation of the actual events, thus providing poor accuracy in forecasting power. Sensitivity analysis on key random parameters is the most commonly adopted methodology in the direction of including uncertainty, as for example in Nordhaus and Popp (1997) and Gerlagh and van der Zwaan (2004). However, not assigning probability weights to different realizations of random variables or parameters often doesn't shed enough light on the issue at stake and leaves the decision-maker with the unresolved question of what strategy to pick among those calculated for each of the different states of nature. Haurie (2003) represents the changes of states of nature by some stochastic jump processes where the system is deterministic between two successive random jumps. Monte Carlo simulation represents a step further in the representation of uncertainty, because well-defined probability measures (deduced from real data or assessed by experts) are assigned to different states of the world; see for example Webster *et al.* (2001). The decision-maker can work with probability distributions of optimal strategies and can concentrate in minimizing the probability of undesired events. But even when probability can be assigned to each individual scenario, separate prescription obtained for one of them may be inconsistent with the other and hedging strategies cannot be designed. This, together with the need for modeling the evolution of the available set of information, has led to a vast literature, mainly based on two-stage dynamic programming models

and focused on the comparison between deferring strategies and immediate action, given the role of learning processes. Two strands of literature can be outlined. The first mainly dealing with the issue of the value of perfect information, among others the work by Manne and Richels (1994), Nordhaus and Popp (1997) and Min Ha Duong, Grubb and Hourcade (1997); the second concerns the optimal timing of the abatement effort, see for example Hammit, Lempert and Schlesinger (1992).

The present paper focuses on the incremental arrival of information concerning the process of knowledge accumulation, modeled as a multi-stage stochastic programming problem.

3. Learning in the FEEM Model

The analysis is conducted by means of a numerical climate-economy model, i.e. the FEEM-RICE. The FEEM-RICE model, briefly outlined here in its deterministic features, is an extended version of Nordhaus and Boyer (2000)'s RICE model. This is a Ramsey-Koopmans multi-region, single-sector optimal-growth model suitably extended to incorporate the interactions between economic activities and climate. Within each region a central planner chooses the optimal paths of two controls, fixed investment and carbon energy input, so as to maximize welfare, defined as the present value of per capita consumption. The value added, absorbed from production (net of climate change) according to a constant returns technology, is used for investment, consumption and R&D investments, after subtraction of energy spending. The technology is Cobb-Douglas and combines the inputs from capital, labor and carbon energy together with the level of technology. Population (taken to be equal to full employment) and technology levels grow over time in an exogenous fashion, whereas capital accumulation is governed by the optimal rate of investment. The carbonenergy input is modeled as being the source of GHGs emissions in the production process, and cumulated emissions (i.e. concentrations) cause an increase in the worldwide temperature. To close the circle, global temperature (relative to pre-industrial levels) is responsible for the wedge between gross output and output net of climate change effects.

In FEEM-RICE each region plays a non-cooperative Nash game in a dynamic setting leading to an Open Loop Nash equilibrium. This is a situation where, in each region, the planner maximizes the utility subject to the individual resource and capital constraints and the climate module for a given emission production of all the other players. The objective function for each region is:

(1)
$$
W(n) = \sum_{t} U[C(n,t), L(n,t)]R(t) = \sum_{t} L(n,t) \{ \log[c(n,t)] \} R(t)
$$

where the pure time preference discount factor is given by $R(t) = \prod_{v=0}^{t} [1 + \rho(v)]^{-1}$ *v* $R(t) = \prod_{i=1}^{n} |1 + \rho(v_i)|$ 0 $(t) = \prod [1 + \rho(v)]^{-10}$, $c(n, t)$ is per capita consumption, $C(n,t)$ is total consumption and $L(n,t)$ is population.

