# Endogenous Technological Change in Climate Change Modelling

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# Endogenous technological change in climate change modelling

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#### Abstract

This article investigates the impact on optimal  $CO_2$  abatement and carbon tax levels of introducing endogenous technological change in a macroeconomic model of climate change. We analyse technological change as a function of cumulative capacity, as incorporated recently in energy-systems models. Our calculations confirm that including endogenous innovation implies earlier emission reduction to meet atmospheric carbon concentration constraints. However, the effect is stronger than suggested in the literature. Moreover, the development of non-fossil energy technologies constitutes the most important opportunity for emission reductions. Optimal carbon tax levels, reducing fossil energy use, are lower than usually advocated. © 2002 Elsevier Science B.V. All rights reserved.

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#### 1. Introduction

Both technological change and economic growth are seen as major determinants of future global energy demand levels, the associated carbon dioxide  $(CO_2)$  emissions, and global climate impacts (Nakicenovic et al., 1998). Until recently,

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however, the modelling of energy-economy-climate interactions has largely regarded technological progress as an exogenous process, rather than as endogenous technological change. For the purpose of this paper, the energy models described in the literature can be roughly divided into two categories: a class related to top-down (or macroeconomic) models; and one to bottom-up (or energy-systems) models. Bottom-up models include technological progress mainly as an exogenous process of cost and efficiency improvements of a relatively rich set of specific energy technologies (see e.g. Nakicenovic et al., 1998). Top-down models can include technological change in a variety of ways. In these models, economic output is given by a production function including technological progress, capital and labour, sometimes explicitly complemented by energy or electricity, as production factors. Technology is often included in these macroeconomic models as a separate coefficient in the production function, e.g. as an overall productivity factor augmenting over time as an autonomous energy efficiency increase (AEEI).<sup>1</sup> Examples of these models are MERGE, CETA, DICE and RICE (Manne et al., 1995; Manne and Richels, 1997; Peck and Teisberg, 1992; Nordhaus, 1993, 1994).

Only recently, the literature has begun to include technological progress as an endogenous process. Technological improvements no longer fall as 'manna from heaven', but depend on up-front investments. As for bottom-up models, Messner (1995) was the first to include technological progress in a systems-engineering model. She implemented endogenous technological change in MESSAGE, a dynamic linear programming energy model with a detailed Reference Energy System (RES). Subject to a given exogenous level of final energy demand and exogenous assumptions on costs, efficiencies and market penetration constraints, MESSAGE minimises the discounted costs of supplying energy. New in the approach of Messner (1995, 1997) is that the investment costs of specific technologies are - via so-called learning curves - explicitly linked to the cumulative installed capacity. This reflects the notion of learning-by-doing: the costs of specific energy technologies decrease as commercial investments and installed capacities accumulate. The inclusion of endogenous technological progress leads to earlier investments in energy technologies, a different mix of technologies and a lower level of overall discounted investments, as compared to the case of exogenous technological progress.

Meanwhile, others have confirmed the results of Messner. Barreto and Kypreos (1999), conclude in their bottom-up energy systems study that the incorporation of learning curves results in significantly different model outcomes than those obtained from traditional approaches with exogenous technological progress. When endogenous learning is present, the development of new innovative technologies can be expected as optimal solutions to the model. Grübler and Messner (1998) take this approach a step further by linking the MESSAGE model to a carbon cycle model in order to address the question of the optimal timing of  $CO_2$ 

<sup>&</sup>lt;sup>1</sup> Strictly speaking, the AEEI includes all reductions of the energy intensity of an economy, e.g. with respect to GDP, that are not price-induced. Besides efficiency improvements, these comprise, for instance, reductions resulting from a fuel switch or from structural societal or behavioural changes.

abatement via a given set of  $CO_2$  concentration stabilisation targets. Their findings suggest that the treatment of technological progress as an endogenous process implies an optimal emission trajectory with lower emissions in the near term. The differences, however, are rather small.

