Induced technological change under carbon taxes

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Abstract

We study changes in fossil fuel and non-fossil energy use and carbon dioxide emissions induced by carbon taxes. We develop a partial energy equilibrium model with capital and labor as production factors, and endogenous technological change through learning by doing and learning through research, distinguishing between private and public innovations. Our model reproduces the learning curves typical for energy system engineering models. The model also produces an endogenous S-curved transition from fossil fuel energy sources to non-fossil energy sources over the coming two centuries. It is shown that, (i) induced technological change accelerates the substitution of non-fossil energy for fossil fuels substantially. Also, (ii) a temporary carbon tax has a permanent effect on the technological progress of the non-fossil energy and advances the transition towards it.

Induced technological change under carbon taxes

1. Introduction

It has become increasingly clear that environmental taxes and regulation not only reduce pollution by shifting behavior away from polluting activities, but also encourage the development of new technologies that make pollution control less costly in the long run (Newel *et al*. 1999; Popp 2002). Understanding of the response of technology to economic incentives – dubbed induced innovation or induced technological change (ITC) – will prove crucial for designing appropriate environmental policies (Jaffe *et al*. 2002). The aim of this paper is to present and apply a numerical model, namely the DE-carbonization Model with Endogenous Technologies for Emission Reduction, version 2, where only the Energy sector is considered (DEMETER 2E). DEMETER 2E assesses the potential contribution of ITC to carbon dioxide emissions reduction, and to compare this contribution of ITC with the contribution of substitution between carbon dioxide emitting and carbon free energy sources for a given technological state. In the literature, the subject of ITC has been studied mostly in the context of one representative aggregate technology (e.g. Verdier 1995, Beltratti 1997, Newell *et al*. 1999, Goulder and Matthai 2000, Nordhaus 2002). In that context, technology is treated as a production factor, and ITC stands for a substitution of the factor technology for other production factors. This paper extends the literature as it addresses ITC in the context of two competing technologies (energy sources).

Induced technological change is receiving considerable attention in the climate change related literature where the potential contribution of ITC to policies aiming at greenhouse gas emission reductions is subject of a yet undecided debate. Some studies try to estimate empirically the impact of ITC relative to the substitution effects without technological change (Carraro and Galeotti 1997, Goulder and Schneider 1999, Nordhaus 2002, van der Zwaan *et al*. 2002, Buonanno *et al*. 2003, Gerlagh and van der Zwaan 2003). But the estimated contribution of ITC varies considerably between the studies. Carraro and Galeotti (1997) employ an econometric model for the EU and come to an optimistic conclusion. ITC can bring about a double dividend when proper R&D incentives will reduce emissions without the need for decreasing consumption. Goulder and Schneider (1999) and Nordhaus (2002) are more pessimistic and conclude that, though ITC is not negligible, its contribution to greenhouse gas emission abatement is small when compared to the contribution of fixed-technology substitution. The somewhat disappointing result of these two studies may, however, be explained by the set up of the analyses. Nordhaus'(2002) study is based on one representative technology, and assumes that the reduction of carbon dioxide emissions requires the substitution of knowledge for energy. It abstracts from changes in energy composition, that is, the substitution of carbon poor energy sources for carbon rich energy sources. The substitution between energy sources is included in the other study by Goulder and Schneider (1999), who consider fossil fuels versus renewable energy sources. These two energy sources are, however, treated as complements (elasticity of substitution below unity), so that substitution and competition is limited. Such an approach may be quite realistic in the short run, as global energy demand is ever increasing and renewables are, not yet, substitutes. They may become so in the long run, which is the context of our analyses.

ITC plays a more prominent role in a context with multiple competing energy sources (van der Zwaan *et al*. 2002, Gerlagh and van der Zwaan 2003) and such a context would also be in line with many so-called Integrated Assessment Models (e.g. Peck and Teisberg 1992; Manne *et al*. 1995). To constrain climate change, the substitution between various energy sources is essential. In the long term, energy savings will be insufficient for substantial abatement levels of carbon dioxide emissions, since energy is an essential production factor. Instead, if a substantial emission abatement strategy is aimed for, a shift away from fossil fuel based energy sources towards carbon-free energy sources is unavoidable (Chakravorty *et al*. 1997). For this reason, in studying the added value of ITC, we have to take into account the effect of ITC on the relative contribution of various competing technologies used for energy production (Weyant and Olavson 1999).[1]

The significance of ITC for policy making is wider and not restricted to energy and climate change alone. Understanding ITC is essential for assessing resource policy analyses and the use of partial equilibrium models for this purpose.

The objective of this paper is twofold. First, we have a methodological objective, namely to bridge the gap between energy-system engineering and neo-classical economic approaches. Second, we present some policy analyses, to verify whether as a weak impulse can have a long-term impact on emission levels and whether a weak impulse may change the learning curve too.