The process of technical change (TC) is endogenous in the model and in particular it is assumed to take two distinct forms: the evolution of energy intensity of production and of carbon intensity of consumed energy. These two features of the economy are assumed to be affected through time by a Technical Progress index, which accounts for both Learning-by-Researching and Learning-by-Doing. Innovation is brought about by R&D spending which contributes to the accumulation of the stock of existing knowledge. R&D is a further strategic variable of the model that contributes to output productivity and emission reduction. Learning-by-doing is an external effect, deriving from the efforts made in the past in order to reduce emissions and it is modelled in terms of cumulated past abatement efforts. Abatement flows each year are measured as the difference between optimal emissions and emissions you would have without endogenous technical change. Thus, Technical Progress, *TP*, is defined as follows:

$$
(2) \tT P(n,t) = K_{LbD}(n,t)^c K_{known}(n,t)^d,
$$

where $K_{know}(n,t)$ is the stock of knowledge and $K_{LbD}(n,t)$ represents the stock of cumulated abatement, defined as:

(3)
$$
K_{\text{known}}(n, t+1) = \xi_{\text{known}}(I_{\text{known}}(n, t)) + (1 - \delta_{\text{known}})K_{\text{known}}(n, t),
$$

 δ_{known} being the depreciation rate of knowledge, I_{known} the yearly expenditure research and $\zeta_{\text{know}} \in [0,1]$ being the effective learning factor for R&D accumulation.

(4)
$$
K_{LbD}(n,t+1) = \xi_{LbD}(I_{LbD}(n,t)) + (1 - \delta_{LbD})K_{LbD}(n,t),
$$

 δ_{Lbd} being the depreciation rate of cumulated experience, I_{LbD} the abatement flow with respect to emissions in the exogenous baseline and $\xi_{\text{LdD}} \in [0,1]$ being the effective learning factor for experience accumulation.

Let us first consider the effect of Technical Progress on factor productivity (the energy intensity effect). The production function is the following:

(5)
$$
Q(n,t) = A(n,t)[K_c(n,t)^{1-\alpha_n(T_P)-\gamma}CE(n,t)^{\alpha_n(T_P)}L(n,t)^{\gamma}] - p_{CE}(n,t)^*CE(n,t),
$$

where *Q* is output (gross of climate change effects), *A* the exogenously given level of technology, K_F , *CE* and *L* are the inputs from physical capital, carbon energy and labor, respectively, and p_{CE} is the price of carbon energy. Moreover:

(6)
$$
\alpha_n = \alpha_n [TP(n,t)] = \frac{\beta_n}{2 - \exp[-\phi TP(n,t)]},
$$

where β_n is a region specific parameter and ϕ controls for the intensity of the TP effect. Thus, an increase in the endogenously determined Technical Progress variable reduces – *ceteris paribus* – the output elasticity of the energy input. It is worth noting that the output technology in (1) also accounts for TC evolving exogenously.

Let us now turn to the effect of Technical Progress on the carbon intensity of energy consumption. Effective energy, $E(n,t)$, results from fossil fuels input use, from the exogenous evolution of TC in the energy sector and from the endogenous component of TC. Indeed, *TP* serves the purpose of reducing, *ceteris paribus,* the level of carbon emissions:

(7)
$$
E(n,t) = h[CE(n,t), TP(n,t)] = \varsigma(n,t) \left[\frac{1}{2 - \exp[-\psi TP(n,t)]} \right] CE(n,t),
$$

where *E* are industrial CO₂ emissions, while ζ is an idiosyncratic carbon intensity ratio which *exogenously* declines over time and ψ is the parameter controlling for the effect of the endogenous TC. Here an increase in *TP* reduces progressively the amount of emissions generated by a unit of fossil fuel consumed.

Finally, R&D spending absorbs some resources, that is:

(8)
$$
Y(n,t) = C(n,t) + I_c(n,t) + I_{know}(n,t)
$$

where *Y* is output net of climate change effects, *C* is consumption, I_C gross fixed capital formation, *Iknow* research and development expenditures. As in Popp (2004), in order to account for the difference between private and public return to investments in R&D, four dollars of private investment are subtracted from the physical capital stock for each dollar of R&D crowded out by energy R&D, so that the net capital stock for final good production is:

(9)
$$
K_C(n,t+1) = K_C(n,t)(1-\delta_C) + (I_C(n,t) - 4 \lambda^* I_{\text{know}}(n,t)),
$$

where λ , the crowd out parameter, represents the percentage of other R&D crowded out by energy R&D.

