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A SENSITIVITY ANALYSIS OF TIMING AND COSTS OF GREENHOUSE GAS EMISSION REDUCTIONS

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Abstract. This paper analyses the optimal timing and macro-economic costs of carbon emission reductions that mitigate the global average atmospheric temperature increase. We use a macro-economic model in which there are two competing energy sources, fossil-fuelled and non-fossil-fuelled. Technological change is represented endogenously through learning curves, and niche markets exist implying positive demand for the relatively expensive non-fossil-fuelled energy source. Under these conditions, with a temperature increase constraint of 2 °C, early abatement is found to be optimal, and, compared to the results of many existing top-down models, the costs of this strategy prove to be low. We perform an extensive sensitivity analysis of our results regarding the uncertainties that dominate various economic and technological modeling parameters. Uncertainties in the learning rate and the elasticity of substitution between the two different energy sources most significantly affect the robustness of our findings.

1. Introduction

Both an enhanced development of energy saving technologies and a shift towards non-greenhouse-gas-emitting energy sources are seen as major elements of policies aiming at a stabilization of atmospheric carbon-dioxide concentrations. Until recently, however, most integrated assessment models (IAMs) of global warming, developed to study climate change policies, focused on the energy saving option as the main route to reach emission reductions. Well-known examples of these are CETA, DICE, MERGE, RICE and FUND (Peck and Teisberg, 1992; Nordhaus, 1994; Manne et al., 1995; Nordhaus and Zhang, 1996; Tol, 1999). Though some of these models include non-carbon energy sources, carbon-free energy deployment is considered a too expensive option for emission reductions by most of them. They sometimes regard non-carbon energy as an (expensive) option to be used only when more conventional (e.g., fossil) sources are no longer cheaply available, or, at other instances, as a 'backstop' alternative, which some authors – like Nordhaus – define as a technology that can supply energy at constant marginal costs (that are typically higher than current energy costs) regardless of energy demand.

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Meanwhile, energy system engineering studies have come to the conclusion that significant learning effects may exist for renewable energy sources, offering potential prospects for their future competitive use. Along similar lines of thought, Chakravorty et al. (1997) portray an optimistic future of rapidly decreasing costs for renewable energy sources, and subsequently a massive transition of the global energy system towards these resources during the 21st century. Notably, Chakravorty et al. (1997) argue that such a transition can occur autonomously, so that the problem of the enhanced greenhouse effect could be resolved without the need for explicit climate change policies.

Most of the energy system studies, however, are less optimistic regarding the (autonomous) rate of adjustment towards renewable energy sources. They emphasize the need for up-front investments that allow bringing down future energy production costs through learning-by-doing. Anderson and Bird (1992) made an early numerical analysis investigating the relation between short-term investments and the decrease of long-term production costs for renewable energy sources. Messner (1995) incorporated learning-by-doing in a cost-minimization model of energy production, and analyzed its effect on the optimal timing of new energy investments. Grübler and Messner (1998) extended this modeling exercise by adding a climate change module to their previous calculations and analyzing the timing of carbon emission abatement. They found that the inclusion of learning-by-doing implies, in terms of optimality, (somewhat) more emission reductions in the near term.

Most of the literature above is specifically oriented towards an analysis of emission reductions and energy production costs, but it connects to a more general analysis on economic growth. In this wider perspective of economic growth, there is a long history in analyses of learning effects, technological development, innovation and diffusion. Wright (1936) introduced the concept of learning-by-doing in his seminal paper on the airplane industry. Arrow (1961) interpreted the experience effect as an overall productivity growth in the economy-wide context.

Today, an abundant literature exists on endogenous growth, presenting a large variety of models that include productivity gains or technological changes as endogenous processes within the economy. These models, however, typically describe technological changes and spill-over effects on an economy-wide level, abstracting from the increasing-returns-to-scale that appear when (clusters of) technologies develop. The increasing returns within technology clusters are essential for understanding energy technology dynamics, and comprehending them is especially fundamental when it comes to making scenarios for possible carbon-dioxide emission paths. For example, we can think of fossil-fuel technologies as a cluster with many internal spill-over effects, and renewables as another cluster having its own internal spill-over effects. In such a setting of increasing returns, it may be optimal to specialize in one of the technology clusters, which then becomes dominant, while the other technology cluster vanishes or will play only a minor role. A key question is how the selection of a certain cluster of technologies is essentially resolved. There are two views. On one side is the belief that patterns of specialization are generated by historical accident; the economy subsequently gets locked in through cumulative learning. On the other side is the view that the key determinant for choices of equilibrium is expectations; in other words, a decisive element exists of self-fulfilling prophecies (Krugman, 1991).

The proponents of evolutionary economics generally adhere to the first view. They see the technology allocation mechanism as a stochastic process that has no unique convergence point. Thereby, allocation paths exhibit path-dependency (see, for example, Dosi et al., 1994). Exponents of this view are in particular Arthur et al. (1987), Dosi (1982), and Nelson (1995), who stress that technological regimes and technological lock-ins exist, and that the past strongly determines the future, especially in cases concerning technological development.

In mainstream economics, with its emphasis on individuals with rational behavior who possess certain levels of foresight, many proponents can be found of the second view, that is, economists who believe in self-fulfilling prophecies. A well-known example is Krugman (1991), who states that it is the task of policy makers to create convergent expectations around investments in technologies that are preferable from an aggregate point of view. Chen and Shimomura (1998) describe a model in which only self-fulfilling expectations matter in selecting a given technology set. Recently, Kremer and Marcom (2000) also suggest that government should follow a policy that selects a socially preferable equilibrium out of a set of multiple perfect foresight equilibria.

Yet, present energy supply is specialized in fossil-fuel energy sources, and the choice for renewable energy sources as the basis of our energy system will require a costly transition. Nonetheless, for the long run, to at least a certain level, such a transition seems inevitable, given our understanding that there are only two main options to reduce carbon-dioxide emissions. These two are energy savings, on the one hand, and a transition to the use of non-carbon energy, on the other hand. Energy savings are essential for reaching emission reduction targets, especially in the short term, but since energy is essential for economic production (Berry et al., 1978), it needs to be complemented by a (long-term) transition in the energy production system. In fact, since the emission intensity of energy production will finally have to drop to near zero (Wigley et al., 1996), the energy system transformation option seems fundamental.

Making a significant transition to new energy technologies may take a long time. The timing of emission reductions is the first major topic of this paper. After a technology becomes competitive, it enters the market through diffusion. This requires the development of new vintages of products in which that technology is used. Diffusion often requires a time scale several times the lifetime of such products (Knapp, 1999). This does not imply, however, that emission reductions have to wait. Since it requires time to build up the capacity for renewable energy supply, one has to start investing in renewable energy sources sooner rather than later. That is, for a deep cut in long-term emissions, we also need significantly lower emissions (than today) in the short term. Our previous study of this subject matter (van der Zwaan et al., 2002; Gerlagh and van der Zwaan, 2003) indicated that our results contrast with the typical findings of many analysts (e.g., those of Wigley et al., 1996), who suggest that a delay of emission abatement is more efficient than immediate stringent measures, also under a tight temperature increase constraint of 2 °C.

The second topic of this paper concerns the costs involved in the transformation of the energy production system. As mentioned above, non-carbon-emitting energy sources are seen as an expensive emission reduction mechanism, since their present production costs exceed the production costs for standard fossil-fuel technologies by often a factor of two to three, or in some cases even by an order of magnitude (see, e.g., IEA/OECD, 2000). Implicit in calculations that use the fact that renewable energy production costs exceed those of conventional fossil energy resources is usually the assumption that various energy technologies are perfect substitutes. However, different energy technologies have different characteristics, and are thus generally no perfect substitutes. The variety that exists between energy technologies also explains the presence of niche markets for specific energy technologies at specific locations and at specific points in time. Thanks to these niche markets, photo-voltaic electricity is profitably produced in remote areas with no grid connection at prices above the usual grid electricity price. Decreasing costs of photo-voltaic electricity will probably increase its global market share. On an aggregate level, we could capture this process by using a smooth demand function representing that the quantity demanded is increasing when energy prices decrease as a result of decreasing production costs. In terms of technological development, this represents an increasing market for maturing technologies. Meanwhile, production costs further decrease through learning as the production level increases. In theory, the feed-back relation between production costs and demand opens the possibility of a self-enforcing transition towards the non-carbon-emitting technology. Overall, there may finally even be no costs involved in such an autonomous transition. Whether stringent greenhouse gas emission reductions are possible at no costs is a question that in the end can only be sensibly resolved by observing how practice unfolds. The answer will depend on the speed of learning for non-carbon-emitting energy sources, as well as on how their market share evolves as a function of market prices (that are closely related to production costs).[1]

To address both the timing and costs of carbon emission reductions, we use an integrated assessment model that was specially developed to study policy questions related to global warming and technological change. The model, DEMETER,[2] is a relatively simple general equilibrium model incorporating a rudimentary climate change simulation. It does not display the technological detail of many energy systems-engineering models. Not considering it necessary to describe again the model in full detail (see Gerlagh et al. (2000), for an extensive description), we nevertheless highlight four of its main elements. First, it includes two competing energy technologies, one of which has zero net CO_2 emissions. This allows emission reductions to be achievable through a transition towards a carbon-free technology, as an alternative to the substitution of energy by capital and labor (the energy savings option). Second, it distinguishes old from new capital, in such a way that substitution possibilities between production factors only apply to new capital stocks. This so-called 'vintage' approach allows for using different substitution elasticities for the short and long term, and can, in particular, describe a slow diffusion process. Third, it includes learning-by-doing through the use of learning curves. In this way, a transition towards alternative technologies leads to lower energy production costs for these alternative technologies, and thereby enhances their opportunities and accelerates the transition process. This part of the model is inspired by the MESSAGE optimization model as used by Messner (1995). Fourth, it includes niche markets, in which new technologies can spread relatively easily – even though production costs are high – before these technologies become fully mature.

