**CENTRO EURO-MEDITERRANEO
PER I CAMBIAMENTI CLIMATICI**

CIP – Climate Impacts and Policy Division

Stabilisation Targets, technical Change and the Macroeconomic Costs of Climate Change

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Working Papers

2006 ■ WP 3
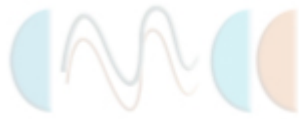
Stabilisation Targets, technical Change and the Macroeconomic Costs of Climate Change

Summary
The issue of greenhouse gas (GHG) stabilization stands on three critical open questions. Namely, what are the impacts deriving from different levels of climate change and their distribution. What are the levels at which GHG concentration should be stabilized in order to avoid unacceptable impacts. And, finally, what are the costs and what are the instruments available to reach such stabilization targets. In the present paper, we address the latter question, in the specific attempt of shedding some light on the debated role of technological progress in lowering the costs of GHG stabilization. In particular, we use an optimal growth climate-economy model, where technical change is endogenously driven by learning by researching and learning by doing. In the model, when an ambitious stabilization target has to be reached, some additional technological innovation and diffusion is induced. The magnitude of this induced effect substantially affects the costs of stabilizing greenhouse gasses and may even make a well-designed climate policy a win-win strategy. A sensitivity analysis on the model crucial parameters is performed to account for structural and parametric uncertainties on learning effects, on the relationship between knowledge accumulation and the energy and carbon intensity of the economic system, and on the crowding out of investments in the energy sector R&D with respect to other research fields.

Keywords: Climate Policy, Environmental Modelling, Integrated Assessment, Technical Change

JEL Classification: H0, H2, H3
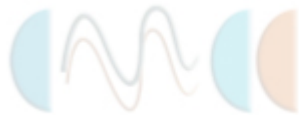
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1. Introduction

Technological change (TC hereafter) is a major force in a country's economic growth. Since before the industrial revolution, economies and societies have evolved as a result of technological change. This evolution has been largely beneficial, even though asymmetrically distributed within and across societies. However, the economic growth fostered by technical changes has had and still has a large impact on natural resources and the global environment. Among these impacts, the release of large amounts of carbon into the atmosphere is certainly a potentially damaging one, at least in the long-run. The scientific consensus is that these emissions will contribute to changing the earth's climate, with the consequent expected effects on e.g. average temperature, sea level, precipitation patterns, and consequently on agriculture production, coastal zone urban settings, biodiversity, vector born diseases, and so on.

Controlling the influence of human activities on climate is not an easy task. The international agreements that have so far come into force have only had and will have a very small impact on greenhouse gas (GHG) atmospheric concentrations. Stabilizing these concentrations at, for example, twice the pre-industrial levels requires per capita global emissions to peak and then decline to (at least) half their 1990 value by the end of the twenty-first century.[1] This seems to be feasible only through drastic technological change in the energy sector, i.e. technological innovation is increasingly seen as the main way of reconciling the current fundamental conflict between economic activity and environmental protection.

No one really believes or is ready to accept that the solution to the problem of climate change is to reduce the pace of economic growth. Instead, it is believed that changes in technology will bring about the long awaited de-coupling of economic growth from the generation of polluting emissions. There is a difference in attitude in this respect, though. Some maintain a faithful view that 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 therefore has to be fostered by appropriate policy actions.

Technological change generally leads to the substitution of obsolete and dirty technologies with cleaner ones. It must be borne in mind, however, that technical change is not per se always environment-friendly, as it can lead to the emergence of new sectors and industries with new kinds and degrees of pollution problems, like the generation of new harmful

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[1] See Bosetti, Galeotti, and Lanza (2004) for a detailed analysis.

pollutants. There are therefore no substitutes for policy in directing the innovation efforts toward fostering economic growth and helping the environment at the same time (see the evidence in Galeotti, 2003).

All the above remarks are reflected in climate-economy 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, however, models have been proposed where technology changes endogenously and/or its change is induced by deliberate choices of agents and government intervention. Both bottom-up and top-down models, a long standing distinction in energy-economy-environment modelling, have been recently modified in order to accommodate forms of endogenous technical change. As it turns out, the bottom-up approach has mostly experimented with the notion of Learning by Doing (LbD henceforth), while a few top-down models have entertained the notion of a stock of knowledge which accumulates over time via R&D spending.

We do not intend to review here the recent literature on the role of TC in the economics of climate change and on the endogenisation of TC in climate-economy models. This has been done elsewhere (see, for instance, Carraro and Galeotti, 2002, 2004; Löschel, 2002; Sijm, 2004).[2] Our intention here is rather to identify the main features that a model of technological change should possess (see Clarke and Weyant, 2002, for a similar exercise) and then develop a new climate-economy model in which most of these features are taken into account.

In the new model, dubbed FEEM-RICE v.3, that will be presented and tested in this paper, changes in technology affect the economy and climate through modifications of both the energy intensity of production and the carbon emission intensity of energy consumed. The driver of these intensity ratios is a new, crucial variable, deemed Energy Technical Change Index (ETCI), which is a convex combination of two stocks, an abatement-based one and an R&D-based one. These stocks are designed to capture the two main modes of endogenous TC, Learning-by-Doing (LbD) and Learning-by-Researching (LbR). We hypothesize that these two sources of technical change cannot easily substitute one another.

As there is basically little guidance to the calibration of the crucial TC parameters, in particular in the context of a regional climate-economy model of the world economy like the one proposed in this paper, we carry out a number of optimisation runs in which the key TC

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[2] A very recent exercise is the Innovation Modelling Comparison Project (IMCP), the results of which are summarized in Edenhofer, Lessmann, Kemfert, Grubb, and Köhler (2005).

parameters are modified and their impacts on the energy and carbon intensity in different regions of the world are quantified. This sensitivity analysis will enable us to test the robustness of the model, and to identify which parameters drive our main results.

After having described and tested the model, this paper focuses on a few policy exercises designed to assess the effects and costs of measures aimed at stabilising GHG concentrations. In this paper we concentrate on the specific target of stabilizing CO_2 concentrations.[3] Article 2 of the United Nations Framework Convention on Climate Change (UNFCCC) had established the central goal of "stabilization of greenhouse gases (GHGs) concentrations in the atmosphere" In its Third Assessment Report the IPCC, the scientific advisory board to the UNFCCC laid out various long-term stabilization scenarios for GHG concentrations with associated ranges of expected increases in global mean temperature (IPCC, 2001).

In the light of these institutional endorsements, we follow the bulk of the literature and adopt in this paper a concentrations target.[4] Because of the uncertainty characterizing long-term stabilisation targets, we consider three alternative numerical values corresponding to more and less ambitious goals.

The remainder of the paper is as follows. Section 2 briefly surveys the recent literature on endogenous and induced technical change in climate-economy models, and identifies the main features that an ideal model should possess. Section 3 presents the FEEM-RICE v.3 model and provides a technical discussion on how TC has been modelled. Section 4 discuss the model calibration procedure, while Section 5 tests the sensitivity of our formulation of technical change to changes in its main parameters. Section 6 presents the main results of our analysis of different stabilization scenarios and outlines the macroeconomic costs of alternative policy measures. Some concluding comments and suggestions for further research close the paper.

2. Modelling Endogenous Technical Change: A Brief Overview

Endogenous TC does not involve the mere passage of time, but it stems from deliberate research and the innovation decisions of economic agents. These decisions are influenced by a variety of economic factors, that are not limited to the changes in relative prices. In other

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[3] Let us stress that this is not the only target that could be selected. As a matter of fact, alternative goals could be adopted along the climate cycle. Different targets present advantages and shortcomings as thoroughly discussed by, for instance, Pershing and Tudela (2003) and Bosetti, Galeotti e Lanza (2004). In general, focusing on earlier stages (such as production or emissions) means having more precise information on what the required effort should be, but it may not produce effectively the desired effects, mainly because of the loose relationship between actions and climate damages. The reverse is true for targets imposed on later stages.