In terms of including endogenous technological change in top-down models, much of the focus has been on the effect of R & D expenditures, rather than on learning-by-doing. Nordhaus (1999) incorporated induced innovation in an up-dated version of his globally aggregated DICE model, called R&DICE. In the DICE model, capital and labour can substitute for carbon energy. The economic mechanism at work is that increases in the price of carbon energy, relative to other production inputs, induce users to purchase more fuel-efficient equipment or employ less energy-intensive products. In the R&DICE model, on the other hand, the use of carbon energy is controlled by induced technological change. A rise in the price of carbon energy induces firms to develop new processes and products that are less carbon-intensive than existing products. Nordhaus' major conclusion is that endogenous technological change is likely to be a less powerful factor influencing climate change policy than substitution of energy by capital and labour. Goulder and Schneider (1999) investigate the impact of including induced technological progress in the form of expanded R & D efforts. The basis behind this is that carbon taxes might lead to increased R & D involving a reduced reliance on conventional fuels. These additional R&D expenditures might, in turn, lead to technological progress. Their main finding is that increased climate R & D efforts might 'crowd out' R & D by non-energy sectors and carbon-based energy sectors. The overall effect might be a slowdown in output and GDP in general. Goulder and Mathai (1998) incorporate induced technological progress in two separate ways. First, as a function of the stock of R & D expenditures, second, in the form of learning-by-doing, with the stock of knowledge being a function of the level of abatement. They find that their results depend on the form the technological progress takes (R & D or learning-by-doing), as well as the criterion used to judge the results, cost-benefit or cost-effectiveness. If knowledge is gained through R & D, it is justified to shift abatement to the future. If knowledge is gained by more abatement (learning-by-doing) and the aim is cost-efficiency, the results suggest a generally small but positive impact on the (earlier) timing of abatement.

Clearly, the bottom-up and top-down approaches of endogenising technological change are fundamentally different. Both have their advantages. The purpose of this paper is to utilise the advantages of both approaches by combining them in a single model. By doing so, we contribute a new element to the literature in this field. We employ a macroeconomic model that distinguishes between two different energy technologies (carbon and carbon-free), which, as in the bottom-up case, are subject to learning-by-doing. The costs of the carbon-free technology now depend on the cumulative capacity installed.

Our approach differs from the existing literature in the following way. It is different from the traditional bottom-up approach à la Messner, since it includes energy demand as an endogenous rather than an exogenous variable. Effects of emission reduction measures and endogenous technological progress on energy demand are now explicitly reflected. Our approach differs from the traditional top-down models such as CETA, since technology is no longer modelled as exogenous (though time-dependent), but technological progress takes the form of cost reductions of energy technologies that are dependent on the cumulative capacity installed. The approach is new compared to the R & DICE model (Nordhaus, 1999) and the model by Goulder and Mathai (1998), since we distinguish — at the highest possible level in the production function — between two separate energy technologies rather than assuming one single abatement function. This allows to explicitly derive conclusions on the feasibility of certain policies to make a transition between various energy options. Furthermore, these technologies are allowed to realistically develop along learning curves.

Still, we are largely trying to answer the same type of questions:

- 1. What is the effect of including endogenous technological progress, as modelled in bottom-up approaches, in a macroeconomic model on the optimal timing of the abatement of greenhouse gases?
- 2. What is the effect on the optimal path of the taxes and subsidies required over time?

The model developed for this purpose, and presented in this article, is called DEMETER: the DE-carbonisation Model with Endogenous Technologies for Emission Reductions. The model is introduced in Section 2. Section 3 gives an overview of the data used for calibrating the model. We define, in Section 4, four scenarios allowing an analysis and comparison of four different simulation methods in relation to a business-as-usual scenario. Section 5 analyses and compares the various results. In Section 6, conclusions are drawn and discussed.

#### 2. Model description

First, we describe the standard general equilibrium model assuming exogenous technological change. At a second stage, we extend the model by distinguishing between old and new capacities, which enables us to introduce the learning-by-doing phenomenon.

### 2.1. The model without learning-by-doing

In DEMETER, consumer goods are produced by one representative firm, which allows the use of a single CES production function, expressed by:

$$Q(t) = \left[ A(t) \left( K_{\rm C}(t)^{\alpha} L(t)^{1-\alpha} \right)^{\gamma} + B(t) \left( (F(t)^{\chi} + N(t)^{\chi})^{1/\chi} \right)^{\gamma} \right]^{1/\gamma}, \tag{1}$$

in which Q(t) is aggregate production or gross output, A(t) is the level of technological progress for the capital/labour composite,  $K_{\rm C}(t)$  is the capital stock

required for the production of the consumer good, L(t) is labour input, B(t) is the specific level of energy technological progress or energy technology stock, F(t) is the fossil energy input and N(t) is the non-fossil energy input, all dependent on time t.<sup>2</sup> The parameters  $\alpha$ ,  $\chi$  and  $\gamma$  are time-independent,  $\alpha$  expresses the value share of capital in the capital/labour composite,  $\chi$  represents the elasticity of substitution between fossil and non-fossil energy use,  $\gamma$  represents the elasticity of substitution between the capital/labour composite, on the one hand, and the fossil/non-fossil energy composite, on the other hand.<sup>3</sup> Note that the CES aggregation of F(t) and N(t) is an important deviation from the standard linear aggregation as employed in CETA (Peck and Teisberg, 1992) and MESSAGE (Messner, 1995). By avoiding linear aggregation via the use of positive elasticities of substitution between fossil and non-fossil energy alternatives, we create the existence of niche-markets, since such elasticities ensure that it is always efficient to use at least a certain minimum amount of non-fossil fuels. Technically, we assume that F(t) and N(t) are good substitutes by employing an elasticity of substitution equal to 3, that is  $\chi = 2/3$ . This is considerably higher than in a Cobb-Douglas aggregation of the two energy options.<sup>4</sup> In the first periods, when production costs of N(t) exceed the production costs of F(t) by almost an order of magnitude, the CES aggregation ensures that there is still positive demand for N(t). Alternatively, linear aggregation in Eq. (1) could be represented by employing  $\chi = 1.$ 