The DEMETER model has been used in a few papers already, for the analysis of a number of different subject matters (see Gerlagh et al., 2000; van der Zwaan et al., 2002; Gerlagh and van der Zwaan, 2003). Whereas in none of these papers a sensitivity analysis was of prime interest, robustness aspects were addressed to some extent in each of them. Specific consideration received the sensitivity of abatement timing as depending on the inclusion or not of learning-by-doing in van der Zwaan et al. (2002). The sensitivity of emission reduction levels and carbon taxes vis-à-vis the presence of niche markets was assessed in Gerlagh et al. (2000), and the robustness of our findings on welfare and Gross World Product under stringent emission reductions was investigated in Gerlagh and van der Zwaan (2003). In this paper, we analyze and describe the timing and costs of a stringent climate change policy, when constraining the global average temperature increase to 2 °C above the 'pre-industrial level'. In contrast to our previous work, we now particularly, and in full extent, focus on the sensitivity of our results regarding changes in the most relevant central model parameters. Thereby, we follow the suggestions by Harrison et al. (1993) and Abler et al. (1999), who argue that applied general equilibrium analyses should routinely be subjected to systematic sensitivity analysis, in order to capture the intrinsic uncertainties involved in the calibration of models. In many ways, our global warming robustness analysis is comparable to the natural scientific approach towards sensitivity analyses as employed by Hasselmann et al. (1997) in their climate change study with a simplified structural integrated assessment model (SIAM). Whereas Hasselmann et al. (1997) use their model to study the sensitivity of computed optimal emission paths, with respect to various critical input assumptions, we use our model (DEMETER) to investigate the sensitivity of carbon emission reduction timing and costs, regarding these assumptions.

This paper is organized in the following way. Section 2 concisely describes the DEMETER model as designed for the analysis of greenhouse gas policies on a world economy level. Section 3 describes the calibration of this model, and discusses its various central input parameters, as well as the range of the values used for them as found in the literature. Section 4 specifies two scenarios, one benchmark or 'business as usual' scenario, and a scenario that aims at a ceiling on the global atmospheric temperature increase of 2 °C. For both scenarios, emission, energy consumption, and cost paths are simulated for different choices of the main parameters used. These are compared with the paths found for the central parameter values. Section 5 summarizes our findings and concludes.

2. Model Description

The DEMETER model is an optimal-growth model of the world economy. It is designed to maximize the discounted value of utility obtained from the consumption of the consumer good C_t,

$$\max \sum_{t=1}^{\infty} (1+\rho)^{-t} Pop_t \ln(C_t/Pop_t), \tag{1}$$

where ρ denotes the pure time preference rate, and Pop_t denotes the size of the world population at time t. Welfare is maximized subject to a number of economic, technological and climatic constraints. The model describes three production sectors, one for the consumer good, and two for energy production. The two energy sectors use different technologies: the first 'old' technology uses fossil-fuels, while the second 'new' technology uses backstop energy sources such as photo-voltaic systems with assumed zero carbon-dioxide emissions. Sectors are denoted by superscripts, $j = C, F, N$ respectively (for the Consumer good, the Fossil-fuel based energy source, and the Non-fossil-fuel based energy source). The production of the consumer good is denoted by Y_t^C, and the production of final commercial energy (services) by the two different energy technologies by Y_t^F and Y_t^N, respectively (the latter two are sometimes shortly referred to by F_t and N_t, merely for notational convenience). DEMETER uses a vintage approach to describe production processes. Distinguishing various vintages has the advantage that one can differentiate between the short-term and the long-term elasticity of substitution between various inputs. In each period, a new vintage is installed, and the variables representing the most recent vintage are denoted by tildes ($\sim$). By definition, the new vintage of capital is equal to the investments of one period before, $\tilde{K}_t^j = I_{t-1}^j$.

The production of the consumer good is described by a nested CES-function. Capital, labor, and energy from the two different sources are used as production factors:

$$\begin{aligned}\tilde{Y}_t^C \;=\; & ((A_t^1 \tilde{K}_t^{\alpha} \tilde{L}_t^{(1-\alpha)})^{(\gamma-1)/\gamma} + (A_t^2 (\tilde{N}_t^{(\sigma-1)/\sigma} + \\ & + \tilde{F}_t^{(\sigma-1)/\sigma})^{\sigma/(\sigma-1)})^{(\gamma-1)/\gamma})^{\gamma/(\gamma-1)},\end{aligned} \tag{2}$$

where A_t^1 and A_t^2 are coefficients representing an exogenous path of technological growth. The capital/labor composite has a fixed value share α for capital. The elasticity of substitution between the two energy sources, F and N, is denoted by σ. The CES aggregation of F and N marks an important extension of the model compared to existing models. It describes a strictly positive demand for the new technology N, even if the price of the new technology exceeds the price of the old technology F by an order of magnitude. The CES aggregation effectively describes the phenomenon of niche markets, in which a specific technology possesses a comparative advantage. Consider the following example. Photo-voltaic energy is used in remote areas where the cost of an electricity grid exceeds the costs of the photo-voltaic energy source. We can also think of an example in which non-fossil-fuel-based energy sources are almost competitive, compared to fossil-fuel based energy sources, and where a small decrease in the production costs of non-fossil-fuel energy sources would lead to a sharp increase in its demand. When aggregating demand for such small markets, we can employ a smooth demand function, such as represented by a CES function.

From a modeling perspective, it is important to have a value for the elasticity of substitution σ that is bounded and larger than one. In contrast, if one assumes linear additivity, equivalent to taking $\sigma = \infty$, following typical bottom-up models such as MESSAGE and CETA, one abstracts from substitution possibilities on the aggregate level between various technologies resulting from advantages some technologies may possess for specific markets. Assuming $\sigma = \infty$ substantially increases the costs of substitution of energy produced by the non-fossil-fuel technology for energy produced by the fossil-fuel based technology, since it abstracts from circumstances where the non-fossil-fuel technology may have an advantage over the fossil-fuel technology. On the other hand, we don't find enough justification for assuming complementarity between the energy technologies, like Goulder and Schneider (1999) do by taking $0 < \sigma < 1$. Finally, we abstract from any intrinsic advantages in the use of one particular technology over the other. Hence, we don not attach weight parameters to F and N in our CES aggregation.[3]

Production of energy by a new vintage, $\tilde{Y}_t^j$ $(j = F, N)$, requires investments in the previous period and maintenance costs:

$$\tilde{Y}_t^j = a_t^j I_{t-1}^j, \qquad (j = F, N) \tag{3}$$

$$\tilde{Y}_t^j = b_t^j \tilde{M}_t^j, \qquad (j = F, N) \tag{4}$$

where we maintain subscripts t for the technology parameters a_t^j and b_t^j to describe decreasing costs resulting from learning-by-doing. We now elaborate on the learning process. Production costs decrease as experience increases through the installation of new vintages. To capture the process of gaining experience, we introduce the variable X_t that represents the experience, or the accumulated installed vintages at the beginning of period t:

$$X_{t+1}^j = X_t^j + \tilde{Y}_t^j. \qquad (j = F, N) \tag{5}$$

Furthermore, we use a scaling function $g^j(X) \rightarrow [1,\infty)$ that describes the relative costs of one unit of output $\tilde{Y}_t^j$ as compared to potential long-term costs, given cumulative experience X_t^j. For example, $g(0) = 2$ means that, initially, twice as much input is needed for producing one unit of output as compared to the amount of input needed when the learning effect has reached its maximum value. We assume that production costs decrease as experience increases, $g'(.) \leq 0$, and that production costs converge to a strictly positive floor price (when a minimum amount of input is required, corresponding to a maximum learning effect) given by strictly positive a_∞^j and b_∞^j, and $g^j(\infty) = 1$. We also assume a constant learning rate $lr > 0$ for technologies at the beginning of the learning curve (that is, for small values of X). This means that, initially, production costs decrease by a factor (1–*lr*), for every doubling of installed vintages.

A function $g^j(.)$ that is consistent with all these assumptions is:[4]

$$g^j(x) = c^j(1 - d^j)x^{-d^j} + 1, \tag{6}$$

for $0 < d^j < 1$. We define the learning-by-doing parameters a_t^j and b_t^j, by dividing the long-term productivity parameters a_∞^j and b_∞^j by the average value of the scaling function $g^j(.)$:

$$a_t^j = a_\infty^j(X_{t+1}^j - X_t^j) \Big/ \int_{X_t^j}^{X_{t+1}^j} g^j(x)dx, \qquad (j = F, N) \tag{7}$$

$$b_t^j = b_\infty^j(X_{t+1}^j - X_t^j) \Big/ \int_{X_t^j}^{X_{t+1}^j} g^j(x)dx. \qquad (j = F, N) \tag{8}$$

Rewriting (3) and (4) using (5), (7) and (8) gives:

$$G^j(X_{t+1}^j) - G^j(X_t^j) = a^j I_{t-1}^j, \qquad (j = F, N) \tag{9}$$

$$G^j(X_{t+1}^j) - G^j(X_t^j) = b^j \tilde{M}_t^j, \qquad (j = F, N) \tag{10}$$

for time independent $a^j \equiv a_\infty^j$ and $b^j \equiv b_\infty^j$, and for the primitive function G(.), given by:

$$\mathrm{G}^j(x) = c^j x^{1-d^j} + x. \tag{11}$$

Equations (9) and (10) give a convenient description of investments and maintenance costs as a function of the increasing accumulated vintages.

Finally, the output from the first sector is used for consumption, investments I in all three sectors, and for maintenance M in both energy sectors:

$$C_t^+ I_t^C + I_t^F + I_t^N + M_t^F + M_t^N = Y_t^C. \tag{12}$$

The production using the new vintages adds to the production of previous vintages. Old vintages are depreciated by a factor $(1 - \delta)$, so that we have:

$$Y_t^C = (1 - \delta)Y_{t-1}^C + \tilde{Y}_t^C, \tag{13}$$

$$M_t^j = (1 - \delta)M_{t-1}^j + \tilde{M}_t^j. \qquad (j = F, N) \tag{14}$$

Labor is supplied inelastically, and is assumed to increase proportionally with population levels. Carbon emissions, E_t, are proportional to the use of fossil-fuel-based energy F_t, via the aggregate carbon emission factor ε_t:

$$E_t = \varepsilon_t \; F_t. \tag{15}$$

The factor ε_t is assumed to be time-dependent (but exogenous), to be able to account for the de-carbonization process to which the use of fossil fuels has been subject since the early times of industrialization, by a transition – in chronological order – from wood to coal, from coal combustion to that of oil, and most recently from coal and oil to natural gas. Carbon emissions are linked to the atmospheric carbon-dioxide concentration, which in turn determines the global average surface temperature, using a 1-box representation as in the early DICE model, and a climate sensitivity of 3 °C per doubling of the atmospheric CO_2 concentration (Nordhaus and Yang, 1996).