[4] See the papers forthcoming in the special issue of the Energy Journal (Edenhofer, Lessmann, Kemfert, Grubb, and Köhler, 2005).

words, endogenous TC refers to both shifts *of* the production isoquant, and shifts *along* the production isoquant. Policy measures adopted at the local, national or international level may play an important role in stimulating these technological changes.

As noted by Clarke and Weyant (2002), theoretical work on endogenous TC is comprised of essentially two strands: innovation theory and endogenous growth theory.[5] Innovation theory has a microeconomic focus, looks at individual firms and industries, and stresses the incentives and the inefficiencies that result from the failure to share the benefits of the innovation activity. Endogenous growth theory has a macroeconomic focus, and analyses how investment in innovation by private agents can be a source of aggregate economic growth.

Climate-economy models typically try to combine aspects of both theories. They both stress the importance of knowledge as being a public good and highlight the importance of spillovers, as the incomplete appropriability of the benefits from innovation by private firms creates positive externalities. Spillovers cause underinvestment in innovation. Most theoretical work shows and empirical work confirms that markets do not invest efficiently in innovation and that underinvestment is significant enough to warrant attention by policy makers. This situation is known as "innovation market failures" and should represent an essential aspect of endogenous TC modelling.

It is a useful exercise to consider the main ingredients of endogenous TC and the various aspects of innovation market failures. Consideration of these elements will provide a sort of checklist that can be used against the climate-economy models incorporating endogenous TC that have appeared in the recent literature. And, above all, it will be useful to identify the main features of the new model that will be described below.

Let us therefore summarize the main features that an ideal climate-economy model with endogenous TC should possess (see Clarke and Weyant, 2002):

- Because spillovers are a fundamental source of economic growth, they ought to be incorporated in any model aiming to model the long-term process of TC. A full accounting of spillovers in climate-economy models is probably asking too much, as they occur within industries, across industries within countries, and across countries. Clearly, however, to account for intersectoral spillovers a model must be disaggregated by sector, while to account for international spillovers the model must include regional disaggregation.

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[5] This is not to say that theorizing in the field of TC is limited to these two areas only. Innovation and endogenous growth are the two areas most directly relevant for modeling endogenous TC in climate-economy models.

- The difference between private and social returns associated with innovation activity ought to be acknowledged. Private returns to R&D tend to be appreciably smaller than social returns, in proportions of 20-30% to around 50% according to the empirical studies considered.

- Climate-economy models with endogenous TC must specify the mechanism through which technological change takes place and the way it alters technology. The two mechanisms that have been considered to date are research and development spending and experience building. An advantage of the LbD approach is its simplicity and its reduced calibration requirements relative to the R&D approach. The latter, on the other hand, allows for more room for policy maneuvering (energy/environmental R&D can be subsidized or stimulated) and additional control variables to rely on. Clearly, neither approach is a complete picture of what goes on in reality, so models based on one or the other formulation inevitably miss something important. While no model can closely approximate the real world, the question is whether and at what modeling cost it is possible to account for both varieties of endogenous TC in a satisfactory manner.

- Besides the choice between R&D vs. experience drivers, it is also important to specify where and how those drivers actually bring about a change in technology. One distinction is between energy and non-energy sector. Our modeling strategy is to start with endogenous TC in the energy industry, leaving other TCs as exogenous. While, as previously noted, it is true that intersectoral spillovers are important, it would probably be too complex to include the complex interrelations between energy technologies and other techonlogies. The resulting model would be too abstract or too cumbersome to be of any use.

- It is worthwhile considering two sources of energy-saving or carbon-saving improvements: decarbonization of energy services and reduction in the energy intensity of economic activities. The second source is more complicated to account for since it involves R&D in sectors other than the energy industry. In the light of the previous remark, modelers may consider assumimg that the evolution of the energy intensity of non-energy technologies is exogenously generated.

- There are complementary sources of technological advance. One is public sector R&D: publicly financed research will accompany subsidies to private R&D in the form of TC fostering policies. Another source is intersectoral spillovers, already mentioned above. The final source of TC is major innovations and breakthroughs. What do these

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complementary sources tell us about modeling TC? The implication is that ultimately some technological progress must remain exogenous.

- Technological heterogeneity is an important issue. One potential implication is discontinuous TC. Even if innovation is continuous and incremental in individual technologies, the aggregate production function's response to innovation investment may be non-linear and exhibit discontinuities. What do endogenous TC models miss when they aggregate technologies? Aggregate models are not able to account for the relevance of emerging technologies and the associated notion that the *allocation*, not only the *absolute level*, of innovation is important. Models can in principle account for heterogenous technologies. Bottom-up models are best suited for the purpose, whereas top-down models can probably at most distinguish between carbon-intensive and non-carbon-intensive technologies.

- TC is an uncertain process. Uncertainty affects both the rate and direction of TC. It also characterizes the potential for new technologies, that is the extent to which individual technologies will respond to R&D or experience, and the heterogeneity and discontinuities in technology development. Essentially these are "parameter" uncertainties, where the parameters refer to the response of technology to innovative effort or R&D. The uncertainties can be addressed by basing that response on expected values of uncertain parameter distributions.

- Innovation takes time and is risky. To the extent that markets have different preferences for risk and time than society preferences, markets will invest in innovation differently than would be socially optimal. Risk aversion and discounting start to play a role when we consider technological heterogeneity, and emerging environmental technologies in particular. This aspect can be then best addressed by bottom-up models which are capable of distinguishing between more mature and newer technologies, and between more and less competitive technologies. The deviation of private risk aversion and time preference from socially preferred values can however also be captured, though in an ad hoc fashion, by bottom-up models that arbitrarily increase the price of R&D resources or adjust the spillover parameter(s) upward.

- Not all investment activity can be captured by models assuming rational behavior. Entrepreneurial spirit can also guide innovation choices. While climate-economy models are likely to face serious difficulties in explicitly accounting for this aspect, they can nevertheless allow for an implication of quasi-rational, or routine-based behavior (as in

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evolutionary theories): the tendency to undertake research efforts on technologies already in use will bias private sector behavior toward dominant technologies. The effect is therefore similar to the one made in the previous point .

- The very essence of evolutionary economics and historical evidence suggest that technological change evolves with a lot of inertia. It is, in other words, characterized by path dependence. This implies that the rate, and especially the direction, of TC may respond sluggishly to economic stimuli relative to the no-friction standard neoclassical models. More problematically, it also implies that what we do today affects how the economy will respond in the future, i.e. today's actions redirect the future path of TC. Incorporating path dependence into climate-economy models is probably prohibitively complicated, unless perhaps if we resort to adding time lags to the process of technology development.

- A final point refers to technology diffusion as opposed to technology innovation. One obvious way to account for this aspect is the introduction of time lags. This strategy does not do justice to the importance and implications of technological diffusion vis-à-vis technology development, but it may represent a reasonable shortcut, an acceptable compromise to make especially in top-down models.

To date the literature includes only a few examples of climate-economy models where TC is explicitly endogenised. The list is however expanding (see Edenhofer, Lessmann, Kemfert, Grubb, and Köhler, 2005). As said above, we do not review these various models here. We simply mention these models and refer to Table 1 below for a picture showing which of the above ideal aspects each individual model does or does not address.