Both the general and energy-specific technology stocks are assumed to increase exogenously. The growth of A(t) represents economic growth that is neutral in the use of production factors, whereas the growth of B(t) is chosen such as to reproduce an exogenous path for the AEEI. The labour force, proportional to population and to labour productivity, is assumed to grow according to a time-dependent growth rate  $g_{\rm L}(t)$ . In order to produce fossil energy F(t), an energy producing capital (or capacity) stock  $K_{\rm F}(t)$  is required, as well as maintenance and operation (M & O) efforts, expressed by  $M_{\rm F}(t)$ . The relation between these quantities are assumed to have the form:

$$K_{\rm F}(t) = a_{\rm F}F(t) \qquad M_{\rm F}(t) = b_{\rm F}F(t), \tag{2}$$

in which  $a_F$  expresses the capital intensity of fossil energy use and  $b_F$  the corresponding intensity of required M & O efforts. In a similar way, the model provides for non-fossil energy N(t) production via the relations:

$$K_{\rm N}(t) = a_{\rm N}N(t) \qquad M_{\rm N}(t) = b_{\rm N}N(t), \tag{3}$$

<sup>&</sup>lt;sup>2</sup> The model employs discrete time steps of 5 years each.

<sup>&</sup>lt;sup>3</sup> The elasticity of substitution parameter  $\chi$  is related to the elasticity of substitution  $\varepsilon$  by the relation  $\varepsilon = 1/1(1 - \chi)$ . Similarly, the elasticity of substitution parameter  $\gamma$  is related to the elasticity of substitution  $\sigma$  by the relation  $\sigma = 1/(1 - \gamma)$ .

<sup>&</sup>lt;sup>4</sup> Employing a Cobb-Douglas aggregation would result in a sharp increase in the share of non-fossil energy already in the first period. This we consider unrealistic.

with  $K_{\rm N}(t)$  representing non-fossil energy capital,  $a_{\rm N}$  the capital intensity of non-fossil energy use and  $b_{\rm N}$  the corresponding intensity of required M&O efforts  $M_{\rm N}(t)$ .

The capital stocks  $K_{\rm C}(t)$ ,  $K_{\rm F}(t)$  and  $K_{\rm N}(t)$  depreciate with a fixed rate  $\delta$ . Gross investments are denoted by  $I_{\rm C}(t)$ ,  $I_{\rm F}(t)$  and  $I_{\rm N}(t)$ , respectively:

$$K_i(t+1) = (1-\delta)K_i(t) + I_i(t), \quad \text{with } j = C, F, N.$$
 (4)

Gross output Q(t), is used for consumption C(t), investments in non-energy capital  $I_{\rm C}(t)$ , investments in both fossil and non-fossil energy capacity  $I_{\rm F}(t)$  and  $I_{\rm N}(t)$ , and maintenance costs for both energy production alternatives  $M_{\rm F}(t)$  and  $M_{\rm N}(t)$ :

$$Q(t) = C(t) + I_{\rm C}(t) + I_{\rm F}(t) + I_{\rm N}(t) + M_{\rm F}(t) + M_{\rm N}(t).$$
(5)

The use of fossil fuels for energy production leads to emissions of  $CO_2$ , the most important greenhouse gas. The emissions of  $CO_2$  are expressed as a function of time by E(t), and are related to the use of carbon energy F(t) via the aggregate carbon emission factor  $\varepsilon(t)$ :

$$E(t) = \varepsilon(t)F(t).$$
(6)

The factor  $\varepsilon(t)$  is assumed to be time-dependent, to account for the de-carbonisation process to which the use of fossil fuels is subject (e.g. by a transition from coal combustion to that of natural gas).

Carbon dioxide emissions are linked to the atmospheric carbon dioxide concentration, which in turn determines the global average surface temperature, following DICE (Nordhaus, 1994). The relations are not explicitly stated here.<sup>5</sup> Similar to other welfare maximising IAMs such as CETA and DICE (Peck and Teisberg, 1992; Nordhaus, 1993), it is assumed that the inclusion of a temperature constraint in the model results in a positive shadow price for carbon emissions. These can be interpreted as the level of the carbon tax required to meet the temperature constraint.