The model as described so far can be used to calculate first-best solutions. Similar to other welfare maximizing IAMs, the inclusion of a temperature constraint in the model results in a positive shadow price for carbon emissions. This shadow price can be interpreted as the tax required on carbon emissions to meet the temperature constraint. The learning spill-over is also internalized in the first-best solution. Since investments in non-fossil-fuel energy production lower future costs of energy production, the shadow price for the investments lies below the immediate costs, that is, below the consumption foregone. The gap between the shadow price and the immediate costs can be interpreted as the subsidy on investments that internalizes the learning effect.

The model also includes a complete set of first-order conditions that allows us to calculate equilibrium allocations that are not optimal from a social welfare perspective. For example, if the learning spill-over effect is non-rival and non-exclusive, we may assume that production parameters a_t^j and b_t^j are treated as exogenous variables by the firms, and the firms will charge the user with the direct production costs. That is, the learning spill-over effect is not internalized, unless the government subsidizes investments in the non-fossil-fuel energy source. As part of our sensitivity analysis, we calculate a scenario in which the government does not internalize the learning spill-over.

3. Calibration

The base-case values employed for some of the most important parameters used for deriving results with DEMETER are presented and justified in this section, as well as the range of values of these parameters used for analyzing the sensitivity of the results of our model. Table I displays a summary of the parameters used, as well as their meaning, and the lower bounds, central values, and upper bounds employed for the sensitivity analysis. The sensitivity analysis focuses on the parameters determining the energy production evolution paths and the associated carbon dioxide emission dynamics. We do not perform an explicit sensitivity analysis with respect to parameters that relate to e.g. world population growth or to detailed characteristics of carbon cycle dynamics, since these fall beyond the scope of this paper. However, our sensitivity analysis does include an investigation of different policy scenarios – through a comparison of modeling constraint variations regarding the imposed temperature increase or, as an alternative, the imposed CO_2 concentration stabilization level – which in many respects is comparable to a carbon cycle sensitivity analysis.

The world population (described by the parameter Pop_t) is assumed to grow from 5.89 billion in 1997 at a rate of 1.45% per year, leveling off and reaching 11.4 billion by 2100 (World Bank, 1999; and Nakicenovic et al., 1998). We did not perform a sensitivity analysis for this parameter, but leave this as a subject for other (future) research.

The dynamic parameters A_t^1 and A_t^2 describe autonomous technological changes. Setting aside changes in energy production costs, changes in the parameter A_t^1 describe production and consumption growth per capita with a proportional increase in energy use. Gross World Product (GWP) in 1997 is assumed to have been 25.1 trillion U.S.\$1990 (World Bank, 1999) and its future annual per capita growth rate is assumed to be 1.5%. As a lower and upper bound for the growth of consumption per capita, denoted by GCPC, we choose 1.0% and 2.0% for our sensitivity analysis.

Changes in the parameter A_t^2 describe the autonomous improvement in energy efficiency. More precisely, A_t^2 describes the productivity of the CES aggregate of the fossil-fuel and non-fossil-fuel energy sources, which we may interpret as a measure for the productivity of energy services. Thereby, changes in A_t^2 describe the autonomous energy services efficiency improvement (AESEI). Its assumed value is 1.0% per year. For the sensitivity analysis, as a lower and upper bound, we choose values for the AESEI of 0.5% per year and 1.5% per year. The value of the AESEI is not exactly the same as the value of the autonomous energy efficiency improvement (AEEI), commonly used in other studies. The AEEI measures the productivity increase of the linear aggregate of energy sources (two in our case), whereas the AESEI measures the productivity increase of our CES aggregate. Under the central parameter choice (AESEI = 1.0%/yr) and with no climate change control (the situation to which we refer as the baseline scenario), however, the two

Table I
Parameters subject to sensitivity analysis

Parameter	Meaning [a]	Lower value	Central value	Upper value
σ	Elasticity of substitution between the two energy sources (.)	2.0	3.0	4.0
γ	Elasticity of substitution between the capital/labor composite and energy composite (.)	0.2	0.4	0.8
δ	Annual capital depreciation (yr^{-1})	0.05	0.07	0.1
GIR [b]	Gross Investment Ratio (.)	0.2	0.25	0.3
LR	Decrease in production costs per doubling of installed vintages/learning rate (.)	0.1	0.2	0.3
LTCN	Long-term costs for the non-fossil-fuel energy source ($/J)	0.75	1.25	2.25
r [c]	Real interest rate (yr^{-1})	0.03	0.05	0.08
AESEI	Autonomous energy services efficiency improvement (yr^{-1})	0.005	0.01	0.015
GCPC	Growth of consumption per capita (yr^{-1})	0.01	0.015	0.02
LSI	Dummy expressing whether learning spill-over effects are internalized through subsidies (.)	0	1	1

[a] Units of measurement are between brackets. Brackets (.) denote that the parameter has no dimension.
[b] The capital share parameter α is calculated on basis of the GIR.
[c] The pure time preference rate ρ is calculated on basis of the real interest rate r.

parameters are almost identical. The combined assumptions on population growth, GWP growth and the value of AESEI result in an energy consumption growth rate of 1.9% per year in 2000, which decreases to 0.6% per year in 2100.

The aggregation of final energy supply over various energy sources such as electricity and heat is facilitated by conversion of all final energy data in primary energy equivalents. Specifically, for electricity, energy flows measured in ExaJoule per year (EJ/yr) are divided by 0.33, the typical conversion efficiency from heat to electricity, while electricity prices, measured in U.S. dollars per GigaJoule ($/GJ), are multiplied by 0.33, to arrive at volumes and prices, respectively, in primary energy equivalents. Over the year 1997, commercial final energy supply (in primary energy equivalents) based on fossil-fuel energy sources is estimated to have been some 307 EJ, and related carbon emissions are assumed to have been 6.3 GtC. Carbon emissions related to land-use changes and industrial processes are around 1.3 GtC, and are assumed constant over time. By dividing the fossil-fuel carbon emissions of 6.3 GtC and the fossil-fuel commercial final energy (services) supply of 307 EJ, one obtains the carbon emission intensity of fossil-fuel commercial final energy (services) supply, ε_t, which amounts to 0.021 gC/kJ in 1997. The fossil-fuel technology is assumed to be subject to a 'decarbonization' of 0.2% per year, which continues until a floor is reached of 0.016 gC/kJ.

The pure time preference rate, ρ, is linked to the real interest rate, r, and the consumption growth per capita, g (or GCPC), via the Ramsey rule, $r = \rho + g$. Since we assume an almost constant per capita consumption growth path (see the discussion above), we determine the level for ρ by choosing a 'realistic' real interest rate r, and subtracting the assumed consumption growth rate. As a central value, we use a real interest rate of 5% per year. For the sensitivity analysis, we choose a lower and upper bound of 3% and 8% per year, respectively.

In most IAMs that are comparable with DEMETER, the capital depreciation factor δ has a value of 10% per year, see e.g., DICE (Nordhaus, 1994). However, some of the empirical literature (e.g., Romer, 1989) suggests a much lower value for capital depreciation of 4% per year. As our central value, we therefore choose 7% per year, with a lower and upper bound of 4% and 10% per year, respectively, for the sensitivity analysis.

The share of capital α in the capital-labor composite determines the capital-output ratio, and in turn the gross investment ratio (GIR), that is, the level of gross investments relative to gross production that is necessary to maintain the capital stock, given the depreciation factor. We follow the inverse procedure, and assume that in the baseline scenario the model approximately follows a balanced growth path during the first periods. That is, initially, output, consumption, investments and energy production grow at about the same rate. Choosing the gross investment ratio for these periods, we can determine the associated capital share factor α. The DICE model uses a gross investment ratio of 20%. Romer (1989) finds a GIR between 25% and 30% for a selected group of OECD countries. Mankiw et al. (1992) confirm the findings of Romer (1989) and emphasize that human capital should be counted as capital, and investments in education should be counted as part of gross investments. This approach would considerably increase the GIR. For our calculations, we choose 20% as lower bound, 25% as central value, and 30% as upper bound for the GIR.

The long-term elasticity of energy consumption to energy prices is described by the parameter γ, for which the central value is $\gamma = 0.4$, following Manne (1999). For the sensitivity analysis, we take a lower bound of $\gamma = 0.2$, describing an economy in which energy is truly essential for production, and we take an upper bound of $\gamma = 0.8$, describing an economy in which, in the long term, capital and labor are moderate substitutes for energy.[5]

The parameter σ describes the long-term elasticity of substitution between the fossil-fuel and non-fossil-fuel energy sources. Approximately, the parameter determines the share of the fossil-fuel based energy source relative to the share of the non-fossil-fuel energy source, (F_t/N_t), given their relative production costs, (p_t^F/p_t^N), as follows:

$$(F_t/N_t) = (p_t^F/p_t^N)^{-\sigma}. \tag{16}$$

On the basis of the database developed for the IIASA-WEC study (Nakicenovic et al., 1998), final commercial energy consumption in 1997 is estimated to be (in primary energy equivalents) 320 EJ.[6] From the same database, the share of fossil-fuel technologies in energy production (in 1997) is estimated to be 96%. This corresponds to the 307 EJ mentioned above. The remaining share of 13 EJ is non-fossil-fuel energy. Thus, in Equation (16), the ratio at the left-hand-side is about 24. Prices, in primary energy equivalents, for energy derived from natural gas technologies vary in a range from 2 to 3 \$(1990)/GJ.[7] Since coal, oil and natural gas are, *grosso modo*, competitive, a good reference price in our calculations for the average fossil-fuel energy resource is 2.5 \$/GJ, in the model start-off year 1997 (this price in primary energy equivalents corresponds to a price of $2.5 \times 3.33 = 8.3$ \$/GJ in final electricity units). A large spread exists in production costs for energy from e.g., wind and solar energy (electricity) options. Prices, in primary energy equivalents, for commercial final electricity from wind turbines varied in 1995 between 2 and 7 \$(1990)/GJ, in the highest-cost and lowest-cost production cases, respectively.[8] Electricity production costs for photo-voltaic systems are still significantly higher than that for wind energy.[9] We consider a realistic range for the ratio of production costs (non-fossil vs. fossil) to be a factor varying from 2 to 5, consistent with an elasticity of substitution ranging from about $\sigma = 2$ to $\sigma = 4$. As central value, we take $\sigma = 3$. Given fossil-fuel energy prices of 2.5 \$/GJ, this value for σ is consistent – see (16) – with production costs for the non-fossil-fuel energy source of 7.2 \$/GJ, in the year 1997 (this latter price in primary energy equivalents corresponds to a price of $7.2 \times 3.33 = 24$ \$/GJ in final electricity units). For the basis parameter values, in 1997, energy production accounts for about 2.7% of GWP. As lower bound for σ we take $\sigma = 2$, and we adjust the initial production costs for the non-fossil-fuel energy source accordingly, to 12.2 \$/GJ. As upper bound we take $\sigma = 4$, and we adjust initial non-fossil-fuel prices to 5.5 \$/GJ.