Table 1: Induced TC Features of Some Climate Models

	R&D	Learning	Technology Spillovers	Private/social returns to R&D Opportunity cost of R&D	ITC in non-energy	Energy saving ITC	Carbon saving ITC	Public R&D complementary sources of TC	Technological heterogeneity	Technological uncertainty	Path dependence	Diffusion
R&DICE	yes	no	no	yes	no	no	yes	yes	yes	no*	no	no
ETC-RICE	yes	yes	yes	no	yes	no	yes	yes	no	no	no	no
Demeter 1	no	yes	no	no	no	yes	yes	yes	yes	yes	no	no
MERGE	no	yes	no	no	no	yes	yes	yes	yes	no**	yes	yes
ERIS/MARKAL/ MESSAGE	no	yes	no	no	no	yes	yes	no	no	no	yes	yes
Barreto & Kypreos	yes	yes	yes	no	no	yes	yes	no	no	no	yes	yes
Entice	yes	no	no	yes	no	no	yes	yes	no	no	no	no
Demeter 2	yes	yes	no	no	no	yes	yes	yes	yes	no	no	no
Entice-BR	yes	no	no	yes	no	no	yes	yes	yes	no	no	no
WIAGEM	yes	no	yes	yes	yes	yes	no	yes	yes	no	no	no
FEEM-RICE	yes	yes	yes	yes	no	yes	yes	yes	no	yes	no	no

* Uncertainty on technology is however discussed in Nordhaus, W. D. and Popp, D. (1997), "What is the value of Scientific Knowledge? An application to global warming using the PRICE Model", The Energy Journal, 18-1, 1-44

** Uncertainty on technology is however discussed in Manne, A. S. and Richels, R.G. (2003), "Stabilizing Long-Term Temperature", Working Paper, Stanford University

The models considered are, in the bottom-up energy systems class, versions of the multi-regional MESSAGE-MARKAL model (Messner, 1997; Barreto and Kypreos, 2002a; Criqui, Klaassen, and Schrattenholzer, 2000; Miketa and Schrattenholzer, 2002; Barreto and Kypreos, 2002b, 2004). These are dynamic linear programming models of the energy sector that are generally used in tandem with MACRO, a macro-economic model which provides economic data for the energy sector (Manne, 1981; see also Seebregts, Kram, Schaeffer, Stoffer, Kypreos, Barreto, Messner, and Schrattenholzer, 1999; Manne and Barreto, 2004). These models yield the optimal choice between several different technologies using given abatement costs and carbon emission targets. In addition, they feature a learning or experience curve describing technological progress as a function of accumulating experience with production (LbD for manufacturers) and with use (learning-by-using – LbU – for consumers) of a technology during its diffusion.

Among top-down models, we consider Manne and Richels (1992)'s MERGE model, a regional intertemporal growth model which combines a top-down perspective on the remainder of the economy together with a bottom-up representation of the energy supply sector. In a recent version of the model (Manne and Richels, 2002), one of the previous two electric backstop technologies, the low-cost one, is replaced by a LbD process. Another model which exploits the notion of LbD to endogenize technical change is DEMETER, a global model proposed by van der Zwaan, Gerlagh, Klaassen, and Schrattenholzer (2002) (see also Gerlagh and van der Zwaan, 2000; Gerlagh, van der Zwaan, Hofkes, and Klaassen, 2000; Gerlagh and van der Zwaan, 2004). A macroeconomic (top-down) model is specified which distinguishes two different energy technologies, carbon and carbon-free. The costs of the latter are dependent upon the cumulative capacity installed. Thus the model is expanded with learning curves previously used in energy system (bottom-up) models.

A recent evolution of DEMETER is the partial equilibrium model of energy supply and demand elaborated by Gerlagh and Lise (2003). DEMETER-2E, as it is called, entertains two energy technologies for the production of a carbon-rich and a carbon-poor input. R&D is combined with LbD: R&D-based knowledge is combined with capital and labour in a technology which produces more and more energy input over time thanks to LbD.

An example of multi-region, multi-sector integrated assessment model with endogenous TC is Kemfert (2002)'s WIAGEM. In this recursive dynamic computable general equilibrium model, R&D spending affects the productivity of the energy input in the production process. More R&D therefore results in increased energy efficiency. It is to be noticed that R&D

enters the model as a flow, whereas most of the other R&D-based models adopt the stock of knowledge, accumulated through R&D investments, as the driver of TC.

Finally, there are models of endogenous TC that extend the Nordhaus' RICE/DICE family of models. In particular, we consider the optimal growth (regional) RICE model elaborated by Buonanno, Carraro, Castelnuovo, and Galeotti (2000) and Buonanno, Carraro and Galeotti (2002). This model, called ETC-RICE, extends Nordhaus and Yang (1996)'s RICE model to allow for a R&D-based formulation of endogenous TC. In the vein of Goulder and Mathai (2000), in subsequent work Castelnuovo, Galeotti, Gambarelli, and Vergalli (2005) specify a version of the ETC-RICE model that features instead an experience-based endogenous TC.

The new version of the RICE/DICE model (Cf. Nordhaus and Boyer, 2000) is used by Nordhaus (2002) to lay out a model of endogenous innovation brought about by R&D efforts. Nordhaus' work is extended by Popp (2004a) with his ENTICE model. As in Nordhaus, R&D is four times more costly than physical investment, to account for the divergent social and private rates of return associated with R&D. In addition, the author assumes that 50% of other R&D is crowded out by energy R&D, thus raising the opportunity cost of the latter.[6] In a very recent variation, dubbed ENTICE-BR, Popp (2004b) extends the ENTICE model to also include an energy backstop technology. Finally, Popp (2004c) uses the ENTICE model to study the role of government subsidies to climate-friendly R&D. These are found to significantly increase R&D, but to have little effect on climate damages.

As it can be seen from this brief overview – and above all from Table 1 – existing models fall short of addressing the ideal features of endogenous TC that were outlined at the beginning of this section. This is why, in the next section, we will present a new model of endogenous TC that we hope will prove more satisfactory than previous ones.

3. Modelling Endogenous Technical Change: The FEEM-RICE v.3 Model

The FEEM-RICE v.3 model is an extended version of the RICE 99 model by Boyer and Nordhaus (2000).[7] RICE 99 is a Ramsey-Koopmans single sector optimal growth model suitably extended to incorporate the interactions between economic activities and climate. There is one such model for each of the eight macro regions into which the world is divided: USA, Other High Income countries (OHI), OECD Europe (Europe), Russia and Eastern

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[6] As stated, unlike Nordhaus' R&DICE model, Popp's ENTICE model does not impose zero substitution possibilities between energy on the one hand and capital and labor on the other when research is endogenously determined.

[7] RICE 99 is an extension of the RICE 96 model described in Nordhaus and Yang (1996).

European countries (REE), Middle Income countries (MI), Lower Middle Income countries (LMI), China (CHN), and Low Income countries (LI).

Within each region a central planner chooses the optimal paths of two control variables, fixed investment and carbon energy input, so as to maximize welfare, defined as the present value of per capita consumption. The value added created via production (net of climate change) according to a constant returns technology is used for investment and consumption, after subtraction of energy spending. The technology is Cobb-Douglas and combines inputs from capital, labour and carbon energy together with the level of technology. In RICE 99, 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 production function of the original RICE 99 model is (n indexes regions, t time periods):

$$Q(n,t) = A(n,t)[K_F(n,t)^{1-\gamma-\alpha_n} CE(n,t)^{\alpha_n} L(n,t)^{\gamma}] - p_n^E CE(n,t) \tag{1}$$

where Q is output (gross of climate change effects), A the exogenously given level of technology and K_F, CE and L are the inputs from physical capital, carbon energy and labour, respectively, and p^E is fossil fuel price. Carbon emissions are proportional to carbon energy, that is:

$$E(n,t) = \zeta(n,t) CE(n,t) \tag{2}$$

where E is industrial CO_2 emissions, while ς is an idiosyncratic carbon intensity ratio which also exogenously declines over time. In this way, Nordhaus and Boyer (2000) make the assumption of a gradual, costless improvement of the green technology as time goes by. This treatment of technical change appears inadequate for a model designed to study issues related to climate change and climate policy. This is why we developed an extension of RICE 99 in which technical change is endogenous and responds to climate policy as well as to other economic and policy incentives.