4. Including Uncertainty in the Picture

Let us now consider uncertainty affecting the endogenous mechanisms of technological evolution and its effect on the economic system. In particular, the central value of parameters is chosen in order to approximate baseline emissions of the SRES B2 scenario and following a set of assumptions on carbon and energy intensity trends described in Bosetti, Carraro and Galeotti (2005). We investigate the sensitivity of crucial variables to different uncertain parameters. In particular, we concentrate on parameters controlling for effectiveness of learning accumulation of both R&D investments and experience, ξ_{know} and ξ_{LbD} ; on the crowd out parameter, λ ; on the two parameters controlling for the effectiveness of technical progress in affecting the energy and the carbon intensities, ψ and ϕ .

We report the sensitivity of two endogenous variables (emissions and stock of knowledge) to changes in the five parameters within the ranges specified in Table 1. Results are given as percentage changes with respect to the central value case, and are reported both as short-term effects (for period 2045) and long-term effects (for period 2095).

The impact on emissions of changes in the effectiveness of R&D investments, ξ *know* , (see chart on the left hand side of Figure 1) is highly dependent on when the effect is measured, this reflects the modelled lag time dividing the time when investment in research is undertaken from the time when the discovery affects the level of emissions. Indeed, emissions in 2095 vary from +9% to -19% depending on the value of ξ *know* whereas emissions at mid term, in 2050, are less affected with a decrease of 3% for the highest value of ξ *know* . Predictably, the value of the total world knowledge (see right hand side chart in Figure 1) is highly sensitive to the effectiveness of R&D spending accumulation.

Follows, in the left hand side chart of Figure 2, the analysis of the impact on emission levels exerted by different assumptions on the effectiveness of learning by doing, $ξ$ _{*LbD*}. When compared to that of ξ_{know} , the effect is relatively stronger, although similarly more evident in later periods, when emissions range between +7.6% and -34.8% their central value. Changes in the value of ζ_{LbD} also dramatically affect the stock of knowledge (see right hand side chart of Figure 2). In particular, in the long run the effect becomes visible even for very small perturbations of the value.

The effect of different assumptions on λ , the parameter accounting for the crowding out effect, is asymmetric (see Figure 3). Below its central value, λ implies higher relative changes in emissions and world knowledge than above the central value. The direction of the effect follows our expectations.

The results of the sensitivity analysis relative to parameters controlling for the effectiveness of technical progress on the carbon and energy intensities of the economy, ψ and ϕ are summarized in Tables 2 and 3.

Given higher sensitivity to changes in the effective learning accumulation rates, we concentrate our analysis on those parameters. While λ , ψ and ϕ are assumed to remain constant to their calibrated base year value, a different emphasis is given to these two learning factors. Indeed, while base year values are calibrated on real data, we assume that they evolve in time in a stochastic manner, following a distribution inferred analysing historical data. Economy may eventually be locked in a technological path, so that for a certain amount of time investments in R&D will ply almost no effect. Else, it may well be that some relatively younger energy-generating technology enters a virtuous path of fast learning. Or any combination of these effects may occur. We develop a stochastic approach in order to take into account the fact that the economic system, and in particular the decisions concerning emissions and investments in R&D, will react in response to the future technological path that the economy will actually enter into. Indeed, what is particularly relevant in policy terms is the effect on the actual strategies -undertaken prior to the revelation of such information- to account for these multiple possible futures.

Formally, uncertainty is represented by a multilevel event tree which defines the possible sequences over the whole planning horizon of finite realizations of the random parameter, *ξ(t)*, having a discrete probability distribution, *p(ξ(t))*, which are named scenarios. In other words, a scenario, *s*, is represented in the event tree by a path from the root to the leaf (see Figure 4).