In carrying out policy analyses, we study the response of a carbon tax on CO_2 emissions, when taking account of technological change. Most applied numerical studies so far assumed a technological state that dynamically developed over time, but that was independent of emission policies. We assess by how much these results may change if we include induced technological change (ITC), following emission policies. We have two specific sub-questions.

First, what is the significance of ITC for the responsiveness of cumulative emissions to constant carbon dioxide taxes? To measure this response, we take the reduction in cumulative carbon dioxide emissions over the period 2000-2100 following a constant carbon tax of say 20 \$/tC. We compare the reduction in cumulative emissions without ITC, and with ITC. The ratio between the two is a good measure for the impact/significance of ITC. This number is important,

[1] More in general, a representative aggregate technology does not perform well when there are increasing returns to scale at the disaggregate level (Basu and Fernald 1997).

since most analyses with applied general equilibrium models assume given technology, and this may be realistic or too pessimistic dependent on the ITC 'impact factor'.

Second, we want to study the implications of temporary taxes on the present carbon dioxide emission intensity of production and its future paths. Will a carbon tax direct technological innovations towards 'cleaner' production of energy, that is, towards renewables, so that after the tax is dropped, emissions remain below their levels that would appear without tax (the so-called BAU)? That is, is the change in technology persistent?

To study these questions, we develop a partial energy model, DEMETER 2E, that has the following features. Total energy demand is fixed. There are two energy sources (carbon and non-carbon) that compete. The model describes technological innovations through learning by doing and research and development (R&D) in the tradition of the endogenous growth models with natural resources that have been specified to study growth and sustainability (Gradus and Smulders 1993; Bovenberg and Smulders 1995; den Butter and Hofkes 1995; Verdier 1995; Bovenberg and Smulders 1996; Beltratti 1997; Smulders 1999). The level of R&D is driven by economic incentives, that is, by the value of an innovation to the innovator.

We are aware of the limitations of the neoclassical approach we follow, which is an abstraction of the reality where producers do more than only maximizing profits. Our specific model is an abstraction of the reality, where we neglect taxes, and other market distortions. To compensate for these limitations, we try to find a harmony between our neoclassical approach and energy-system engineering approaches. We calibrate the model to generate a benchmark scenario that is in line with other studies, and then, we study the effect of a temporary 20 \$/tC emission tax: 20 years, (2005-2025), 40 years (2005-2045), and a permanent tax of 20 \$/tC for which the situation with and without ITC is considered.

Section 2 describes the basic features of the model for the energy sector and one energy source. Section 3 extends the model to take account of two competing energy sources. Two different energy sources are considered. Furthermore, the impact of energy production on carbon emissions and global average temperature is discussed, as well as the growth of world population in the model. Section 4 describes the empirical calibration of the model. Section 5 provides the results of the two-energy source simulation model. The final section discusses the implications of our analysis for climate change policies. Two Appendices are added to the paper. Appendix 1 presents the first order conditions of the model, while the numerical values, as found in the calibration, are presented in Appendix 2.

2. Endogenous technology for energy production

We model energy as an intermediate good. The raw energy source is processed and used as a production factor for other production processes. This section presents the basic elements of our model for energy production and innovation, describing one energy source. *FIGURE 1* provides an overview of the model. We distinguish between knowledge gained through experience, so-called learning by doing, and knowledge produced through research carried out by innovators. The research-based technology is described as an expanding library of ideas that can be used in the production process. Innovation is a cumulative process; each innovation builds on the stock of existing knowledge. Energy producers can make use of all past and present innovations, that is the total stock of knowledge, and pay a license fee to all innovators that have developed the innovations that are currently in use. In turn, the innovators receive the license fees from all present and future energy producers that use their innovations. Both innovators and producers of final goods take prices as given. We do not consider product variety and price setting under monopolistic competition as in many other endogenous growth models (see Barro and Sala-i-Martin 1995 for an overview).

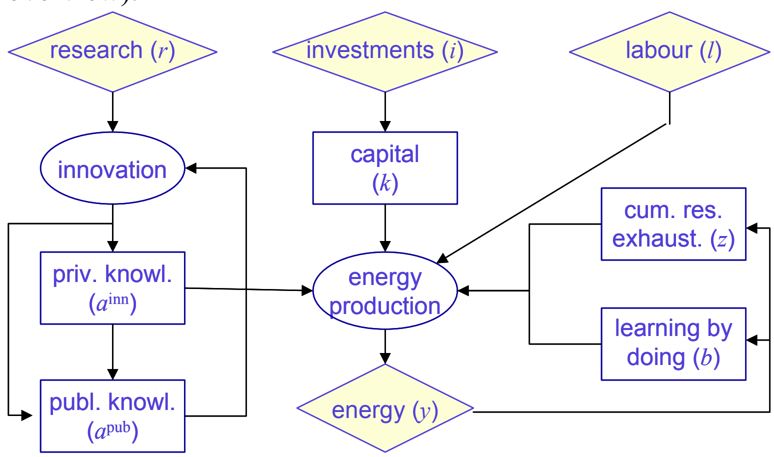

FIGURE 1. *Schematic overview of innovation and energy production in the model. The innovation and energy production processes are presented in an ellipse. Stocks are presented in rectangles.*