Finally, we come to the parameters a^j, b^j, c^j, and d^j, describing the production costs for both energy sources in the long-term (a^j and b^j), and the learning curve, that is, the learning rate and the initial production costs given past cumulative investments in both energy sources (c^j and d^j). For fossil fuels, the assumed distribution of costs over investments and maintenance and operation (M&O) is 20:80, where for convenience the fuel part of the costs is integrated in the M&O costs. For non-fossil technologies, the assumed ratio is 80:20 (Schönhart, 1999).[10] In combination with the central assumption on energy prices for 1997, one sees that investment costs for non-fossil-fuel energy are assumed to be currently about 10 times those for fossil-fuel energy. For the long term, still a substantial cost reduction is assumed to exist for new gas and coal technologies. The long-term floor price for fossil-fuel technology is fixed at 1.25 \$/GJ. Also non-fossil-fuel technologies are subject to substantial price decreases. The long-term lower bound price for non-fossil technologies is fixed at the same price of 1.25 $/GJ. That is, for the long term we do not assume a comparative advantage of fossil fuels over non-fossil fuels, or the other way around. For the sensitivity analysis, as a lower and upper bound for the long-term production costs for the non-fossil-fuel energy source, we take 0.75 $/GJ and 2.25 $/GJ.

The learning rate for non-fossil-fuel energy resources is assumed to be 20% per doubling of installed vintages, in line with the empirical evidence on this variable for solar power and wind suggesting that the rate ranges from 8 to 35% (McDonald and Schrattenholzer, 2000). For the sensitivity analysis, we take a lower bound and upper bound for the learning rate of 10% and 30% per doubling, respectively. When the non-fossil-fuel energy technology matures, its learning rate falls.[11] On the other hand, the fossil-fuel energy technology is assumed to have used most of its learning potential already. The cumulative capacity of installed vintages up to the year 1997 is estimated to be about 1200 EJ and 32 EJ for the fossil-fuel energy option and the non-fossil-fuel energy alternative, respectively.[12] Under the baseline scenario, the cumulative capacity of installed vintages for the carbon-free energy technology is doubled by 2020. Consequently, under the central parameter choice, production costs have decreased by 20%, and for $\sigma = 3$ the market share will have increased by approximately 75%, corresponding to an increase of 3% in total energy supply, from 4% to 7% (see also Figure 3, in the next section).

4. Results

In this section, we analyze two scenarios. The first, ‘business as usual’ (BAU) or baseline, scenario assumes no control on carbon-dioxide emissions. It also assumes that there is no policy stimulating the use of the non-fossil-fuel energy source, that is, it abstracts from both taxes and subsidies, even while subsidies may be necessary to internalize learning spill-overs. The second scenario sets a ceiling on the average global temperature increase. This temperature is not allowed to rise above a 2 °C increase compared to its pre-industrial value. Such a temperature constraint may be necessary to prevent major ecological impacts of global warming. This scenario is labeled ‘2DC’ (an abbreviation for ‘2 Degrees Celsius’). It is an ambitious scenario that involves taking drastic steps that realize, first, a slow-down of and, eventually, sharply decreasing emissions of carbon dioxide. It is partly inspired by Schneider and Azar (2001), who argue that such a tight temperature target is both necessary and cost efficient.[13] In contrast to the first scenario, in the 2DC scenario it is assumed that not only taxes on carbon emissions are applied, but that also subsidies are available for investments in the non-fossil-fuel energy source. These subsidies internalize learning spill-overs. As part of our sensitivity analysis, we also include a calculation for the 2DC scenario in which it is assumed that learning spill-over effects are not internalized.

For a comparison between the BAU and 2DC scenarios, we first calculate the 'timing of action', that is, the optimal evolution of the emission path over time (Figure 1). We then calculate the relative importance of energy savings versus the transition from fossil-fuel energy sources towards non-fossil-fuel energy sources for reaching our climate stabilization objective (Figures 2 and 3). We present the sensitivity to our main modeling parameters, regarding our results on allowed emissions, the share of energy savings in total emission reductions, and the share of carbon-free energy sources in total energy supply, in 2020 (Table II). For policy-making arguments, we also present the net present value (NPV) of consumption in both the BAU and 2DC scenario. From these NPV results we derive the costs incurred by constraining the temperature increase (Table III). Next, we calculate the costs of the assumed climate stabilization objective, per period, in terms of the decrease in consumption under the 2DC scenario, as compared to that in the BAU scenario (Figure 4). The sensitivity of cumulative costs (as well as of taxes and subsidies) with respect to the modeling parameters examined is presented as well (Table IV). We have also calculated the optimal carbon emission paths under four additional policy scenarios (Figure 5). We end by presenting the sensitivity of our emissions and costs results to these four policy scenarios (Tables V and VI). While we performed a sensitivity analysis for all parameters that we judged relevant, for reasons of exposition it is impracticable to depict in the figures all corresponding time-paths, associated with various parameter choices. Therefore we only display time-paths that substantially deviate from the path associated with the central parameter choice. On the other hand, we report, for arguments of completeness, our results for all parameter values in the various elaborate tables.

4.1. MECHANISMS FOR ACHIEVING THE 2 °C TEMPERATURE INCREASE CEILING

Figure 1 shows the emissions of carbon dioxide over time for both the BAU and the 2DC scenario. The figure shows two bundles of paths. The upper group of paths with solid markers represents the set of BAU scenarios, each generated with different parameter values. The lower group of paths with non-solid markers represents the set of 2DC scenarios. The upper most path, with emissions up to 24 GtC/yr in 2100, represents the BAU scenario when the growth of per capita consumption is assumed to be 2% per year throughout the 21st century (GCPC = 2% per year). This emission path almost precisely matches the scenario that assumes the central value for consumption growth (GCPC = 1.5% per year), but that assumes less autonomous improvement in the energy services efficiency (AESEI = 0.5%, not included in the figure). The explanation for this outcome is rather comprehensible: both high levels of economic growth and low levels of energy efficiency improvement lead to rapidly increasing energy use, and hence carbon-dioxide emissions. Emissions reach the level of 16 GtC/yr in 2100, when the non-fossil-fuel energy source has a learning rate of only 10%. The reason is that the non-fossil-fuel en-

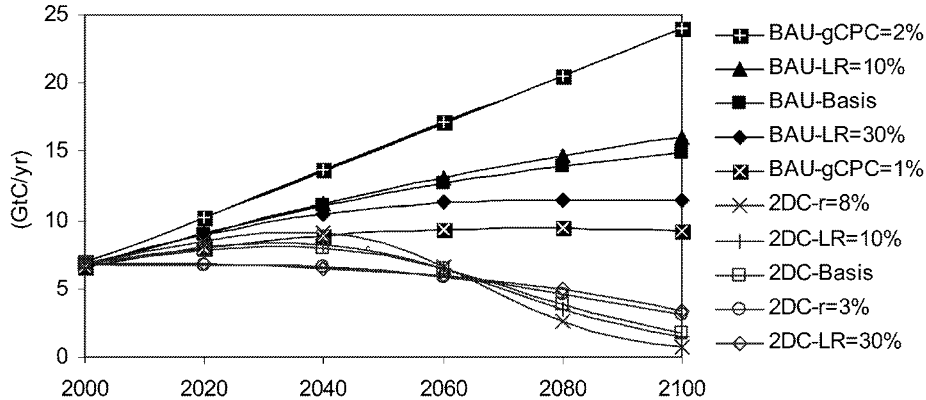

Figure 1. Carbon-dioxide emissions.

ergy source develops more slowly into a competitive alternative for the fossil-fuel energy source if it has only a small learning rate. In this case, the increase in carbon emissions more closely follows the increase in energy use than when the learning rate is higher.