More specifically, note that nodes in the event tree are associated with decision points while arcs represent realizations of random parameters. In particular, the root is associated with the firststage decision variables while leaves are related to all the possible last-stage ones (also corresponding to the total number of represented scenarios). Levels in the tree are associated to time stages. In particular, if we denote with $\Omega(t)$ the set of nodes at the *t*-th level, then each node

 $\omega_s(t) \in \Omega(t)$ represents a particular realization sequence $\{\xi(\tau)\}_{\tau=2}^t$ of the data process and it can be thought as a particular state of the system at a given time. A probability p_{ω} is associated with each node, $\omega_s(t)$, such that $p_\omega = p\{\xi(t)|\xi(t-1),\ldots,\xi(2)\}\)$. Hence, arcs in the tree represent the probability distribution of *ξ(t)*. In order to deal with the growing numerical complexity of the problem and for the sake of compactness, the stochastic problem is formulated implicitly. Indeed, there exist two different ways of writing the deterministic equivalent (or projected problem) of a stochastic programming model, namely implicit and explicit formulations. They differ in the way they deal with the issue of non anticipativity, i.e. the issue of preventing a decision being taken now by using information that may become available in the future. If, instead of modeling non anticipativity constraint explicitly, the information given by the scenario tree structure is exploited, a reduced set of decision variables can be defined for which the non-anticipativity constraints are implicitly satisfied. This more compact formulation proves very useful when dealing with an increasingly large number of variables.

Therefore, to build the implicit stochastic formulation of the problem, we redefine model decision variables on each bundle, B_n , of scenarios passing through node $\omega_s(t) \in \Omega(t)$ at any stage t. Moreover, we introduce a relation that maps a bundle at stage t to the bundles in stage $t + 1$ which are composed of the same scenarios, namely we define antecedent and subsequent relationships among nodes.

Moreover, the objective function stated in (1) becomes:

(8)
$$
W(n) = \sum_{\omega_s(t)\in\Omega} p_\omega \{L(n,\omega_s(t))\{\log[c(n,\omega_s(t))]\}R(\omega_s(t))\}
$$

Random elements which are defined on the event tree are, in our case, the stochastic evolutions of the two effective learning accumulation parameters. In particular, the stochastic evolutions of the stocks of knowledge and experience, previously expressed in equation (2) and (3), now become:

(9)
$$
K_i(t+1,\omega_s(t)) = \xi_i(t,\omega_s(t))^* I_i(t,\omega_s(t)) + (1-\delta_i)K_i(t,\omega_s(t)), \text{ for } i = \text{know}, LbD.
$$

The scenario tree describing the values of the parameters in the root and in the subsequent nodes depicted in Figure 4, shows four alternate scenarios which result from the combination of high versus low values of the two effective learning accumulation parameters.

They combine: high $ξ_{LbD}$, for a fast learning-by-doing, meaning a fast decrease of abatement price with increased capacity; low ξ_{LbD} , for a slow learning-by-doing, slow decrease of abatement price with increased installed capacity; high ξ_{know} , where investment in R&D is very efficient and translates into useful discoveries and there is little inertia in technology diffusion; low ξ_{know} , where learning is slow and the system is characterized by high inertia. The event tree is decomposed in two stages: a first stage where the parameters ξ_{know} and ξ_{LbD} are fixed to their central values and a second stage combining the four scenarios. Decisions in the first three periods are thus taken under knowledge accumulation and learning-by-doing uncertainty. The values of the parameters and the description of the scenarios are given in Table 4.

Values and probabilities associated with nodes in the tree are chosen in order to replicate moments of the estimated distribution of parameters, which has been inferred by historical data. In the estimation process more recent data and trends play a more important role, accounting for the fact that an increased rapidity has characterized learning in more recent years. ξ *know* time-series is built for years 1974-1990 using two historical datasets, namely the US Research & Development Stocks (Coe and Helpman, 1995) and the US Energy Research & Development investments (Dooley and O'Sullivan, 2001). Moreover, following Popp (2004) we assume that 2% of the total stock of knowledge capital is dedicated to the energy sector. Assuming for knowledge accumulation a dynamic as stated in (3), then the value of ξ_{know} lies in the range 0.018-0.58; the mean value is 0.22 and the standard deviation is 0.14. The distribution for ξ_{know} is plotted in Figure 5, scaled by the density probabilities. Values of parameter ξ_{LbD} are estimated assuming learning in energy technology, in terms of progress ratio, of approximately 21%.