In FEEM-RICE v.3, we consider simultaneously both *LbD* and *LbR* as inputs of endogenous and induced technical change and we focus on the effects of technical change on both the energy intensity of production and the carbon intensity of energy use. These features of the model allow us to address both energy-saving and energy-switching issues. To clarify this

aspect it is perhaps useful to refer to a time-honoured concept in environmental economics, namely the Kaya's identity, which in the present specific case reads as follows:

$$E(t) = \sum_n \left(\frac{E(n,t)}{CE(n,t)} \right)\left(\frac{CE(n,t)}{Q(n,t)} \right)\left(\frac{Q(n,t)}{L(n,t)} \right) L(n,t) \tag{3}$$

where E is world emissions, CE is carbon energy, and L is population. Hence, world emissions are a product of two 'forces': techno-economic forces, given by carbon intensity (E/CE) and energy intensity (CE/Y), and socio-economic forces, given by per capita output (Y/L), as well as demographic dynamics L. In addition to socio-economic forces – income and population – which are commonly modelled in endogenous growth models, our model allows us to endogenise both techno-economic forces, namely energy and carbon intensity.

The main novelty of our new formulation hinges on the relationship between technical change and both Learning-by-Researching and Learning-by-Doing *at the same time*. We assume that energy-saving and climate-friendly innovation is brought about by R&D spending which contributes to the accumulation of the stock of existing knowledge.[8] In addition to this Learning-by-Researching effect, the model also accounts for the effect of Learning-by-Doing, now modelled in terms of cumulated abatement efforts. Thus, our index of technical change, *ETCI* (Energy Technical Change Index), is defined as a convex combination of the stocks of knowledge and abatement:

$$ETCI(n,t) = K_R(n,t)^c ABAT_S(n,t)^d \tag{4}$$

where $K_R(n,t)$ is the stock of knowledge and $ABAT_s$ represents the stock of cumulated abatement, in turn defined as:

$$ABAT_S(n,t+1) = \delta_A ABAT_F(n,t) + (1-\delta_B)ABAT_s(n,t). \tag{5}$$

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[8] Therefore, the focus is on energy-related R&D. It has to be pointed out that analysing R&D expenditure is complicated because (i) R&D is not always amenable to measurement and (ii) there is a great deal of uncertainty in the ability of R&D to generate technological change. These words of caution should be therefore borne in mind by the reader when going through the paper.

$ABAT_F$ the abatement flow, δ_A the learning factor, i.e. the amount of abatement which translates into a learning experience, and δ_B being the depreciation rate of cumulated experience. The stock of knowledge $K_R(n,t)$ accumulates in the usual fashion:

$$K_R(n,t+1) = R\&D(n,t) + (1-\delta_R)K_R(n,t),$$
(6)

where δ_R is the depreciation rate of knowledge. Without loss of generality, we assume that *d=(1-c)*.

How does our index of energy technical change affect the rest of the economy? The variable ETCI is assumed to affect both energy intensity (i.e., the quantity of energy required to produce one unit of output) and carbon intensity (i.e., the level of carbonization of primarily used fuels). As seen in equation (1), the factors of production are labour, physical capital and carbon energy. Let us first consider the effect of technical progress on factor productivity (the energy-intensity effect). In our model, the production function (1) is replaced by the following equation:

$$Q(n,t) = A(n,t)[K_F(n,t)^{1-\alpha_n(ETCI)-\gamma}CE(n,t)^{\alpha_n(ETCI)}L(n,t)^{\gamma}] - p_e(n,t)CE(n,t)$$
(1')

where:

$$\alpha_n = \alpha_n[ETCI(n,t)] = \frac{\vartheta_n}{2 - \exp[-\beta_n ETCI(n,t)]}$$
(7)

and θ_n and β_n are region specific parameters, calibrated to have -in the base year- α_n exactly as in the original formulation of the production function. Thus, an increase in the endogenously determined *ETCI* reduces – *ceteris paribus* – the output elasticity of the energy input. It is worth noting that in (1') $A(n,t)$, the Hick's neutral component of technological progress, accounts for a fraction of technical change which evolves exogenously, thus following an explicit suggestion by Clarke and Weyant (2002).

Let us now turn to the effect of energy technical change on the carbon intensity of energy consumption. As shown in (2), effective energy results from both fossil fuel use and (exogenous) technical change in the energy sector. In our model, we assume that *ETCI* serves

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the purpose of reducing, *ceteris paribus,* the level of carbon emissions. More precisely, equation (2) is replaced by:

$$E(n,t) = h[CE(n,t), ETCI(n,t)] = \varsigma(n,t)\left\{\frac{1}{2-\exp[-\psi_n ETCI(n,t)]}\right\}CE(n,t). \qquad (2')$$

Again, parameters in equation (2') have been calibrated in order to replicate the base year in the original formulation. Here an increase in *ETCI* progressively reduces the amount of emissions generated by a unit of fossil fuel consumed. Finally, we recognize that R&D spending absorbs some resources, that is:

$$Y(n,t) = C(n,t) + I(n,t) + R\&D(n,t), \qquad (8)$$

where *Y* is output net of climate change effects, *C* is consumption, *I* is gross fixed capital formation and *R&D* is research and development expenditures.

In order to account for the difference between private and public return to investments in R&D, we follow Popp (2004a) and model the positive externality of knowledge creation by assuming that the return on R&D investment is four times higher than the one in physical capital. At the same time, the opportunity cost of crowding out other forms of R&D is obtained by subtracting four dollars of private investment from the physical capital stock for each dollar of R&D crowded out by energy R&D, so that the net capital stock for final good production becomes:

$$K(n,t+1) = K(n,t)(1-\delta) + (I(n,t) - 4*\lambda*R\&D(n,t)), \qquad (9)$$

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

The optimal dynamic path of all variables of the model is determined by solving an intertemporal optimisation problem. Control variables (physical investments, R&D investments and energy demand) are computed within a game-theory framework. Each country plays a non-cooperative Nash game in a dynamic setting which yields an Open Loop Nash equilibrium. This allows us to account for externalities and spillovers and to analyse how policy measures are then influenced. In particular, the

strategic underinvestments in R&D that were emphasised by Clark and Weyant (2002) (see Section 2 above) can be captured by our model.

4. Calibration of the Baseline

To further clarify our formulation of endogenous and induced technical change, let us highlight the dynamic interrelationships between the different variables and their role in the model. First of all, let us notice that R&D is a control variable, whereas the stock of knowledge and cumulated abatement are state variables. Therefore, R&D can be used strategically by regulators in each region of the model, whereas LbD is an output of the regulator's strategic behaviour. This is quite clear at the beginning of the game (see Figure 1). At stage one, only LbR through R&D investments occurs. This modifies our index of energy technical change ETCI and yields some amount of abatement, i.e. some abatement experience which becomes LbD. Both LbR and LbD then affects ETCI in the subsequent stages.