As we may expect, opposite changes in parameter values imply lower future emission levels. Emissions reach much lower levels when we assume a low consumption growth path (GCPC = 1%), or assume a high autonomous improvement of energy efficiency (AESEI = 1.5%). Emissions then increase less rapidly and remain below 10 GtC/yr during the entire 21st century. If the non-fossil-fuel energy source has a learning rate of 30%, it sooner becomes a competitive alternative to the fossil-fuel energy source than with a low learning rate, so that emissions increase more slowly. Specially dedicated climate change policies are less urgent in these cases than in the other examples. With GCPC = 1%, emissions reach a level of 9 GtC/yr in 2100, almost a factor 3 below the level in that year of the upper path. This long-term emission level, however, is still far too high with respect to the level required to stabilize the temperature increase at 2 °C. From these BAU graphs one concludes that baseline emission scenarios are very sensitive to assumptions on economic growth, energy efficiency improvements, and, to a lesser extent, learning rates. Variations in other parameters (not shown in this figure) have less (though still possibly substantial) impact on simulated emission paths.[14]

As for the lower bundle of emission paths, representing the 2DC scenario for different parameter values, it appears that, in comparison to the BAU scenarios, the range of emission paths is much narrower. The temperature ceiling defines a small corridor of feasible emission paths, leaving the model only the freedom to determine the timing of emission abatement. One sees that the central scenario has emissions of 7.8 GtC/yr in the year 2020 (see also Table II), which is a reduction of 14% relative to the BAU level in that year (for the same central parameter values). Over the 21st century, and for the basis parameters, cumulative emissions fall from 1200 GtC in the BAU scenario to 630 GtC when the 2DC constraint is implemented. As a comparison, we note that, under the same temperature constraint, the DICE99 model calculates emissions in the year 2020 of 8.7 GtC/yr,[15] which is at the high end of our estimates. For the timing of emission abatement, in our model, the levels of the discount rate and the learning rate turn out to be of most importance. Employing a pure discount rate consistent with a real interest rate of 8% per year, instead of 5% per year (the central value), implies that it is optimal to delay abatement as much as possible. This scenario produces the upper emissions curve for the years 2000–2060 (emissions amount to 8.5 GtC/yr in the year 2020), which becomes the lowest curve for the years thereafter. Inversely, employing a pure discount rate consistent with a real interest rate of 3% per year implies immediate action, and emissions of only 6.8 GtC/yr in the year 2020. Another important parameter for the timing of emission reductions is the learning rate. Under an optimistic learning rate of 30%, an ambitious emission path is calculated of only 6.7 GtC/yr in 2020, that continues to decrease thereafter. As one can see from Table II, when assuming a pessimistic learning rate of 10%, emissions in 2020 amount to 8.0 GtC/yr, implying less emission reductions compared to the baseline level.

We next consider the mechanisms through which emission reductions take place. In Figure 2, we present the share of emission reductions, relative to the BAU benchmark, that is reached through energy savings measures (the first policy option). The remainder of the emission reductions is reached through the second policy option (a transition to non-fossil-fuel energy sources). In formal terms, the emission reductions share is represented by:

$$\frac{(E_t^{\mathrm{BAU}} - E_t^{\mathrm{2DC}})}{E_t^{\mathrm{BAU}}} \Bigg/ \frac{(Em_t^{\mathrm{BAU}} - Em_t^{\mathrm{2DC}})}{Em_t^{\mathrm{BAU}}}, \tag{17}$$

where Em_t^{BAU} are emissions in the BAU scenario, Em_t^{2DC} are emissions in the 2DC scenario, E_t^{BAU} are energy levels in the BAU scenario, and E_t^{2DC} are energy levels in the 2DC scenario.

For the central parameter values, in the short term, about half of the emission reductions is reached through energy savings. The other half is accomplished by an increased use of the non-fossil-fuel energy source. The figure also shows that energy savings is an option mainly for the short and medium term. At the end of the 21st century, for all parameter choices, the policy option of energy savings is not used anymore, or to only a limited extent. By 2100, the non-fossil-fuel energy source has become sufficiently competitive to take over the role of the fossil-fuel energy source as the main contributor to total energy supply (see also Figure 3). Note that the values for the relative importance of energy savings in total emission reduction, for the 2DC scenario, may actually fall below zero. This finding makes clear that a successful transition to non-fossil-fuel energy sources might even enable an expansion of future total energy use, compared to the business as usual benchmark path.

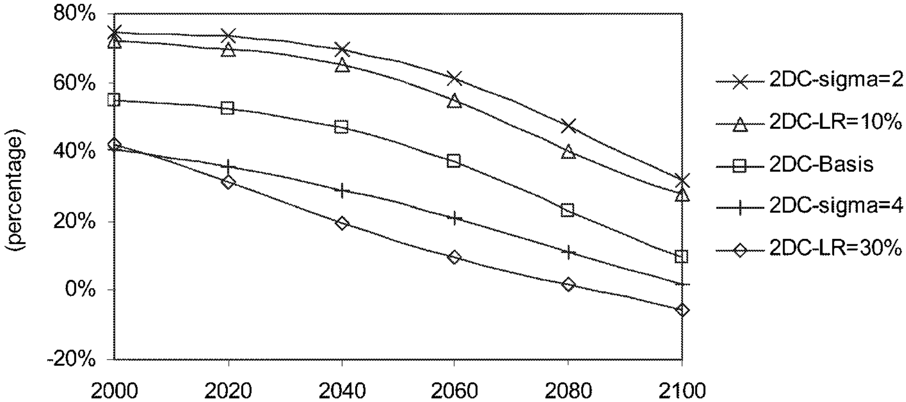

Figure 2. Relative importance of energy savings in total emission reduction for the 2DC scenario.

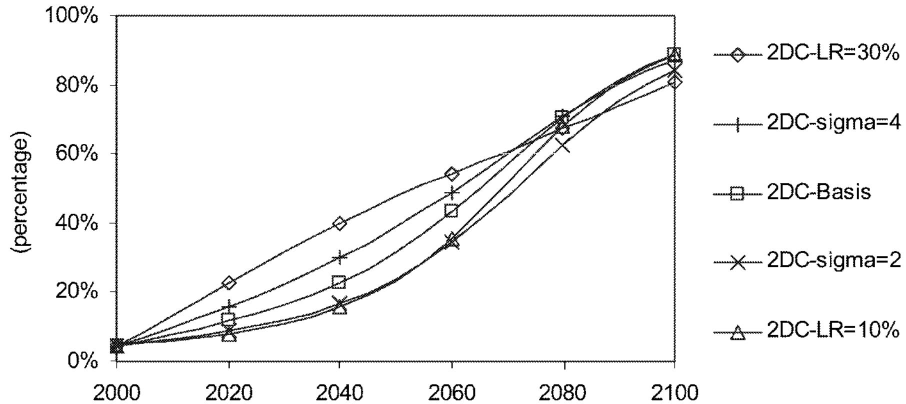

Figure 3. Fraction of energy supply produced by the carbon-free technology.

If the non-fossil-fuel energy source has sufficient potential to replace the fossil-fuel energy source in the short and medium term, that is, if e.g., the learning rate is 30% or the substitution elasticity σ has the value of 4, the transition to the non-fossil-fuel energy source is the main mechanism for emission reductions even in early periods. The lowest line represents the scenario with LR $=$ 30%. This line shows that, for this parameter choice, energy savings constitute only about 40% of emission reductions in 2000, 31% in 2020 (Table II), and almost play no role after 2050. For $\sigma = 4$, savings (also) constitute only about 40% of emission reductions in 2000, and 36% in 2020. Inversely, when the non-fossil-fuel energy source is no good candidate to substitute for the fossil-fuel energy source, that is, when we assume a low learning rate, LR $=$ 10%, or a low substitution elasticity, $\sigma = 2$, energy savings becomes a more important window for emission reductions. For these parameter levels (LR $=$ 10%, $\sigma = 2$), represented by the two upper lines in Figure 2, energy savings constitute between 60% and 80% of emission reductions during the first half of the 21st century.

Figure 3 shows the share of the non-fossil-fuel energy source in total energy supply for the 2DC scenario, which constrains the temperature increase to 2 °C. The lines depicted correspond to some of the paths in the lower bundle of emission scenarios presented in Figure 1. In the long-term, the development of this share turns out to be almost insensitive to choices for the parameter values. For the central parameter choice, the share increases by nearly 1% per year, to a share of about 95% in 2100. This finding portrays a substantial acceleration in the transition of the energy system to non-fossil-fuel energy sources in comparison to the BAU reference scenario (not plotted in the figure). In the BAU scenario, under central parameter values, the share of the non-fossil-fuel energy source increases from 4% in 2000 to 33% in 2100. In the 2DC scenario, if the non-fossil-fuel energy source experiences rapid learning effects, LR = 30%, the transition doubles its speed in comparison to LR = 20%, and the share reaches 24% in 2020 (Table II). Inversely, a non-fossil-fuel energy source with slow learning effects, LR = 10%, reaches a share of only 8% in 2020. This is consistent with the paths depicted in Figure 2, in which it is shown that under this parameter choice, energy savings constitute the major mechanism for emission reductions over the first decades of the 21st century.

Table II summarizes our findings by presenting the values of the variables plotted in the figures, for the year 2020. It extends the figures by presenting the results for all parameters analyzed. The elasticity of substitution between the two energy sources, σ, is an important parameter. Especially if the elasticity is low, energy saving measures will be the major channel through which emission reductions can be achieved over the coming decades. Results are rather insensitive to the price elasticity for energy, γ. A variation in its level has almost no effect. The same applies for the capital depreciation factor, δ, and the gross investment ratio, GIR. For our analysis, the learning rate appears to be the most important parameter. A high learning rate implies a quick transition to the non-fossil-fuel energy source, so that emissions are rapidly cut, while energy savings remain almost unnecessary. On the other hand, a low learning rate implies a delay in the transition to the non-fossil-fuel energy source. It is then more difficult to cut emissions, and energy savings are necessary to reach the climate stabilization objective. Compared to the learning rate, the long-term cost level of the non-fossil-fuel energy source is less important. Admittedly, in the long term, this parameter will probably have a major impact on the energy mix and associated emissions, but for the short and medium term it is of less relevance. Applying a low real interest rate decreases the benefits of delaying costly reductions to the future, hence a larger part of emission reductions is achieved in the short and medium term. On the other hand, a high real interest rate supports a delay of emission reductions. Finally, the autonomous energy services efficiency improvement (AESEI), the assumed growth in per capita consumption (GCPC), and the use of subsidies for internalizing learning spill-overs (LSI) all have only minor effects on the timing of emission reductions.