The results of the stochastic problem are discussed below. We focus on short-term strategies, and in particular on R&D investments and emissions reductions, as these are the main policy levers accounted for in the model. In Figure 6 and 7, the stochastic problem is compared to the expected value problem -i.e. the deterministic problem solved for expected values of the stochastic parameters, named "*exp*" and to the pessimistic problem -i.e. the deterministic problem solved assuming pessimistic realization for both parameters, referred to as "*pes*" in the following discussion. The comparison exercise tells us how misleading it is to leave uncertainty out of forecasting exercises. Different approaches and solutions have been tested on two specific scenarios: the Business as Usual, BaU in Figure 6, case with no limit on carbon emissions but that is implicitly defined by the embedded damage function (cost-benefit scenario); and a stabilization scenario in Figure 7, where atmospheric carbon concentrations are limited below 550 ppmv (cost minimizing scenario).

Table 5 shows how much first-stage solutions of the expected value problem and of the pessimistic problem differ from the first-stage stochastic solution, both in the baseline and in the stabilization scenarios. It is immediately clear that formulating the problem in stochastic programming terms is crucial when a cost-minimizing stabilization scenario is considered. Specifically, the difference between the stochastic solution and other benchmark solutions represents the error we would incur into if we did not include in our analysis the possibility of revising our decision variables when better information becomes available. In particular, we tend to underestimate optimal first stage investment in R&D, whether we take a pessimistic approach on effective learning of R&D and experience, or we consider that parameters will take their expected value. Knowing that we can revise our positions on investments in R&D, once they are found to be less productive than we had expected, then the optimal level of expenditure in new knowledge should be higher in the short-run. Conversely, we would overestimate immediate optimal emission reductions if relying on the "exp" formulation solution. Indeed, policy-makers should undertake some immediate action because there is a possibility that experience will pay back in terms of lower abatement costs; but abatement has a cost, thus it may pay off to moderate abatement and to wait and see how effective learning-by-doing is. On the other hand, should policy-makers choose optimal abatement strategies on the basis of a pessimistic approach, they would underestimate the necessity of at least some immediate action and almost completely dismiss the issue of learning-by-doing.

These conclusions are drawn from an analysis necessarily based on assumptions and simplifications (e.g. on how to describe uncertainty surrounding the two learning factors). However, results have been tested and proved robust to changes in the way the probability distribution is discretized and on the date of arrival of information.

5. Conclusions.

We can now respond to some of the major questions that have been driven our research. Can R&D expenditures be always considered as a hedge against climate change damages? Or does uncertainty of learning processes delay and/or decrease R&D investments? It appears that, accounting for uncertainty and for the future arrival of new and better information, optimal total R&D investment should be higher, especially when considering a cost minimization (stabilization) scenario. Accounting for the flexibility of stepping back in the case research is not driving towards technological breakthroughs, immediate R&D investments turn to be crucial. Indeed, they might produce important discoveries or they might induce, through the reduction of emissions, some Learning-by-Doing effects, or both.

In addition, how does Learning-by-Doing interact with these effects? Should we wait before curbing emissions? Or act now in order to decrease abatement costs? It appears that, accounting for an uncertain Learning-by-Doing effect, some near-future curbing efforts should be undertaken. However, given that in the immediate the cost of reducing emissions are high and the effectiveness of the Learning-by-Doing effect is uncertain, emission reduction should be moderate. In the meantime, waiting and investing in R&D appears to be more effective, in cost-benefit terms.

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8. Appendix: Model Equations

In this appendix we reproduce model equations. In each region, *n*, there is a social planner who maximizes the following utility function (*n* indexes the world's regions, *t* are 10-years time spans).