Figure 1: The Structure of Technical Change in FEEM RICE v.3
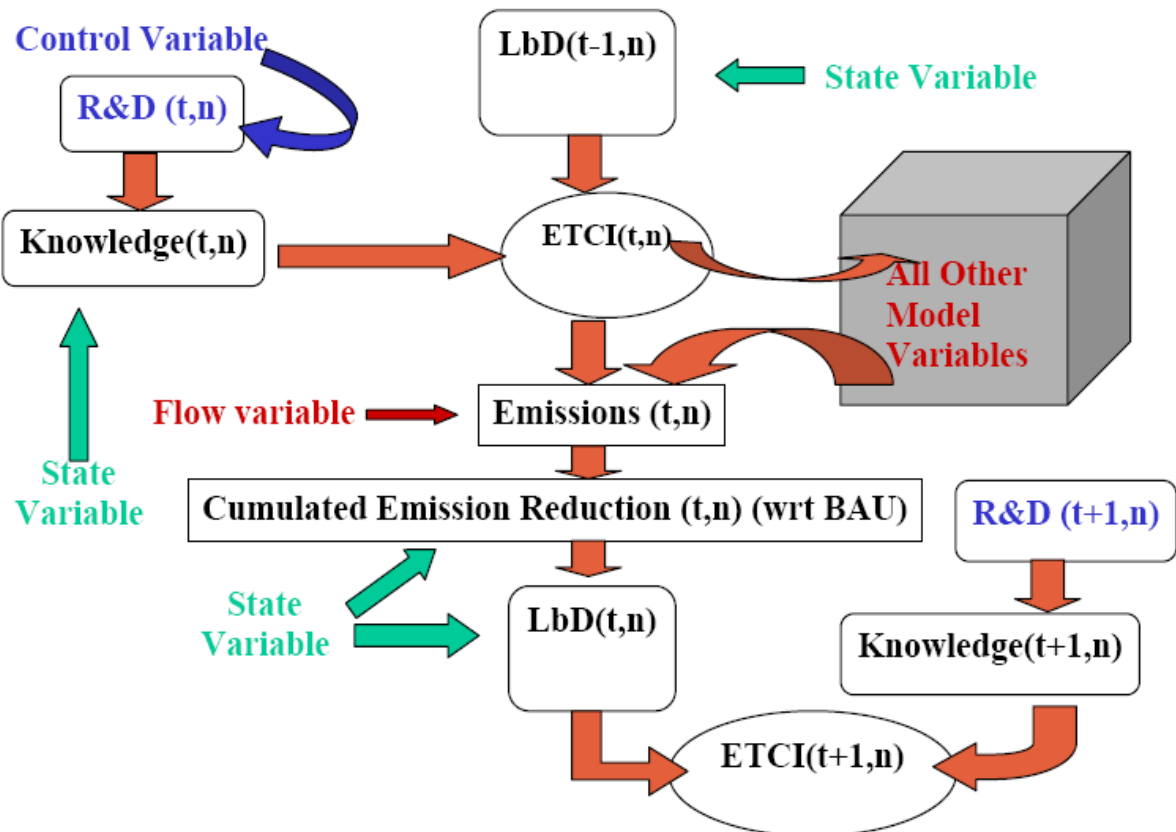
In short, the fundamental driver of technical progress is R&D investment. This induces knowledge accumulation and experience in emission abatement in various regions of the world. In turn, these variables move technology towards a more environment-friendly dynamic path.

Our quite general solution to account for endogenous and induced technical change comes obviously at a cost. Basically, little information to calibrate the model parameters is available. The best strategy we can follow is to calibrate parameters in order to replicate, in the baseline, emissions of the SRES B2 scenario (IPCC, 2000), which are also the baseline emissions in the original RICE 99 model by Nordhaus and Boyer (2000).

Given the high degree of freedom characterizing the calibration process, there exist many distinct baseline models representing different interpretations of what role the exogenous and endogenous components should play in the baseline.

We emphasize this fact by using two versions of the FEEM-RICE v.3, called FAST and SLOW FEEM-RICE. The two versions primarily differ in the value of the learning factor, δ_A, defined as the rate at which accumulation of past abatement becomes effective experience. Therefore, it represents the effectiveness of Learning by Doing. In particular the FAST version of the model assumes a 10% learning factor as opposed to the 5% learning factor of the SLOW version. In addition to this, the two versions of the model differ in the magnitude of the crowding out effect of investment in energy R&D on other research investments, which in turn controls for the profitability of R&D investments. In particular, looking at (10) we set $\lambda=0.25$ in the FAST version and $\lambda=0.5$ in the SLOW version of the model respectively. Differences in these two key features imply a substantially different contribution of the exogenous versus the endogenous component of technical change in the baseline (see Table 4). A comparison of the two versions – also with respect to the original RICE 99 model and with respect to FEEM-RICE without endogenous technical change – is shown in Tables 2 and 3.

Table 2: Contributions of Different Technical Change Components to Lowering Carbon and Energy Intensity in the FAST version of FEEM-RICE v.3 - 1995-2105 cumulated effects

Baseline	Nordhaus RICE 99	FEEM-RICE v.3 with Exogenous TC	FAST FEEM-RICE v.3	FEEM-RICE with only Learning by Researching
Carbon Energy/Production	-2.74%	-10.59%	-26.92%	-10.79%
Carbon Emissions/Carbon Energy	-66.52%	-40.77%	-66.14%	-49.01%

Table 3: Contributions of Different Technical Change Components to Lowering Carbon and Energy Intensity in the SLOW version of FEEM-RICE v.3 - 1995-2105 Cumulated Effects

Baseline	Nordhaus RICE 99	FEEM-RICE v.3 with Exogenous TC	SLOW FEEM-RICE v.3	FEEM-RICE with only Learning by Researching
Carbon Energy/Production	-2.74%	-6.83%	-13.76%	-7.13%
Carbon Emissions/Carbon Energy	-66.52%	-51.59%	-59.47%	-54.29%

A few remarks are in order. TC – whether exogenous or endogenous – affects carbon intensity more than energy intensity. Thus, mostly carbon switching rather than energy saving. This feature is striking in the original RICE 99 model. The situation is less extreme in the FEEM-RICE models, especially in the FAST version, where more learning and less crowding out of R&D enhance the reduction of energy intensity relative to that of carbon intensity.

Another aspect to note is that the exogenous component of TC remains prevalent. It accounts for between 60% and 80% of the whole effect. Moreover, the endogenous component is larger in the FAST version of FEEM RICE v.3 than in the SLOW version (see Table 4). The reason is the enhanced effectiveness of energy technical change in the FAST version, where energy R&D crowds out a smaller amount of other types of R&D and where LbD is faster.

Table 4: Exogenous and Endogenous Share of Total Energy Technical Change Measured as the Effect on the Carbon Intensity Index in the Baseline Scenario (1995-2105)

Baseline	**Exogenous TC**	**Endogenous TC**
FAST FEEM-RICE v.3	62%	38%
SLOW FEEM-RICE v.3	87%	13%

Finally, notice that the effects shown in Tables 2-4 refer to the baseline scenario without any stabilisation target and/or climate policy. More relevant effects on and of technical change will be shown in the next section, where the control variables will be optimised to achieve a stabilisation target and to maximise welfare. In this new context, more technical change will become optimal (namely more R&D investments). Therefore, the endogenous component of energy technical change will be integrated by an induced component (which therefore reduces the share of the exogenous component. See Table 5 below). The FEEM-RICE v.3 model enables us to disentangle the three components of technical change and to quantify the induced (additional) R&D investments in new energy technologies that it would be optimal to carry out in order to achieve a given stabilisation target.

5. Induced Energy Technical Change and the Macroeconomic Cost of GHG Stabilisation

The model described above has been used to analyse the macroeconomic implications of stabilising GHG concentrations at three different target levels: 450, 500 and 550 ppm in 2100.[9] We consider three different concentration levels owing to the uncertainty surrounding quantitative targets set in a distant future. In this section, we present selected results for the SLOW version of the model, which is less optimistic with respect to the future evolution of technical change, thus providing more conservative insights.

We start by assessing how technical change reacts to the introduction of more stringent policy objectives. From Table 5 and from Figure 2 it appears that more ambitious targets imply an increasing investments in R&D and a greater incidence on the endogenous and induced components of energy technical change. In particular, the share of induced technical change

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[9] The reader is reminded that the model is not a multi gas model and therefore accounts for CO2 emissions only.

becomes 13.8% in the 450 ppm scenario, whereas the endogenous component (including the induced one) doubles with respect to the one in the baseline scenario.