Table II

Sensitivity of emissions, of the share of energy savings in total emission reductions, and of the share of carbon-free energy sources in total energy supply, in 2020, when realizing a 2 °C temperature increase ceiling

	Lower value	Basis value	Upper value	Emissions in 2020 (GtC/yr)	Energy savings/ emission reduction in 2020 (%)	Non-fossil share in 2020 (%)
Basis				7.8	53	12
σ	(2.0,	3.0,	4.0)	(7.6, 7.8) [a]	(36, **73**) [a]	(9, 16)
γ	(0.2,	0.4,	0.8)	(7.7, 8.1)	(52, 54) [a]	(12, 12)
δ	(0.05,	0.07,	0.1)	(7.7, 7.9) [a]	(51, 54) [a]	(11, 13)
GIR	(0.2,	0.25,	0.3)	(7.8, 7.8)	(53, 53) [a]	(12, 12) [a]
LR	(0.1,	0.2,	0.3)	(**6.8**, 8.0) [a]	(**31**, 70) [a]	(**8**, **24**)
LTCN	(0.75,	1.25,	2.25)	(7.7, 8.0)	(47, 61)	(10, 14) [a]
r	(0.03,	0.05,	0.08)	(**6.8**, **8.5**)	(47, 53)	(**8**, 21) [a]
AESEI	0.005	(0.01,	0.015)	(7.3, 8.2) [a]	(48, 57)	(9, 16) [a]
GCPC	(0.01,	0.015,	0.02)	(7.4, 8.2)	(48, 56) [a]	(**8**, 17)
LSI	(0,	1)		(7.8, 7.9) [a]	(53, **73**) [a]	(9, 12)
Overall range				**(6.8, 8.5)**	**(31, 73)**	**(8, 24)**

N.B.: The largest extremities reached are in bold and are indicated in the last row as 'overall range'.

[a] Denotes intervals where the lower bound of the sensitivity result is associated with the upper value of the corresponding parameter.

4.2. COSTS AND SUPPORTING POLICIES FOR ACHIEVING THE 2 °C TEMPERATURE INCREASE CEILING

Table III presents the cumulated discounted costs in terms of the loss of the net present value for the central parameter values. Figure 4 presents the distribution of the costs over time. Table IV presents the sensitivity analysis for the cumulated costs. For the central parameter values, under the BAU scenario, the NPV of the future stream of consumption amounts to 884.40 trillion U.S.$(1990). When applying the temperature ceiling, the NPV of consumption decreases to 883.83 trillion U.S.$(1990). Cumulated discounted costs are thus 0.57 trillion U.S.$(1990), or 0.06% of the NPV of consumption (Table III). These calculated costs are remarkably low. A typical calculation made with DICE (Nordhaus, 1994, Table 5.1) shows costs of a comparable climate stabilization strategy of nearly 6%, which differs by a factor of hundred with our calculations. A careful inspection of the dynamics of

Table III
Net present value of consumption and costs of the temperature constraint[17]

	NPV (trillion U.S.$1990)	Costs (trillion U.S.$1990)	Percentage
BAU	884.40	–	–
2DC	883.83	0.57	0.06%

the costs can clarify the origin of the divergence between our calculations and those made with DICE and comparable models.[16]

In DEMETER, when implementing the temperature ceiling, consumption is lower than in BAU during the first two decades, both because of the lower productivity of capital and labor due to energy savings, and because of the additional investments in the non-fossil-fuel energy source. For the central parameters, we find that in 2000 consumption levels are 0.25% below the corresponding BAU levels of consumption (Figure 4). However, from 2020 onwards, the consumers reap the fruits of the early investments in the non-fossil-fuel energy source. Learning in the new technology is enhanced, providing the economy with an alternative energy source that contributes to diversifying the energy system, while the costs involved can continuously decrease over time.

This pattern of costs contrasts with the common results found with most other models (such as DICE). In these models, costs are assumed to be monotonically increasing in the emission reduction level, and almost independent of past emission reductions. Since emissions have to decrease over time to stabilize climatic conditions, while BAU emissions increase over time, reduction levels have to increase; the corresponding costs continuously grow in these models. The costs calculated with DEMETER follow a different pattern, one that is more in line with the analysis by IEA/OECD (2000, e.g., Figure 4.3). This work finds early learning investments followed by substantial benefits later on. For most of the variations in our parameter assumptions, our cost curve follows such a pattern. Still, there are two outlying curves for which costs remain substantial, and positive, over the entire interval 2020–2100.

If the learning curve is relatively flat, that is, the learning rate is 10% (the lowest curve in Figure 4), learning spill-overs and future benefits of present investments in the non-fossil-fuel energy sources are limited. This results in increasing costs of emission reductions, reaching nearly 1.0% of consumption at the end of the 21st century. In this case, total costs amount to 0.16% of the NPV of the consumption stream (Table IV), an increase of almost a factor 3 in comparison to the costs with the central parameter values, but still much below the costs calculated with most

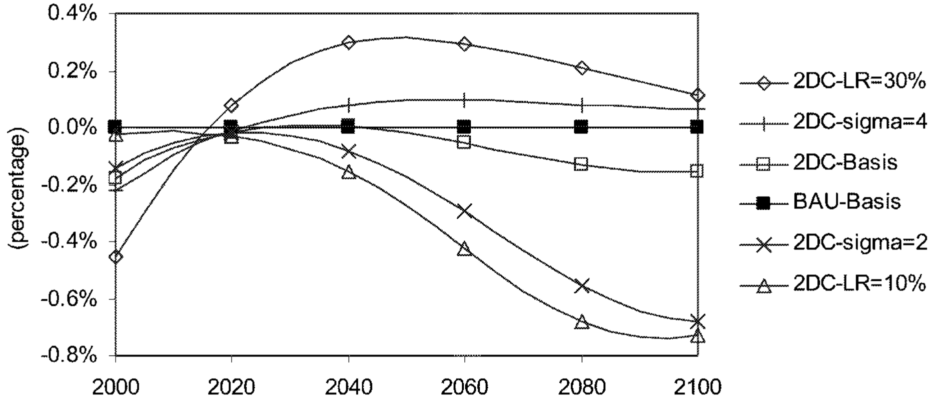

Figure 4. Change in consumption relative to BAU.

other models. The same cost dynamics apply when the two energy sources are no good substitutes, i.e., when $\sigma = 2$, or when the long-term production costs for the non-fossil-fuel energy source exceed the long-term production costs for the fossil-fuel energy source (LTCN = 2.25\$/GJ, not presented in the figure). For these two parameter values, the decrease in NPV of the consumption stream is 0.14% and 0.12%, respectively (Table IV). If we were to abstract from learning, and assumed complementarity between the two energy sources, our model would probably calculate cost patterns and total costs of emission reductions that are comparable to those calculated with other models.

A pattern similar to the 2DC basis scenario, but more pronounced, is found if we assume that the non-fossil-fuel energy source has a steep learning curve, that is, if it has a learning rate of 30%. For this parameter value, it is optimal to boost early investments, decreasing consumption in 2000 by about 0.4%. As a result of high returns on these investments, however, consumption exceeds the BAU level from about 2015 onwards. In this case, there is a double dividend. In addition to the climate objective being met, the NPV of the consumption stream increases by 0.02% compared to the BAU scenario (Table IV), and thus the total costs of the temperature ceiling are negative. The double dividend can occur since subsidies on investments in new technologies, used to transform the energy system towards the non-fossil-fuel energy source, internalize the learning spill-over and bring the economy closer to a first-best allocation in comparison to the BAU scenario. The other parameters, the energy elasticity (γ), the capital depreciation (δ), the gross investment ratio (GIR), the real interest rate (r), the autonomous energy services efficiency improvement (AESEI), the growth of per capita consumption (GCPC), and the use of subsidies for internalizing learning spill-overs (LSI) are less important in terms of their influence on the costs of climate change stabilization.

Two instruments exist that are applied to reach the temperature stabilization objective. The model describes both CO_2 taxes that decrease the demand for

Table IV

Costs of imposing a temperature increase ceiling of 2 °C, and the required taxes and subsidies in 2005

	Lower value	Basis value	Upper value	Costs of 2DC (% NPV)	Taxes in 2005 ($/tC)	Subsidies in 2005 (%)
Basis				0.06	6	24
σ	(2.0,	3.0,	4.0)	(**–0.03**, 0.14) [a]	(4, 9) [a]	(20, **32**)
γ	(0.2,	0.4,	0.8)	(0.06, 0.08)	(6, 6)	(21, 30)
δ	(0.05,	0.07,	0.1)	(0.05, 0.08)	(6, 6) [a]	(21, 27)
GIR	(0.2,	0.25,	0.3)	(0.06, 0.07)	(6, 6)	(24, 24)
LR	(0.1,	0.2,	0.3)	(–0.02, **0.16**) [a]	(4, 9) [a]	(21, 30)
LTCN	(0.75,	1.25,	2.25)	(0.03, 0.12)	(5, 8)	(23, 25) [a]
r	(0.03,	0.05,	0.08)	(0.02, 0.13) [a]	(**2**, **15**) [a]	(24, 24) [a]
AESEI	(0.005,	0.01,	0.015)	(0.02, 0.13) [a]	(5, 7) [a]	(22, 26) [a]
GCPC	(0.01,	0.015,	0.02)	(0.03, 0.11)	(4, 8)	(22, 26)
LSI	(0,	1)		(0.06, 0.08) [a]	(6, **15**) [a]	(**0**, 24)
Overall range				**(–0.03, 0.16)**	**(2, 15)**	**(0, 32)**

N.B.: The largest extremities reached are in bold and are indicated in the last row as 'overall range'.

[a] Denotes intervals where the lower bound of the sensitivity result is associated with the upper value for the corresponding parameter.

the fossil-fuel energy source, and subsidies on investments in the non-fossil-fuel energy sector that stimulate non-fossil-fuel energy demand as well as its development.