(A1)
$$
W(n) = \sum_{t} U[C(n,t), L(n,t)]R(t) = \sum_{t} L(n,t)\{\log[c(n,t)]\}R(t)
$$
,

where the pure time preference discount factor is given by:

(A2)
$$
R(t) = \prod_{v=0}^{t} [1 + \rho(v)]^{-10},
$$

and the pure rate of time preference $\rho(v)$ is assumed to decline over time. Moreover, $c(n,t) = \frac{C(n,t)}{L(n,t)}$. The maximization problem is subject to:

Economic Module:

(A3)
$$
Q(n,t) = A(n,t)[K_F(n,t)^{1-\alpha_n(T_P)-\gamma}CE(n,t)^{\alpha_n(T_P)}L(n,t)^{\gamma}] - p_e(n,t)^*CE(n,t)
$$

$$
(A4) \qquad \alpha_n(TP) = \frac{\beta_{1n}}{2 - \exp^{-\beta_{0n} * TP(n,t)}}
$$

(A5)
$$
Q(n,t) = C(n,t) + I(n,t) + 4 * crowdout * R & D(n,t)
$$

$$
(A6) \qquad K_F(n,t+1) = (1 - \delta_K)K_F(n,t) + I(n,t+1)^4
$$

(A7)
$$
E(n,t) = \varsigma(n,t) \left[\frac{1}{2 - \exp^{-\psi_n * TP(n,t)}} \right] C E(n,t)
$$

$$
(A8) \quad TP(n,t) = [Abat_s(n,t)^{c} * K_R(n,t)^{d}]
$$

$$
(A9) \quad Abat_{S}(n,t+1) = \xi_{LbD} Abat_{F}(n,t) + (1 - \delta_{A})Abat_{S}(n,t)
$$

(A10)
$$
K_R(n,t+1) = \xi_{R\&D} * R \& D(n,t) + (1 - \delta_R)K_R(n,t)^5
$$

(A11)
$$
Q(n,t) = C(n,t) + I(n,t) + R & D(n,t)
$$

$$
(A12) \quad p_n^E(t) = q(t) + \text{markup}_n^E
$$

 \overline{a}

 4 Second, the potential effects of crowding out must be considered. The opportunity cost of a dollar of energy R&D is that one less dollar is available for any of three possible activities: consumption, physical investment, or investment in other R&D. The opportunity costs of the first two are simply valued at one dollar. However, since the social rate of return on R&D is four times higher that of other investment, losing a dollar of other R&D has the same effect as losing four dollars of other investment. Thus, the price of any research that crowds out other research is four dollars. To implement this, four dollars of private investment are subtracted from the physical capital stock for each dollar of R&D crowded out by energy R&D, so that the net capital stock is given by(A) where crowdout represents the percentage of other R&D crowded out by energy R&D. The base ENTICE model assumes 50% crowding out.

⁵ Here it is not clear whether we can find in literature some reliable estimate for the initial value pf x (we want to be published!). If not we could change specification and use Popp's, as in (A10). I already inserted the parameter values he suggests.

Climate Module:

(A13)
$$
M_{AT}(t+1) = \sum_{n} \left[E_n(t) + LU_j(t) \right] + \phi_{11} M_{AT}(t) + \phi_{21} M_{UP}(t)
$$

\n(A14) $M_{UP}(t+1) = \phi_{22} M_{UP}(t) + \phi_{12} M_{AT}(t) + \phi_{32} M_{LO}(t)$
\n(A15) $M_{LO}(t+1) = \phi_{33} M_{LO}(t) + \phi_{23} M_{UP}(t)$
\n(A16) $F(t) = \eta \left\{ \log \left[M_{AT}(t) / M_{AT}^{PI} \right] - \log(2) \right\} + O(t)$
\n(A17) $T(t+1) = T(t) + \sigma_1 \left\{ F(t+1) - \lambda T(t) - \sigma_2 \left[T(t) - T_{LO}(t) \right] \right\}$

(A18)
$$
\Omega_n(t) = \frac{1}{1 + (\theta_{1,n} T(t) + \theta_{2,n} T(t)^2)}
$$

List of variables:

- $W =$ welfare
- $U =$ instantaneous utility
- *C* = consumption
- *c* = per-capita consumption
- $L =$ population
- *R* = discount factor
- *NIP* = net import of permits
- *R&D* = investment in R&D
- *Q* = production
- Ω = damage
- $A =$ productivity or technology index
- K_F = capital stock
- *CE* = carbon energy
- p^E = cost of carbon energy
- *I* = fixed investment
- $E =$ carbon emissions
- M_{AT} = atmospheric CO_2 concentrations
- *LU* = land-use carbon emissions
- M_{UP} = upper oceans/biosphere $CO₂$ concentrations
- M_{LO} = lower oceans CO_2 concentrations
- $F =$ radiative forcing
- *T* = temperature level
- $q = \text{costs}$ of extraction of industrial emissions

List of parameters:

- α , γ = parameters of production function
- δ_K = rate of depreciation of capital stock
- ζ = exogenous technical change effect of energy on CO₂ emissions (carbon intensity)
- ϕ_{11} , ϕ_{12} , ϕ_{21} , ϕ_{22} , ϕ_{23} , ϕ_{32} , ϕ_{33} = parameters of the carbon transition matrix
- η = increase in radiative forcing due to doubling of CO₂ concentrations from pre-industrial levels
- σ_1 , σ_2 = temperature dynamics parameters
- λ = climate sensitivity parameter
- \textit{markup}^E = regional energy services markup
- θ_1 , θ_2 = parameters of the damage function
- M_{AT}^{PI} = pre-industrial atmospheric CO₂ concentrations
- p_{NIP} = price of permits
- O = increase in radiative forcing over pre-industrial levels due to exogenous anthropogenic causes
- $\rho =$ discount rate
- T_{LO} = lower ocean temperature

Parameter	Range of Values	Default Value	
E Sknow	$0.0 - 1.0$	0.25	
ξ_{LbD}	$0.0 - 1.0$	0.1	
	$0.1 - 1.0$	0.5	
	$0.9 - 1.5$		
	$0.1 - 1.0$	0.1	

Table 1. Range of values of the uncertain parameters.

	2025	2045	2095
$1 - 0.4$	0.18%	0.78%	8.73%
$1 - 0.2$	0.10%	0.42%	4.18%
$1 + 0.2$	$-0.12%$	$-0.46%$	$-3.72%$
$1 + 0.4$	$-0.25%$	$-0.96%$	$-6.98%$

Table 2. Sensitivity analysis wrt to^ψ **. Long and short-term percentage changes in emissions relative to the standard case with default values.**

	2025	2045	2095
$0.5 - 0.05$	0.64%	1.04%	7.89%
$0.5 + 0.05$	$-0.70%$	$-1.03%$	-3.48%
$0.5 + 0.1$	-1.44%	$-2.46%$	-8.98%

Table 3. Sensitivity analysis wrt toφ **. Long and short-term percentage changes in emissions relative to the standard case with default values.**

Table 4. Values of ξ *know* **and** ξ *LbD* **in the scenario tree.**

	BaU		550 ppmv	
	EXP	PES	EXP	PES
R&D expenditures (in trillions 1990 USD)	0.00%	11.11%	5.26%	57.89%
World carbon emissions (GTC per year)	$-0.01%$	-0.02%	$-0.13%$	0.46%

Table 5. Difference in "*exp***" and "***pes***" first stage values of R&D expenditures and emissions wrt stochastic solution.**

Figure 1. Sensitivity analysis wrt to ξ *know* **. Long and short-term percentage changes in emissions and stock of world knowledge relative to the standard case with default values.**

Figure 2. Sensitivity analysis wrt to ξ *LbD* **. Long and short-term percentage changes in emissions and stock of world knowledge relative to the standard case with default values.**

Figure 3. Sensitivity analysis wrt to λ **. Long and short-term percentage changes in emissions and stock of world knowledge relative to the standard case with default values.**

Figure 4. The four scenarios as in the simulation experiment.

Figure 5. Distribution of observed values of the effective cumulative learning for R&D investments, ξ *know* , **based on reference data with its best fitted Gaussian density function.**

World Energy Knowledge stock (in trillions \$) World carbon Emissions (in GtC)

World knowledge stock (in trillions \$) World carbon Emissions (in GtC)

Figure 7. The 550 ppmv stabilization scenario.

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