Table 5: Exogenous, Endogenous and Induced Share of Total Energy Technical Change Measured as the Effect on the Carbon Intensity Index in the Three Stabilisation Scenarios (1995- 2105) - SLOW FEEM-RICE v.3

SLOW FEEM-RICE	Exogenous TC	Endogenous TC	Induced TC
450 ppm scenario	74.8%	11.4%	13.8%
500 ppm scenario	75.9%	11.6%	12.5%
550 ppm scenario	79.4%	12.1%	8.5%

Figure 2: The Dynamics of ETCI in the Three Stabilisation Scenarios
**SLOW FEEM RICE v.3**
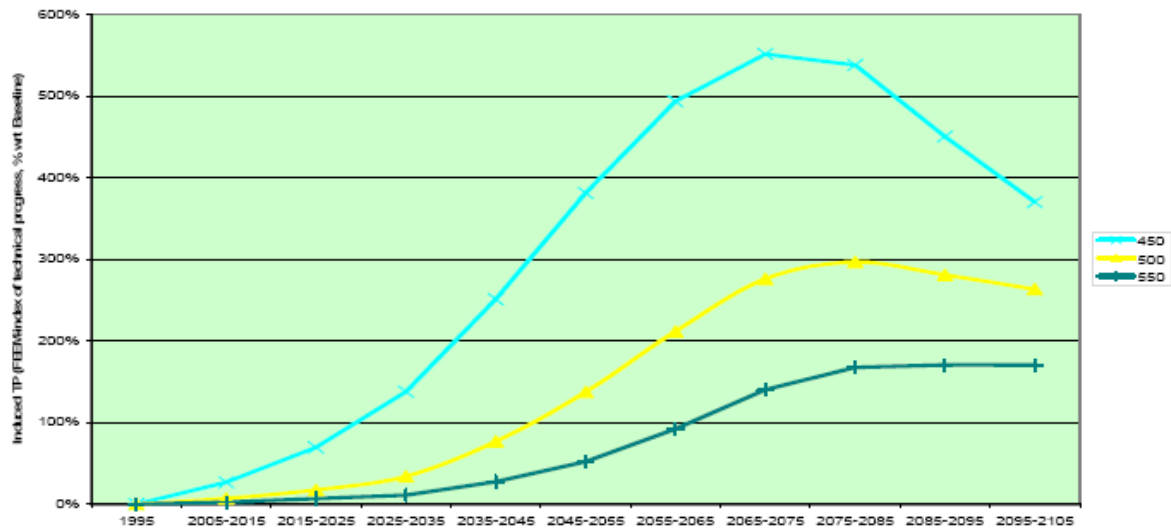
Our index of energy technical change *ETCI* strongly increases as a reaction to the stabilisation target. *ETCI* reaches a peak after the mid of next century as a consequence of the large R&D investments that countries find it optimal to carry out from 2020 to 2050. Figure 3 shows the time profile of the stock of knowledge induced by the three targets. Note the hump shape that gets more pronounced as the target becomes more stringent. This is also the case of induced LbD as revealed by Figure 4.

Figure 3: The Dynamics of Induced Knowledge in the Three Stabilisation Scenarios SLOW FEEM RICE v.3
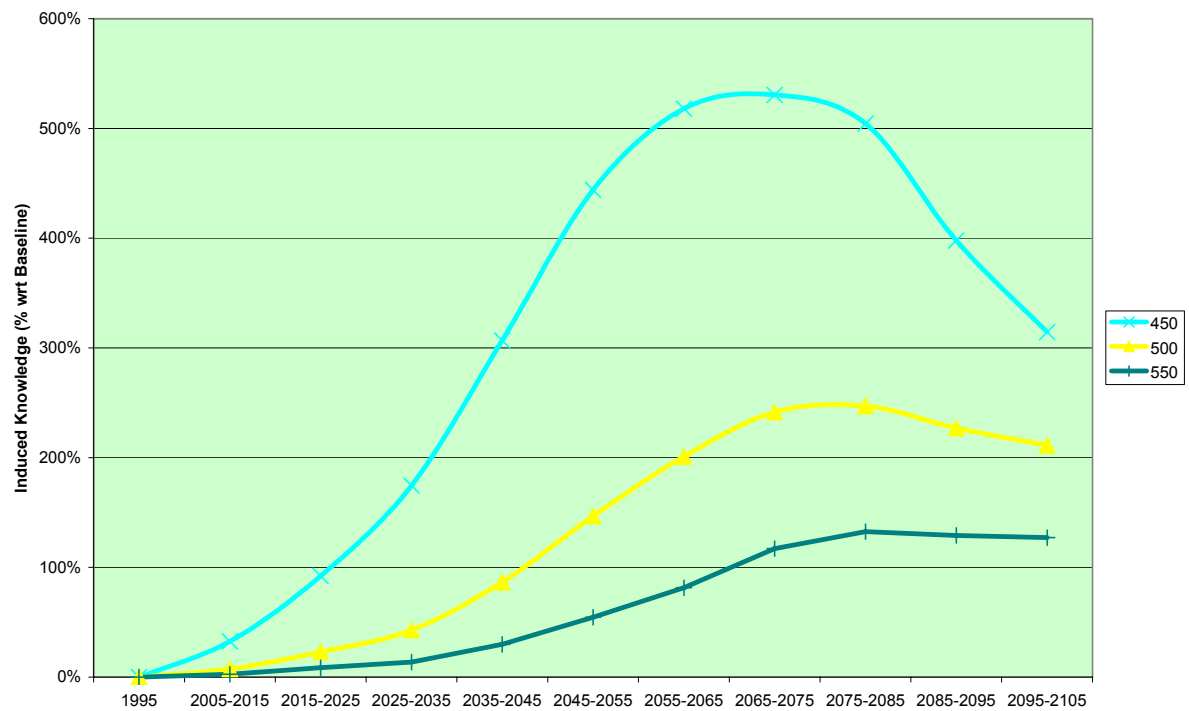
Figure 4: The Dynamics of Induced LbD in the Three Stabilisation Scenarios SLOW FEEM RICE v.3
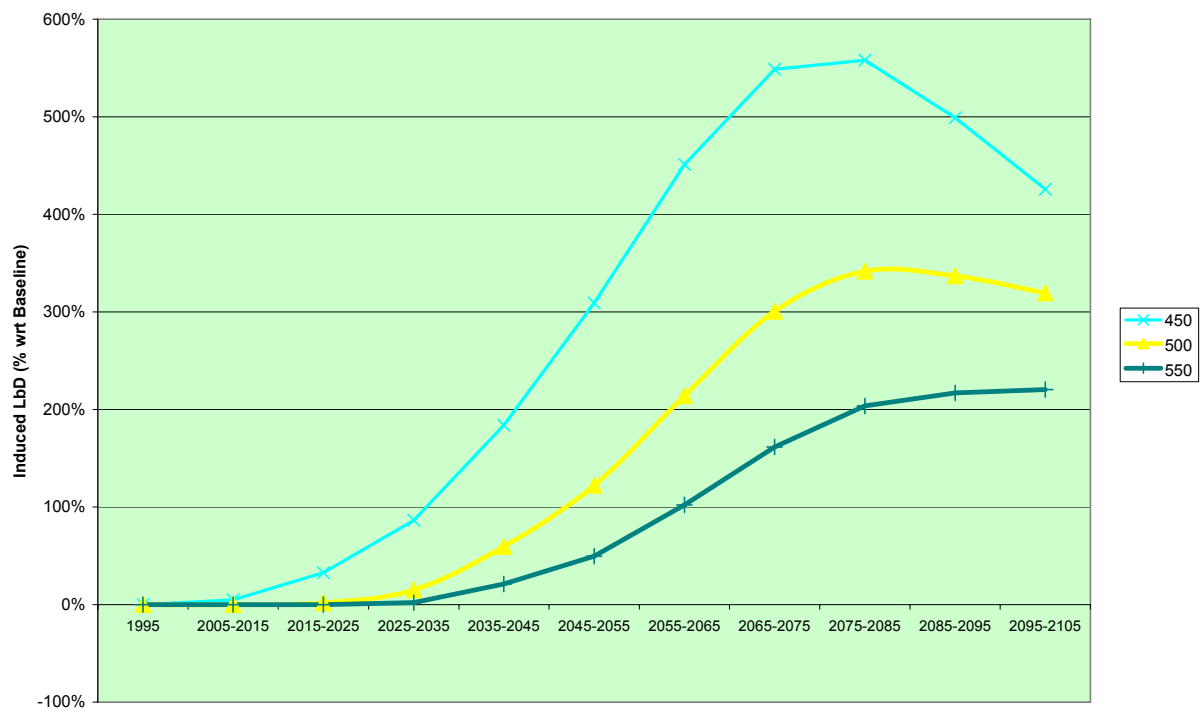
Even though the model takes into account crowding-out effects in R&D investments and even though the focus is only on energy R&D and the related knowledge accumulation, the path of technical change which is necessary to stabilise GHG concentrations at 450 ppm does not seem realistic. Also notice that between two-thirds and three-fourths of the change in *ETCI* is induced by the imposition of a stabilisation target (see Table 6). This again shows that R&D investment three to four times larger than those in the baseline would be necessary to achieve a stabilisation target (see figures 2-4).