Since the equilibrium calculated can be understood as the solution of a welfare maximization problem, the tax can be interpreted as the shadow price of the carbon emissions constraint in the welfare-optimizing framework. The initial tax (i.e., the tax levied in 2005) of about 6 $/tC increases the price for the fossil-fuel energy source by about 5%, reducing its demand by 2%, given the assumed elasticity of $\gamma = 0.4$. The calculated tax steadily increases (not shown in this paper, see van der Zwaan et al., 2002) reaching levels of about 10 $/tC in 2020 and 200 $/tC in 2100. Most changes in parameters do not affect the carbon tax too much. Only the interest rate and the subsidy policy are perhaps two exceptions. Using a higher discount rate of 8% per year implies a lower shadow price of present emission reductions and thus lower taxes, of 2 $/tC, since the temperature ceiling becomes binding only at the end of the 21st century, and the NPV of reaching this temperature constraint is negatively correlated to the interest rate. Using a lower discount rate increases the 2005 carbon-tax to some 15 $/tC. These results are understandable, and are in line with what is found in the literature on this subject matter (for an extensive overview of the discounting discussion, and controversy, in this context, see Portney and Weyant, 1999). We also see in the table that carbon taxes need to be substantially increased, to 15 \$/tC in 2005, if the government does not internalize the spill-overs from the non-fossil-fuel energy source through subsidies (LSI = 0). Thus, when the government does not directly and explicitly stimulate the development of the non-fossil-fuel energy source, it has to do so indirectly through a tax on the competing fossil-fuel energy source.

This brings us to the other instrument, the subsidies on investments for the non-fossil-fuel energy source. For the central parameters, the subsidies cover 24% of the investment costs for the non-fossil-fuel energy source. Since investment costs make up 80% of total production costs for the non-fossil-fuel energy source, these subsidies cover actually about 20% of total production costs. Demand increases rapidly, and, in turn, production costs fall, so that demand is further stimulated. The subsidies internalize the learning spill-over, so that a higher learning rate implies higher subsidy levels. For a learning rate of 30%, optimal subsidies reach the level of 30% of investment costs. For a low learning rate of 10%, optimal subsidies are lowered to 21% of investment costs. As Table IV shows, the optimal subsidy level is less sensitive to changes in almost any of the other parameters (assuming that learning spill-overs are internalized). Only a variation in the assumed price-demand elasticity results in the same level of sensitivity, and a variation in σ induces a wider range of subsidies (for the latter, see Gerlagh et al., 2000).

The use of subsidies needs a further comment. There are various reasons for public agencies not to subsidize investments in non-fossil-fuel energy sources. First, the public authorities may consider it their task to regulate the use of the environment as a public good through the levying of taxes, but may also consider the development of technology-specific knowledge as the responsibility of the private sector. Second, subsidies are often considered not to be the appropriate way to solve market imperfections. The levying of taxes (only), on the other hand, could be the more sound way to reach a social optimum that includes the protection of the environment, viz. the global climate. Third, unlike our simplified model, in reality there are many technologies that may prove a successful alternative to the fossil-fuel energy source, e.g., different types of solar energy, wind energy, or the more conventional hydropower and nuclear energy. The public authority may find it too complex to determine the optimal subsidy policy. It may thus decide that it is the market that should select the appropriate non-fossil-fuel energy source. Fourth, while the recycling of revenues from emission taxes may raise a double dividend – at least it offers the public authority the possibility to lower other taxes – subsidies remain a costly instrument, since they require other taxes to be increased to maintain budget neutrality. Thus, when the public authority avoids the use of subsidies, the use of carbon taxes indeed may serve a double purpose: they internalize the climate change externality, while at the same time they stimulate the development of non-fossil-fuel energy sources.

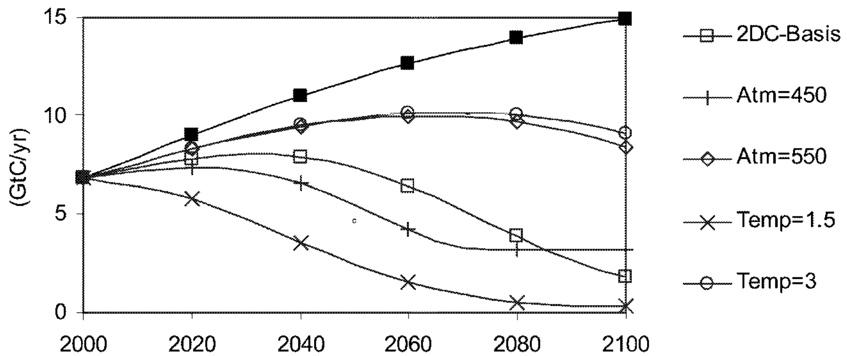

Figure 5. Carbon dioxide emissions under various policy scenarios.

4.3. SENSITIVITY TO POLICY SCENARIOS

We have calculated four additional policy scenarios, with which we can investigate the sensitivity of our results to different climate change targets. Instead of involving a temperature increase constraint of 2 °C (2DC), these four scenarios include, respectively, a temperature constraint of 1.5 and 3 °C, and an atmospheric carbon dioxide concentration constraint of 450 ppmv and 550 ppmv. We point out that the temperature constrained policy scenarios can also be interpreted as sensitivity analyses on the climate sensitivity parameter, with a lower value of 2 °C per atmospheric CO_2 doubling (C/doubling), a central value of 3 °C/doubling, and an upper value of 4 °C/doubling.[18]

Figure 5 shows the carbon dioxide emissions both under business as usual (BAU-Basis; see also Figure 1) and for the various policy scenarios analysed. A 1.5 °C constraint is, naturally, more stringent than a 2 °C constraint, and a 3 °C constraint less stringent. For the long-term, a constraint on the atmospheric carbon dioxide concentration of 450 ppmv (CO_2) is slightly more flexible than a 2 °C constraint. But for beyond the first half of the century, it is a more stringent constraint, since, in general, concentration limits allow less 'overshoots' in emissions compared to temperature limits. As can be seen from Figure 5, the 550 ppmv carbon dioxide concentration scenario resembles the 3 °C constraint scenario.

Table V displays the sensitivity of emissions, of the share of energy savings in total emission reductions, and of the share of carbon-free energy sources in total energy supply, in 2020, for the various policy scenarios. One sees that whereas the emission reduction effort strongly depends on the policy objective aimed at, the nature of the instruments – by which the objective considered is reached – is less dependent on the target. Irrespective of the climate change stabilization target, by 2020, about half of the emission reductions is reached by energy savings, while the other half is reached through a transition towards non-fossil fuels.

Unlike the nature of the instruments used to reach the climate objective (that is, savings versus transition), the costs of reaching the global warming policy are

Table V

Sensitivity of emissions, of the share of energy savings in total emission reductions, and of the share of carbon-free energy sources in total energy supply, in 2020, when realizing various climate stabilization targets

	Lower value	Basis value	Upper value	Emissions in 2020 (GtC/yr)	Energy savings/ emission reduction in 2020 (%)	Non-fossil share in 2020 (%)
Basis				7.8	52	12
CO_2 ceiling (ppmv)	(450		550)	(7.4, **8.3**)	(49, **53**) [a]	(**9**, 14) [a]
Temp. ceiling (C)	(1.5,	2.0,	3.0)	**(5.8, 8.3)**	(**48**, 49) [a]	**(9, 27)** [a]
Overall range				**(5.8, 8.3)**	**(48, 53)**	**(9, 27)**

N.B.: The largest extremities reached are in bold and are indicated in the last row as 'overall range'.

[a] Denotes intervals where the lower bound of the sensitivity result is associated with the upper value of the corresponding parameter.

Table VI

Costs of climate stabilization targets, and the required taxes and subsidies in 2005

	Lower value	Basis value	Upper value	Costs of target (% NPV)	Taxes in 2005 ($/tC)	Subsidies in 2005 (%)
Basis				0.06	6	24
CO_2 ceiling (ppmv)	(450		550)	(0.01, 0.10) [a]	(**4**, 8) [a]	(**21**, 26) [a]
Temp. ceiling (C)	(1.5,	2.0,	3.0)	**(0.003, 0.29)** [a]	**(4, 20)** [a]	**(21, 30)** [a]
Overall range				**(0.003, 0.29)**	**(4, 20)**	**(21, 30)**

N.B.: The largest extremities reached are in bold and are indicated in the last row as 'overall range'.

[a] Denotes intervals where the lower bound of the sensitivity result is associated with the upper value of the corresponding parameter.

very sensitive to the climate stabilization target. A slightly lower bound of the temperature ceiling, from 2 to 1.5 °C, increases the costs dramatically – almost five-fold – from 0.06 to 0.29% of the NPV of consumption. In 2005, the supporting taxes corresponding to this change in temperature objective increase almost four-fold. Subsidies are less sensitive to such a change, since their level for a large part depends on the learning potential, and is only partially dependent on the value of the carbon constraint. The calculated costs, taxes and subsidies are given in Table VI.

5. Conclusions

The novelty of the integrated assessment model of climate change DEMETER is that it includes two energy sources (carbon and non-carbon) and learning-by-doing for both of these energy sources. These modeling features enable us to study the two options for emission reductions. The first is the energy savings option, in which the substitution of capital and labor for energy is allowed for. The second is the energy transition option, in which emission reductions can be achieved through a transition from a carbon energy technology towards a carbon-free energy technology. The first option turns out to be of most importance in the short run, whereas the second option is needed to reach substantial emission reductions in the long run. The finding that the transformation from carbon to non-carbon energy technologies starts to play a major role only after a few decades might create the false impression that little action is called for today. Quite on the contrary, we do *not* want to suggest any delay of action. As a matter of fact, the emission paths determined by DEMETER clearly show that to stabilize climate change at an increase of the atmospheric temperature of 2 °C, substantial emission reductions are also called for in the short and medium term. Such reductions can be achieved by early investments in carbon-free technologies, which are a necessary condition for accelerating the learning process required for long-term carbon emission reductions.

The DEMETER model uses an aggregate production function that represents the phenomenon of niche-markets. Our simulation of niche markets implies a replacement of the fossil-fuel energy source by the non-fossil-fuel energy source that is endogenous to the model. It is smoother than a transition that would result from calculations based on linear substitution possibilities between the two energy sources. This is an important difference with energy technology transitions as simulated elsewhere in the literature, notably in detailed (cost minimization) energy system models that not rarely display corner solutions in the selection of energy technologies, or, alternatively, that involve exogenous transition paths determined by specified bounds for the penetration rates of new technologies.