The optimisation programme to be solved in our cost-effectiveness analysis is a problem in which the objective function of the total discounted sum of global utility, in the form of the natural logarithm of per capita consumption, is to be maximised:

$$\operatorname{Max}\sum_{t=1}^{\infty} (1+\rho)^{-t} N_{t} \ln(C_{t}/N_{t}), \tag{7}$$

subject to the equations given above. In Eq. (7),  $N_t$  denotes population and  $\rho$ 

<sup>&</sup>lt;sup>5</sup> Following DICE, the model abstracts from the feedback that links temperature change to carbon uptake by enhanced vegetation growth.

stands for a utility discount rate of 3.5% per year.<sup>6</sup> The model is solved for 30 periods representing the interval 2000-2150. Results are presented for the time interval 2000-2100.

## 2.2. Including learning-by-doing

Up to this point, the phenomenon by which technological performance increases and production costs decrease, as commercial investments and capacities accumulate, is not incorporated. To allow for this phenomenon, we formulate variables representing the new contributions to stocks in each period of time considered. The tilde ( $\sim$ ) is used to denote the contribution to a stock variable added in a given period. All input and output variables, generically denoted by V(t), can now be written as:

$$\bar{V}(t) = V(t) - (1 - \delta)V(t - 1), \tag{8}$$

which indicates that the amount of V(t) associated with the newly installed capital equals the difference between the total level V(t) and the depreciated level of the previous period being  $(1 - \delta)V(t - 1)$ . This relation is defined for  $\tilde{Y}(t)$ ,  $\tilde{K}_{\rm C}(t)$ ,  $\tilde{K}_{\rm F}(t)$ ,  $\tilde{K}_{\rm N}(t)$ ,  $\tilde{M}_{\rm F}(t)$  and  $\tilde{M}_{\rm N}(t)$ . In particular, since investment is defined as the new stock of capital added in a given period, we have, for the three cases:

$$\bar{K}_i(t) \equiv I_i(t-1), \text{ with } j = C, F, N.$$
 (9)

The relation for aggregate output Eq. (1) now becomes:

$$\tilde{Q}(t) = Q\big(\tilde{K}_{\rm C}(t), \ \tilde{L}(t), \ \tilde{F}(t), \ \tilde{N}(t)\big). \tag{10}$$

To obtain new expressions for fossil and non-fossil energy production, we introduce two variables,  $X_{\rm F}(t)$  and  $X_{\rm N}(t)$ . They denote the cumulative capacity of fossil and non-fossil energy production. The difference between two periods of these cumulative capacity variables expresses the new energy capacity installed in a given period:

$$X_{\rm F}(t+1) = X_{\rm F}(t) + \bar{F}(t), \tag{11}$$

and

$$X_{\rm N}(t+1) = X_{\rm N}(t) + \tilde{N}(t).$$
(12)

Learning-by-doing is incorporated in the model by a scaling function g(X) depending on the cumulative capacity X. This scaling function expresses that with little cumulative capacity installed, it takes relatively more energy-specific capital

 $<sup>^{6}</sup>$  This corresponds to a real interest rate of 5% per year, given an average per capita consumption growth of 1.5% per year.

and M & O efforts to produce a given level of energy than when a high level of cumulative capacity is available. In the case of non-fossil fuels, the relations in Eq. (3) are replaced by:

$$I_{\rm N}(t-1) = \tilde{K}_{\rm N}(t) = g(X_{\rm N}(t)) a_{\rm N} \tilde{N}(t),$$
(13)

and

$$\tilde{M}_{N}(t) = g(X_{N}(t)) \ b_{N}\tilde{N}(t).$$
<sup>(14)</sup>

Equivalent relations hold for fossil energy production, implying that also in this case a price decrease is simulated endogenously.<sup>7</sup> Cost reductions through learning-by-doing for fossil energy production are considered to be much more limited, however.

The usual functional form for g(.) assumes a constant learning rate (lr), at which the cost declines for each doubling of cumulative production. This corresponds to:

$$g(x) = g_0 x^{\alpha - 1},$$
 (15)

where  $\alpha < 1$  and  $g_{0}$  a constant. The value of the exponent  $\alpha - 1$  is the basis of the process of learning-by-doing and defines the speed of learning for the technology considered. The learning rate is given by:

$$lr = 1 - 2^{\alpha - 1}.$$
 (16)

However, Eq. (15) implies ever-decreasing production costs, which seems unrealistic in the long term. Instead, in DEMETER we assume that the production costs converge to a floor price, implying that the learning rate decreases for a maturing technology. Technically, such a floor is set by having a lower limit g(.) = 1 for large values of the argument:

$$g(x) = g_0 x^{\alpha - 1} + 1.$$
(17)

For a new technology,  $g_0 x^{\alpha-1}$  is much larger than 1, so that Eq. (15) and Eq. (17) generate approximately the same paths for production costs. For a mature technology, on the other hand,  $g_0 x^{\alpha-1}$  becomes smaller than 1. Eq. (17) then implies that production costs have reached a floor.