Table 6: Endogenous and Induced Share of Total Energy Technical Change Index. Percentage Variation Between 1995 and 2105 - SLOW FEEM-RICE v.3

SLOW FEEM-RICE	Endogenous TC	Induced TC
450 ppm scenario	24%	76%
500 ppm scenario	29%	71%
550 ppm scenario	37%	63%

If we look at mitigation costs, the impact of stabilisation targets does not seem to be high, at least when costs are measured in terms of GDP losses: see, for example, Figure 5 for the more ambitious and costly target. There are two reasons. First, in the model GDP losses are lowered by the positive effects of stabilisation on the environment (in our model lower concentrations imply lower GDP losses). Second, losses in terms of consumption are compensated by an increase of investments, in particular investments in R&D. Similar conclusions can be shown when costs are defined in terms of welfare losses. In Figure 6 we present the percentage reduction in welfare for all three targets, both when ITC is allowed for and when it is not. The role of ITC in contributing to lessen the negative impact of stabilisation targets on welfare clearly emerges.

Figure 5: The GDP Cost of Stabilising GHG Concentrations at 450 ppm with and without Induced Technical Change

Figure 6: Welfare Cost of Stabilising GHG Concentrations at 450 ppm with and without Induced Technical Change - SLOW FEEM RICE v.3
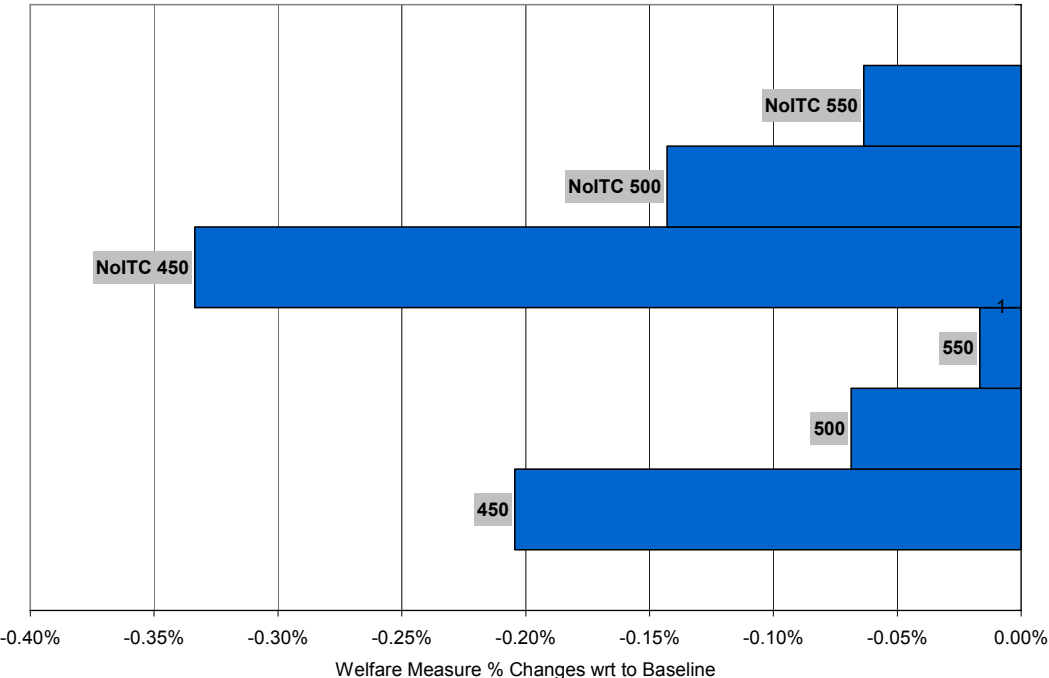
Figure 7: The Dynamics of Emissions in the Three Stabilisation Scenarios SLOW FEEM RICE v.3
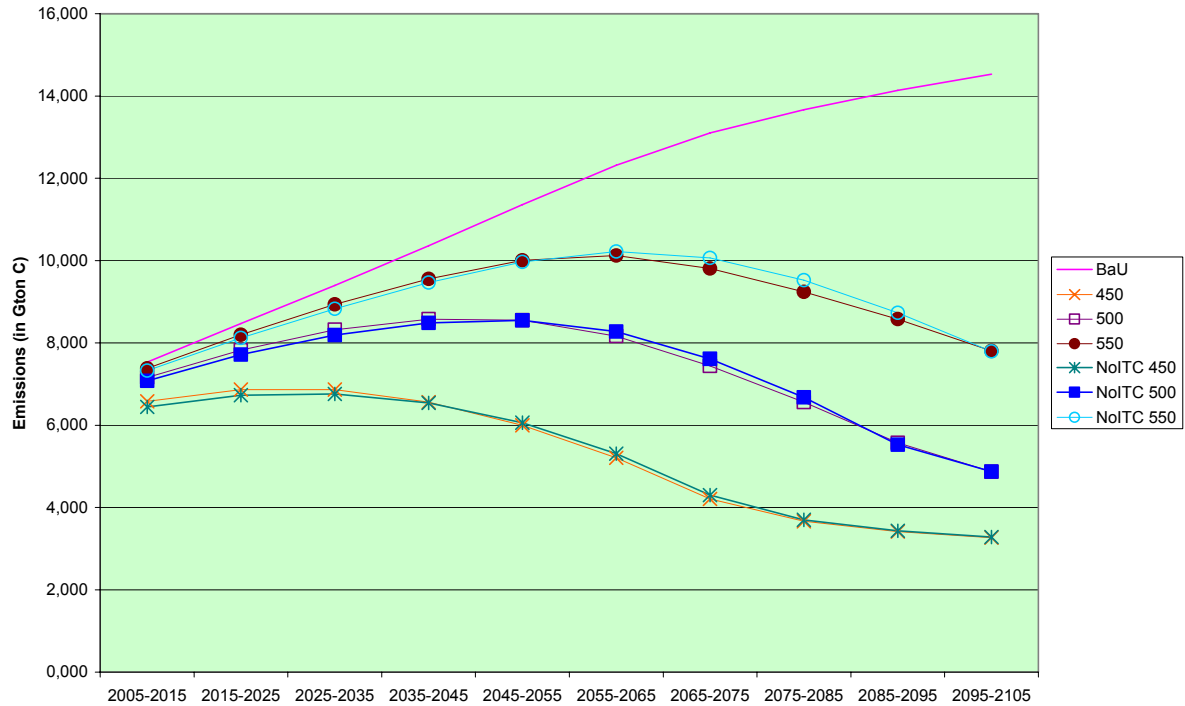

Figure 7 reports the time profile of emissions as implied by the stabilisation targets. Relative to the ever-increasing baseline emissions, the constrained paths share a couple of common features: (i) the difference between ITC and no-ITC is always very small; (ii) a hump shape characterizes all patterns. Here the turning point comes earlier for the more stringent target, at around 2020-2025 in the 450 ppm case. Between 2045 and 2065 emissions start declining in the two remaining cases.