Admittedly, we have considerably squeezed the variety of energy resources in our model, that is, with respect to bottom-up models that usually simulate large ranges of possible energy options. Indeed, representing the possible renewable energy resources by just one variable, N, is a strong abstraction, and estimating e.g., its long-run production cost can only be done rudimentarily. The very reason that we have performed a sensitivity analysis for the latter is to see how timing and cost results are affected by such generalizing assumptions. While from bottom-up models, generally relatively rich in energy technology description, more energy technology specific lessons may be learned, they are typically less apt for analyzing economy-wide phenomena or overall welfare-energy effects and interactions. In this respect we think that top-down models should be considered complementary to bottom-up models, rather than considered either superior (typically by mainstream economists) or inferior (typically by the often natural-scientifically oriented scientists doing bottom-up energy engineering systems analyses) to the latter. We do not think that the results of either of these approaches are insignificant, but in both cases they should be 'handled and interpreted with care', and one should realize that they might be considerably dependent on the values chosen for the parameters involved in the model. With respect to various top-down models, our energy simulation involves an enrichment of technological specification, not only through an inclusion of two explicit energy technologies (carbon and non-carbon) but also by an evolvement of their costs according to observed and expected learning phenomena (for a recent overview of possible enrichments of environmental technological specification in a variety of energy-economy models, see e.g., Carraro et al., 2003).

One of our main conclusions is that by playing around with the numerous parameters and assumptions in economy-energy-climate models one loses lots of the significance of the findings many scientists derive from them. Since this is a fact largely under-recognized, we have made it a main theme of this paper. So, it is both an auto-critique and a broader result with implications for the community of integrated assessment researchers at large.

Overall, our modeling assumptions prove to be important, but the main results regarding overall energy dynamics continue to hold when changing the parameter values. With our simulation, we think to have contributed to understanding and demonstrating under what conditions an expensive but learning non-carbon energy resource can take over a cheap conventional carbon energy option. We think that finding the answer to this question is fundamental to solving the global warming problem, that is, to figuring out how mankind should make a transition during the 21st century from fossil to non-fossil energy use.

The costs of realizing a radical transformation of the energy production and consumption infrastructure, in such a way as to reach the climate constraint of not allowing the global average atmospheric temperature to increase by more than 2 °C, as calculated with DEMETER, are found to be low. They amount to only about 0.06% of the net present value of consumption. This value is substantially lower than the costs calculated with most other IAMs, as has also been pointed out in Gerlagh and van der Zwaan (2003).

The main subject and result of this article, obtained through our sensitivity analysis, is that the patterns of the derived dynamic energy transformation paths are robust against most changes in the values assumed for our model's economic and technological parameters. Still, regarding a few of these parameters, our results prove to be quite sensitive to the particular values used. The numerical results on the costs and timing of emission reductions appear most sensitive to the parameters that characterize the learning curve of the non-fossil-fuel energy source, on the one hand, and the substitution possibilities between this energy source and the fossil-fuel energy source, on the other hand.

The sensitivity of our results to the learning rate is understandable, since this rate determines the intensity of the mechanism that promotes accelerated price decreases. A low learning rate of 10% substantially increases the costs of a climate change stabilization program, in comparison to the costs calculated for central parameter values of the learning rate. A low learning rate also implies a delay of the transition towards the non-fossil-fuel energy source, and hence a delay of emission reductions. A high learning rate of 30% implies that the transition towards the non-fossil-fuel energy source can become a beneficial venture. In other words, costs can become negative in this case. With a high learning rate, it becomes optimal to set in motion the transition as soon as possible: already in 2020 the non-fossil-fuel energy source reaches a share of above 20% of total energy supply, so that already by 2020 carbon emissions reach levels below current values.

The second important parameter in our sensitivity analysis is the elasticity σ, describing the substitution potential between the two energy sources. A low substitution elasticity $\sigma = 2$ decreases the potential of the second carbon mitigation option, i.e., the transition towards the non-fossil-fuel energy source as a mechanism to reach the temperature stabilization objective. With a low value for σ, the corresponding costs are relatively high. A high substitution elasticity, $\sigma = 4$, increases the potential of a transition policy and decreases the calculated costs. Yet the levels of carbon taxes and subsidies for the non-fossil-fuel energy source, required to reach the temperature change stabilization objective, remain relatively independent of the value of this parameter.

In addition to the learning rate and the niche market elasticity, a number of other parameters are subjected to an extensive sensitivity analysis. A few of these provide some further useful insights. The long-term production costs for the non-fossil-fuel energy source defines the floor of the learning curve, that is, the production costs that apply when learning opportunities have been fully exhausted. The long-term production cost parameter has, understandably, substantial impact on the cumulative costs required to reach the temperature ceiling. In the short and medium term, however, changes in this parameter have only a minor effect on the costs and timing of emission reductions.

Variations in the elasticity of substitution between energy and the labor-capital composite, γ, the capital depreciation rate, δ, and the gross investment ratio that determines the capital share α in the capital-labor composite, have only minor impact on calculated emission paths, corresponding costs, and the timing of emission reductions. A change in the real interest rate has an impact on costs and timing as expected: the effect of such a change has been demonstrated extensively in many studies in the literature already. A higher interest rate implies a delay of reduction measures and a decrease of the net present value of costs, while a lower interest rate has the opposite effect. Under the business – as usual benchmark scenario, variations in the assumed growth in consumption per capita and the autonomous improvement in energy (services) efficiency also produce results as expected. Indeed, both parameters have an important impact, in an exogenous way, on the total required production of energy, and hence on the carbon emissions generated. A higher growth in consumption and a lower autonomous energy efficiency improvement both increase the benchmark carbon emissions. These parameters are of limited importance, however, for the costs and timing of emission reductions, when not trespassing a temperature ceiling is the aim.

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Notes

[1] An elaborate discussion of the Japanese experience with photo-voltaic electricity production can be found in IEA/OECD (2000, Ch. 3).

[2] The DE-carbonisation Model with Endogenous Technologies for Emission Reductions.

[3] Under linear additivity, it is common not to give weights to different energy resources before aggregation (see, e.g., Peck and Teisberg, 1992). On the other hand, using a CES aggregation, weights are often used to calibrate the model to empirical data on energy inputs and prices. These weights can substantially differ between various energy resources (see, e.g., Goulder and Schneider, 1999), implying that some energy resources are assumed to have a considerable intrinsic advantage over other energy resources.

[4] The MESSAGE model (Messner, 1995) uses the same function, except for the constant '+1', which in our case assures that the price of energy cannot decrease without bound. For a new technology with a limited level of cumulative experience (small x), the learning rate lr and d satisfy $d = -\ln(1 - lr)/\ln 2$. For small learning rates lr, the approximation $d = lr/\ln 2$ holds. For mature technologies with high levels of cumulative experience, $x \to 8$, the learning rate drops to zero.

[5] An elasticity $\gamma = 1$ would imply a Cobb-Douglas production function in which capital and labour could completely substitute for a decrease in energy use.

[6] This excludes non-commercial biomass use, as well as traditional carbon-free sources such as nuclear and hydropower. We do not consider these energy resources in this analysis.

[7] See, for example, IEA/OECD, 1999, p. 41.

[8] See, for example, IEA/OECD, 2000, p. 54. In Figure 3.3 in this publication, one sees that in 1995 (in the EU) wind energy production costs varied from about 0.02 to 0.08 €(1990)/kWh. Assuming an approximate equivalence between the Euro and Dollar, and applying the conversion factor of 0.0036 GJ/kWh to GJ, and the conversion factor 0.33 going from electricity to primary energy equivalents, one obtains the range [1.8, 7.2] $/GJ as quoted here.

[9] See, for example, IEA/OECD, 2000, p. 21.

[10] Note that this ratio is typically a fair estimate for renewables like wind and solar energy, but that it does not apply for a renewable like biomass, since the use of the latter resembles the use of fossil fuels in many respects, regarding e.g., fuel efficiency and conversion ratios.

[11] See also note 4.

[12] We identify the capacity of a vintage in the energy production sector by the average energy flow that will be generated by the vintage in its first period. Alternatively, we could define the capacity in terms of the peak-load, but the use of the average energy flow is more convenient and does not alter the results. For the fossil-fuel energy source, energy production in 1997 is estimated as 96% of 320 EJ, that is, 307 EJ. The annual growth rate of energy supply is assumed to be equal to the annual growth rate of consumption minus the autonomous energy efficiency improvement, that is, 2.9%–0.5% = 2.4%. Given an annual replacement of $\delta = 7\%$, it follows that the cumulative installed capacity of past vintages is approximately equal to (307 EJ) $\times$ (0.024 + 0.070)/(0.024) = 1202 EJ. For the non-fossil-fuel energy source, a growth rate twice as high is assumed for the past years, resulting in (13 EJ) $\times$ (0.048 + 0.070)/(0.048) = 32 EJ. Note that the calculated cumulative installed capacity depends on parameters (such as δ) that are subject to our sensitivity analysis. Moreover, note that the model might calculate slightly different values when calculations are based on periods of 5 years (as we do), and not on periods of 1 year.

[13] Schneider and Azar also provide plenty of rationale for why performing a temperature increase uncertainty analysis is both necessary and insightful. In particular, in their argument to keep many options open, they state explicitly that retaining low stabilization targets (of 2 °C or 450 ppmv) on the bargaining table for climate policy options is a wise thing to do.

[14] For example, all other parameters kept equal, changing $\sigma = 3$ into $\sigma = 2$ results in baseline emissions reaching 20 GtC/yr in 2100 (instead of about 15 GtC/yr), while a change to $\sigma = 4$ implies emissions reaching 12 GtC/yr in that year.

[15] Own calculations, using the standard interest rate of the DICE99 model, which is slightly below 5%.

[16] Some of these particular findings (but not the sensitivity analysis) have been presented and discussed earlier in Gerlagh and van der Zwaan (2003).

[17] Note that the various paths analysed in this paper may correspond to different real interest rates. For this table, we used the same price deflator as in BAU, to calculate the NPV of both the BAU and the alternative 2DC stream of consumption.

[18] To put it precisely, the 1.5 °C stabilisation policy scenario is equivalent to a 2 °C stabilisation scenario with increased climate sensitivity of 4 °C per doubling of atmospheric CO_2. Similarly, the 3 °C stabilisation policy scenario is equivalent to a 2 °C stabilisation scenario with decreased climate sensitivity of 2 °C per doubling of atmospheric CO_2.

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