Incorporating learning-by-doing results in diverging average and marginal production costs. Since new investments in the non-fossil technology lead to decreasing future production costs, marginal social costs of investments will be less than the direct investment costs. By comparing the direct investment costs with the marginal social costs (the latter being calculated via the shadow prices resulting from a welfare maximising programme) the model is capable of determining the value of the investment costs. Often, individual firms will not be able to internalise learning effects in their prices. In our model, it is assumed that a public agency

<sup>&</sup>lt;sup>7</sup> This is merely done for consistency and convenience, as well as to allow for a model that is flexible with respect to future research endeavours.

internalises these learning effects by subsidising investments that have strong potential learning capacities. This assumption has the advantage that there are no increasing returns on the firm level, and that there is no associated monopolistic production behaviour that requires its own modelling assumptions.

# 3. Calibration

For the calibration of DEMETER, the following initial conditions and model inputs are included. In 1997, the population is assumed to be 5.89 billion and its growth rate 1.45% per year (World Bank, 1999). The population is assumed to reach 11.4 billion by the end of the 21st century, as in the IIASA-WEC study (Nakicenovic et al., 1998). Gross world product (GWP) in 1997 is 25.1 trillion US\$1990 (World Bank, 1999). The growth rate of GWP per capita is assumed to be 1.5% per year over the entire modelling horizon. Final commercial energy consumption in 1997 is estimated to be approximately 265 EJ per year. We assume that the share of fossil fuel technologies in energy production, in 1997, is some 96%. This corresponds to 254 EJ per year. The remaining share of 10.6 EJ per year is non-fossil energy. In 1997, we thus have a total final-energy intensity of approximately 10 MJ/\$.

The average price of final energy from fossil fuel technologies is assumed to be 2.5 \$/GJ in 1997. The average price of final energy by the non-fossil technology is assumed to be 7.2 \$/GJ, in the same year. Of course, a large spread exists in production costs of energy from wind, solar or biomass options. The production price of these renewables is merely taken as a realistic example of some non-carbon energy alternative. To maintain consistency between the energy share for the non-fossil technology of 4% and the price ratio between the fossil and non-fossil technology of 2.9, the elasticity of substitution between the fossil and non-fossil energy is assumed to be 3, as noted before. From the energy intensity and the average energy production price, one now readily concludes that the energy costs constitute 2.7% of GWP in 1997, which is a realistic value.

About the energy consumption growth rate we make two basic assumptions. The AEEI in a business-as-usual scenario is 0.9% per year in the initial time period. This corresponds well to the long-term historical average and improvements of 0.8-1.0% per year, as assumed in the IIASA-WEC scenarios (Nakicenovic et al., 1998). The AEEI decreases gradually to 0.5% per year in 2100. These assumptions imply that the energy consumption growth is 2.0% per year in 2000 and decreases to 1.0% per year in 2100.

Energy-related carbon dioxide emissions are assumed to be 7.3 GtC/year (Giga-ton carbon per year) in 1997. The carbon emission intensity of the fossil technology is thus 0.0287 gC/MJ in 1997. The fossil technology is subject to some decarbonisation processes, e.g. as a result of a transition from coal and oil to gas technologies. The decarbonisation of fossil fuels is assumed to be 0.2% per year. Given the length of our modelled time horizon, this process continues until a floor is reached of 0.023 gC/MJ.

Only minor cost reductions are assumed for new gas, oil and coal technologies. The long-term floor for fossil fuel technology prices is fixed at 2.25 \$/GJ. By contrast, non-fossil fuel technologies are subject to substantial learning-by-doing price decreases. The long-term lower bound price for non-fossil technologies is fixed at 1.125 \$/GJ. This implies that non-carbon energy has the capacity to become half as expensive as carbon energy. The initial learning rate is assumed to be 20% per doubling of installed capacity for both fossil and non-fossil energy resources. The cumulative installed capacity, expressed as the total amount of energy produced up to a given date, is for the fossil energy option 34 TW in the year 2000. In the same year, the cumulative installed capacity for the non-fossil energy alternative is 0.9 TW.

As indicated, two types of energy production costs exist: capital costs and M & O costs. For convenience, the fuel part of the costs is integrated in the M & O costs. The energy production costs are distributed over capital and M & O costs in the ratio 20:80 for fossil energy technologies, and in the ratio 80:20 for non-fossil technologies. These constitute good approximations of actual energy production cost distributions (Schönhart, 1999). In combination with the assumption on total energy production costs, one sees that investment costs for non-fossil energy are currently assumed to be approximately 10 times those for fossil energy. They are assumed to be 2 times the investment costs for fossil energy in the long run. Finally, the long-term elasticity of energy consumption to energy prices is assumed to be 0.4 (Manne, 1999).