Finally, given the uncertainty concerning some crucial parameters of the model, we carried out an extensive sensitivity analysis that helped us to check the robustness of the model and of the conclusions we drew. Due to space limits we focus on the main parameters that define our specification of endogenous technical change. In particular, with the parameter c we control the role of researching vs. learning in the process of technical change, whereas with parameters β and ψ we control the impact of technical progress on energy intensity and carbon intensity respectively (see Figure 8). Again we show results only for the SLOW version of FEEM RICE v.3. The initial values of the main parameters are shown in Table 7 below.

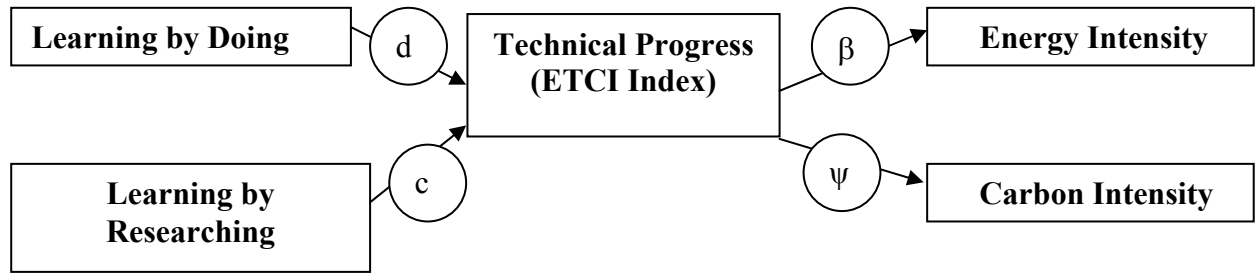**Figure 8: The Crucial Parameters of the Induced TC Model**

Table 7: Initial Parameter Values for the Technical Change Module of the Model

Parameter	$\beta(n)$	$\psi(n)$	c	δ_P	δ_A	δ_B	d
Value	(0.1-0.2)	(0.9-1.2)	0.5	0.05	0.05	0.05	1-c

Extensive sensitivity analysis has been performed on the parameters β, ψ and *c.* The results are shown in Tables 8-10. The most important conclusion is the high sensitivity of R&D expenditure with respect to the three coefficients. The less effective is technical change in reducing GHG emissions the higher the increase in energy-related R&D expenditure which is necessary to stabilise GHG concentrations.

Table 8: Sensitivity With Respect To Energy-Saving Effect Controlling Parameter

β	-0.05	central value	$+0.05$	$+0.1$
Atmospheric concentration of carbon (GTC) in 2100	1.29%	-	-1.30%	-3.18%
Atmospheric temperature (deg C) in 2100	0.94%	-	-1.13%	-2.78%
R&D Expenditure as % of GPD	-6.75%	-	45.22%	116.05%

Table 9: Sensitivity With Respect To Fuel-Switching Effect Controlling Parameter

ψ	- 0.4	- 0.2	central value	+ 0.2	+ 0.4
Atmospheric concentration of carbon (GTC) in 2100	2.69%	1.29%	-	-1.16%	-2.21%
Atmospheric temperature (deg C) in 2100	1.86%	0.94%	-	-0.92%	-1.81%
R&D Expenditure as % of GPD	-15.58%	-6.75%	-	5.18%	9.15%

Table 10: Sensitivity With Respect To Different ETCI Formulations

	c = 0.0	c = 0.25	c = 0.50	c = 0.75	c = 1.00
Atmospheric concentration of carbon (GTC) in 2100	-2.52%	-0.90%	-	1.27%	0.27%
Atmospheric temperature (deg C) in 2100	-2.25%	-1.05%	-	1.00%	-0.29%
R&D Expenditure as % of GPD	-99.77%	-57.39%	-	61.66%	316.60%

6. Concluding Remarks

This paper has presented a new climate-economy model with a detailed formulation of the process of endogenous and induced technical change. In the model, both Learning by Researching and Learning by Doing are explicitly accounted for through an index of energy technical change. This index of technical progress affects both the relationship between the variables of the macro-dynamic model and energy intensity and the one with carbon intensity. R&D investments induce the developments of environment-friendly technologies through which GHG emission abatement can be undertaken. At the same time, these abatement activities increase experience and produce learning, which enhance the effectiveness of environment-friendly technologies in reducing GHG emissions. The emission reduction takes place through both energy-saving and fuel-switching effects. In the model, the different components of technical change have a differentiated impact on both effects.

The model has been used to assess the economic costs of achieving different stabilisation targets. Our results suggest that these costs can be small, if adequate R&D investments can be financed and undertaken. Therefore, models in which technical change is exogenous and/or stabilisation targets induce no change in the optimal trajectory of energy-related innovation are likely to over-estimate the actual stabilisation costs.

An extensive sensitivity analysis with respect to the main parameters of our 2x2 formulation of technical change has been carried out. This sensitivity analysis has shown the robustness of the model when parameters are changed around the calibrated values and the consistency of the results when large changes in the parameters are imposed.

Clearly our model together with its new formulation of technical change is not an ending point. The research agenda is rich. In particular, it would be useful to extend the model in order to include a non-energy sector, thus making it possible to have a better representation of fuel-switching dynamics. Second, the possibility of a growing effectiveness of carbon sequestration technologies could be accounted for in the model. Finally, and most

importantly, stochastic components of the process of technical change – and therefore uncertainty – should be modelled to develop a more realistic analysis of climate policy.

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Appendix

Other Model Equations

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 99 model.

In each region, *n*, there is a social planner who maximizes the following utility function (*n* indexes the world's regions, *t* are 10-year 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.

The maximization problem is subject to:

(A3) $Q_n(t) = \Omega_n(t)\{A_n(t)K_{nF}(t)^{1-\gamma-\alpha}L_n(t)^\gamma CE_n(t)^\alpha - p_n^E(t)CE_n(t)\}$

(A4) $c_n(t) = \dfrac{C_n(t)}{L_n(t)}$

(A5) $K_{nF}(t+1) = (1-\delta_K)K_{nF}(t) + I_n(t+1)$

(A6) $Q_n(t) = C_n(t) + I_n(t)$

(A7) $E_n(t) = \varsigma_n(t)CE_n(t)$

(A8) $p_n^E(t) = q(t) + markup_n^E$

(A9) $M_{AT}(t+1) = \sum_n[E_n(t) + LU_j(t)] + \phi_{11}M_{AT}(t) + \phi_{21}M_{UP}(t)$

(A10) $M_{UP}(t+1) = \phi_{22}M_{UP}(t) + \phi_{12}M_{AT}(t) + \phi_{32}M_{LO}(t)$

(A11) $M_{LO}(t+1) = \phi_{33}M_{LO}(t) + \phi_{23}M_{UP}(t)$

(A12) $F(t) = \eta\{\log[M_{AT}(t)/M_{AT}^{PI}] - \log(2)\} + O(t)$

(A13) $T(t+1) = T(t) + \sigma_1\{F(t+1) - \lambda T(t) - \sigma_2[T(t) - T_{LO}(t)]\}$

(A14) $\Omega_n(t) = \dfrac{1}{1 + \theta_{1,n}T(t) + \theta_{2,n}T(t)^2}$

List of variables:
W = welfare
U = instantaneous utility
C = consumption
L = population
R = discount factor
Q = production

$\varOmega$ = 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 CO_2 concentrations
M_{LO} = lower oceans CO_2 concentrations
F = radiative forcing
T = temperature level
q = 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 CO_2 emissions (carbon intensity)
$\phi_{11}, \phi_{12}, \phi_{21}, \phi_{22}, \phi_{23}, \phi_{32}, \phi_{33}$ = parameters of the carbon transition matrix
η = increase in radiative forcing due to doubling of CO_2 concentrations from pre-industrial levels
σ_1, σ_2 = temperature dynamics parameters
λ = climate sensitivity parameter
$markup^E$ = regional energy services markup
θ_1, θ_2 = parameters of the damage function
M_{AT}^{PI} = pre-industrial atmospheric CO_2 concentrations
O = increase in radiative forcing over pre-industrial levels due to exogenous anthropogenic causes
ρ = discount rate
T_{LO} = lower ocean temperature