### 4. Scenarios

For our Business-As-Usual (BAU) scenario, we assume that climate change is not internalised in the economy. In BAU, the cumulative emissions from 2000 to 2100 amount to approximately 1450 GtC. The atmospheric CO<sub>2</sub> content in 2100 is approximately 640 ppmv, compared to 280 ppmv in the pre-industrialisation era. The corresponding temperature increase in 2100 is 2.4°C, relative to pre-industrial times. This assumption implies a 1.9°C increase relative to 1990. Under BAU, it is assumed that the price of fossil and non-fossil energies is based on the direct production costs, that is, the depreciation costs for capital plus the costs of M & O.

In addition to the BAU scenario, four additional, methodologically different, cases are investigated. In all four of these supplementary scenarios a constraint is set on the average global surface temperature increase. In the current analysis, global temperature should stabilise at a level at most  $2^{\circ}$ C higher than the pre-industrial level. This tight constraint is set to analyse the impact on the optimal timing of abating greenhouse gases of different ways of modelling technological change and energy demand. This approach is similar, in parts, to the one followed by Goulder and Mathai (1998) and Grübler and Messner (1998), in the sense of minimising costs to meet a given target. The approach does not attempt to maximise the net benefits of controlling climate impacts.

The four scenario variants modelled by DEMETER are fundamentally different.

Table 1		
Typology	of	scenarios

Scenario	Temperature constraint	Endogenous technology	Endogenous energy demand
BAU	No	Yes	Yes
METH1	2 C	No	No
METH2	2 C	Yes	No
METH3	2 C	No	Yes
METH4	2 C	Yes	Yes

We have labelled them METH1, METH2, METH3 and METH4. Table 1 summarises the main characteristics of these four scenarios. The methods differ in the way they handle the demand for energy and technological progress. Energy demand can be implemented endogenously or exogenously. Future decreasing energy production costs can be accounted for endogenously, via learning-by-doing or they can be incorporated exogenously. This leaves us with the four scenarios described in detail below.

**METH1** supposes a fixed energy demand, following that in the BAU scenario. Furthermore, the new non-fossil technology cannot mature until its price becomes competitive with the conventional fossil technology, since there are no learningby-doing opportunities. Technological progress is exogenous and leads to decreasing energy production costs along the same path as in the BAU scenario. METH1 is more or less comparable to an old version of MESSAGE, without the learningby-doing phenomenon (Messner and Strubegger, 1995). Because of the rigid exogenous energy demand, it resembles more a cost-minimising (like in most bottom-up energy models) than a welfare maximising programme.

METH2 also employs a fixed energy demand. It includes, however, a representation of the phenomenon of learning-by-doing, and assumes that the positive effects through learning-by-doing are internalised, that is, it calculates a first-best solution. This allows prices for the non-fossil energy to decrease faster: emission reduction costs can reach lower values than under METH1. METH2 is best comparable with the MESSAGE model incorporating learning-by-doing (Messner, 1995, 1997).

**METH3** incorporates a flexible energy demand through the full exploitation of the macroeconomic part of the model. The model then allows for a decrease in energy demand when energy prices increase. In METH3, there is no endogenous simulation of technological change. Technological progress is exogenous and leads to decreasing energy production costs along the same path as in the BAU scenario and in METH1.

METH4 combines the flexible energy demand, through the full exploitation of the macroeconomic part of the model, with an endogenous price decrease through learning-by-doing. Thereby, METH4 is the major new methodological addition. It employs the DEMETER model to its complete extent. It is assumed that the positive effects of learning-by-doing are internalised, resulting (like in METH2) in a first-best solution.

#### 5. Results

In this section we first examine the implications of the different scenarios on the optimal timing of abatement, the level of energy demand, as well as the share of non-fossil energy technologies. We will then analyse the implications for the evolution of energy prices, as well as that of taxes and subsidies over time.

#### 5.1. The optimal timing of abatement

Fig. 1 shows the evolution of the emissions of carbon dioxide, expressed in gigatons of carbon per year (GtC/year). In the four temperature-constrained scenarios — in which an upper bound of 2°C temperature increase is imposed — emissions reach values lower than 10 GtC/year in 2050. Emissions continue to decrease after 2050 in all four cases, reaching values below 3 GtC/year in 2100. METH1 follows closely the BAU emissions for the first two decades in the 21st century. They start to decrease between 2030 and 2040. This emission evolution behaviour is comparable to the simulation results by Wigley et al. (1996) and Nordhaus (1993, 1994). The METH2 scenario depicts emissions falling significantly below those of METH1, already during the first couple of decades of the 21st century. Regarding the optimal timing of abatement, the difference between METH1 and METH2 restates the conclusion of Grübler and Messner (1998) that including technology as an endogenous process leads to an earlier abatement of emissions; since this leads to an overall reduction in (discounted) abatement costs.

Clearly, the same result can be obtained in a macroeconomic model by comparing METH3 and METH4. METH4 differs from METH3 in that it includes technological progress as learning-by-doing. The emissions in both METH3 and



Fig. 1. Carbon dioxide emissions (in GtC/year).



Fig. 2. Energy demand (relative to BAU).

METH4, on the other hand, remain already significantly below those of METH1 and METH2. The reason is that both METH3 and METH4 include the option of reducing energy demand as means to meet the environmental constraint in as far as this is more efficient than shifting to non-fossil fuels. Fig. 2 shows that the energy reduction option is effectively used in METH3 and METH4. This is a major result of our proposed method. By including both technological progress and energy demand in an endogenised fashion, it appears that even earlier reductions in emissions are warranted than previous research suggested. Taking a maximum degree increase of  $2^{\circ}$ C as the aim, the results suggest that it might be optimal to keep global CO<sub>2</sub> emissions at levels below 10 GtC/year throughout the entire 21st century (METH4, the maximum being reached in approx. 2030) rather than allowing them to exceed 10 GtC/year and reach levels below this amount only in 2050 (METH1, METH2 and METH3).

Fig. 3 shows the evolution of the share of the non-fossil resource, expressed as the fraction of total worldwide commercial energy production. In the BAU scenario, the share of the non-fossil technology does not increase rapidly over the 21st century. It reaches some 30% only in 2100. In the four temperature-constrained models, on the other hand, values of at least 90% are reached in that year. The paths to these high shares of the non-fossil technology are rather different for the four carbon-constrained scenarios. The two methods including learning-by-doing (METH2 and METH4) lead to an initially higher share of the non-fossil fuel compared to their counterparts (METH1 and METH3) featuring exogenous technological progress. In the learning-by-doing cases, the share of the carbon-free energy resource already amounts to more than 20% in 2030, whereas they are only little above 10% in the exogenous technological progress case. Only after 2050 (METH2 compared to METH1), respectively around 2070 (METH4 compared to



Fig. 3. Share of the non-fossil energy technology (as the fraction to total world-wide commercial energy production).

METH3), does the share of the carbon-free technology in the endogenous technology learning case dive below the exogenous case to compensate for the early reductions.

# 5.2. The development of energy prices, taxes and subsidies

Fig. 4 shows the evolution of the price of the non-fossil energy. For all scenarios, this price is assumed to start off with a high value of approximately 7 \$/GJ. For the BAU scenario, as well as for METH1 and METH3, the price is exogenously specified and decreases over the entire 21st century to reach approximately 3 \$/GJ in 2100. The scenarios METH1 and METH3 have price paths that are equal to that of BAU. Thereby, they are assumed to develop exogenously. In METH2 and METH4, however, technological change is accounted for endogenously, such that energy production prices are allowed to decrease faster as a result of increased experience in the use of the non-fossil technology, relative to the BAU path. In METH2 and METH4 the price decrease is therefore significantly steeper than that in BAU, especially over the first couple of decades.

As mentioned in Section 2, two important factors are incorporated in the model to instigate the transition of fossil energy production towards non-fossil energy production: subsidies on non-carbon fuels to promote their employment; and taxes on carbon fuels to reduce their use. We note that the model does not specify the share of learning costs that are carried by the individual firm. For policy makers, this is of some importance. If all spill-overs remain within the firm, there is no need for subsidies, since the firms will internalise the learning effect in their prices. Otherwise, government has to stimulate investments in the non-fossil technology



Fig. 4. Price of the non-fossil energy (in \$/GJ).

through subsidies, since without these subsidies firms do not reap the fruits of their contribution to technological change. For illustrative convenience, we assume that technological innovation through learning-by-doing is a public good and is thus both non-rival and non-exclusive, so that the entire learning costs have to be covered by subsidies.

Fig. 5 shows the evolution of the subsidies offered on investments in non-fossil energy capacity. They are expressed as the fraction of total energy production costs. They allow obtaining the carbon emission reduction curves through the enhanced non-fossil energy shares of Fig. 1 and Fig. 2, respectively. In the BAU scenario, no subsidies are available. Neither are they conferred in METH1 and METH3. In these scenarios, technological change is represented exogenously no learning costs exist, so that subsidies are not needed. In METH2 and METH4, it proves optimal to provide a subsidy in 2000 that covers approximately 30% of the investments in non-fossil energy production. After that, they are allowed to decrease gradually to reach a value of a little over 5% in 2100. Note the slight difference in subsidy decrease behaviour we find between METH2 and METH4.<sup>8</sup>

Fig. 6 shows the evolution of taxes on fossil fuels, required for obtaining the carbon emission curves and non-fossil energy shares of Fig. 1 and Fig. 2, respectively. The taxes are expressed in f/tC. In all carbon constraint scenarios, the tax

<sup>&</sup>lt;sup>8</sup> A possible reason could be that in METH4 the market share of the non-fossil fuel is initially, that is up to approximately 2040, slightly higher than in METH2 (see Fig. 3). Consequently, energy prices decrease slightly faster during this period in METH4 (see Fig. 4). This means that subsidies are allowed to have lower values. We realise, however, that this reasoning is not entirely satisfying. One could also argue the other way around, a higher energy share can only be implemented through a higher level of subsidies, a phenomenon which we do not observe.



Fig. 5. Subsidies for the non-fossil energy capacity (as a fraction of total investment costs).

levels start at values close to zero in 2000, and increase moderately during the first few decades after that. From approximately the middle of the 21st century, large differences start to occur between taxes in the four scenarios. The carbon tax evolutions of METH1 and METH3 increase rapidly during the 2nd half of the 21st century, and reach values of approximately 450 \$/tC, respectively, 380 \$/tC, in the year 2100. In METH2 and METH4 the costs of energy produced by the non-fossil



Fig. 6. Taxes on fossil fuels (in f(t)).

fuel is lower than in the METH1 and METH3 cases as a result of the learning-bydoing effect, which is internalised by means of subsidies. Consequently, carbon taxes can increase much more moderately than in METH1 and METH3. In METH2 and METH4, carbon taxes reach values of approximately 230 \$/tC, respectively approximately 175 \$/tC, in 2100.

# 6. Conclusions and discussion

The purpose of this paper is to combine the advantageous features of bottom-up and top-down models with respect to the incorporation of endogenous technological progress. In particular, we employ a macroeconomic top-down model, which distinguishes between two different energy technologies, carbon and carbon-free. Their costs depend, like recently modelled in the alternative bottom-up approach, on the cumulative installed capacity. In our model, the costs of the carbon-free technology are subject to significant learning effects. We focus on the effect of including endogenous technological progress in an optimal timing simulation of the abatement of greenhouse gases, as well as its impact on the optimal path of taxes and subsidies over time.

The model results obtained suggest the following conclusions. Including endogenous innovation in a macroeconomic model implies earlier emission reductions to meet carbon concentration constraints than in a model with exogenous technological progress. This is in line with the recent bottom-up and top-down literature on these issues. A new finding, however, is that our effect is stronger than suggested by existing bottom-up and macroeconomic models. Earlier reductions are warranted, since, in contrast to bottom-up models, total energy demand reductions are included as an additional carbon abatement option, which to a certain degree is an efficient way to reduce carbon emissions.

The model results show that the development of carbon-free energy technologies turns out to be the most important emission reduction option. The inclusion of endogenous technological progress implies that earlier investments in the non-fossil carbon-free technology are warranted than traditional models suggest.

With respect to the timing of taxes it appears that the optimal carbon tax levels are lower during the entire simulation time than without endogenous learning. The reason is that endogenous learning implies that earlier investments in non-fossil energy lead to a reduction in energy production costs and the price of the corresponding technology. The level of subsidies needed to promote the use of non-fossil energy carriers depends on the assumption made on the spill-overs of learning-by-doing effects. In case learning-by-doing is regarded as a public good, subsidy levels of approximately 30% would be needed initially to meet the carbon constraint of 2°C temperature increase. As the non-fossil technology becomes cheaper, these subsidies are allowed to gradually decline over time to a level of approximately 5%.

In terms of climate policy making, the results suggest the following. Our new method to account for endogenous technological change in a macroeconomic model suggests that if a maximum temperature increase of  $2^{\circ}C$  (relative to pre-industrial levels) is the aim, it might be optimal to reduce global CO<sub>2</sub> emissions already at levels of approximately 10 GtC by 2030 rather than 2050, as our simulation of previous methods shows. The optimal policy for this temperature increase stabilisation value should initially focus on the support of carbon-free technologies, possibly via subsidies, and perhaps less on the levying of taxes on the use of carbon fuels. Although numerical results of highly stylised models such as DEMETER could be judged debatable, they unmistakably suggest substantial subsidies for investments in non-carbon renewables, such as solar, biomass and wind.

A number of opportunities for future research appear relevant. Given the considerable effects of incorporating learning-by-doing for non-fossil energy production, it would be interesting to see how our results modify if one takes into account additional learning-by-doing effects for fossil energy production. Another topic worth detailed study would be the extension of the model to learning through R & D. Possible further domains for extending DEMETER include a greater diversification of energy technologies, a multi-region approach, optimisation in a cost-benefit framework, an analysis of the welfare effects under different policy instruments, and the inclusion of uncertainty regarding the performance of new technologies, as well as their physical limits.

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