In this section, for the one sector model, we assume that the demand for energy y_t shows a constant elasticity σ,

$$y_t = \hat{y}_t \, p_t^{-\sigma}, \tag{1}$$

for some exogenous demand variable $\hat{y}_t$, where p_t is the price of energy at date t. In the continuation of this paper, we omit time subscripts when convenient. We assume that energy is taxed at a fee τ. As common for energy taxes, the tax has a physical basis, and thus, adds a constant markup value to the production costs in contrast to a constant markup ratio,[2]

$$p_t = q_t + \tau_t \varepsilon_t, \tag{2}$$

[2] Usually the following expression is used: $p_t = (1+\tau_t) q_t$, where tax is measured as a rate.

where q_t is the production cost and ε_t the energy efficiency as defined later on in equation (13).

Firms, indexed j, produce energy according to

$$y_{j,t} = \varsigma\,(z_t)^{-\mu}(a_{j,t})^{\eta_a}(b_t)^{\eta_b}(k_{j,t})^{\alpha}(l_{j,t})^{1-\alpha}, \quad (3)$$

where ς is an overall productivity parameter, z_t, the public cumulative amount of resource exploitation, is a negative externality of energy source exploitation on output, the variable $a_{j,t}$ denotes the total knowledge stock gained through research, b_t denotes the non-rival knowledge stock gained through learning by doing publicly available to all firms, $k_{j,t}$, is the capital stock, and $l_{j,t}$, is labor use in efficient labor units. Human capital increasing labor productivity is not specified explicitly, as it is considered embodied in the labor good, exogenous to the individual firm.

For fossil fuels, the value of $(z_t)^{\mu}$ reflects the effort required to exploit, say, oil wells. The effort $(z_t)^{\mu}$ increases because of decreasing quality of oil wells when the reserves decrease because of cumulative production. The increased effort is measured by the increase in the variable z_t,

$$z_{t+1} = z_t + y_t. \quad (4)$$

where we omitted the subscript j for the output variable y_t ($=\Sigma_j y_{j,t}$). Equation (3) states that the effort required for energy production, $(z_t)^{\mu}$, increases by 2^{μ} for every doubling of the cumulative resource exploitation level. We assume that the energy sources are owned by the firms that exploit these, hence there is no open access, but there are well-defined property rights. This also implies that the impact on future efforts of energy production is internalized, as resource depletion influences the energy price in our model. For renewable energy sources, there is no exhaustion and we assume μ=0. This eliminates the negative externality on energy production. Variable z_t for non-fossil energy can be interpreted as the cumulative production of and experience with non-fossil energy production. *FIGURE 2* illustrates the difference of fossil and non-fossil cumulative resource exploitation.

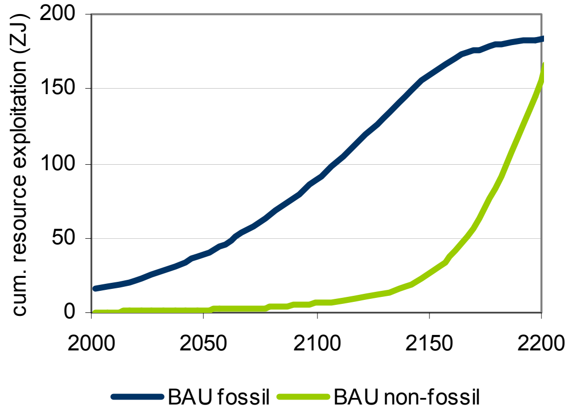

FIGURE 2. *Growth pattern of cumulative resource exploitation over time for fossil fuel and non-fossil energy in BAU.*

FIGURE 2 shows that while the cumulative fossil resources decline over time, the cumulative renewables increase exponentially and gain momentum after 2150 in the BAU.

The knowledge variable $a_{j,t}$ is a measure of the number of innovations that are employed by the *j-th* firm, at date *t*. Let $h \in [0,1]$ denote the innovators, and $a^{inn}_{j,h}$ the (continuous) number of innovations in use by firm *j* owned by innovator *h*. Furthermore, let a^{pub} denote the innovations in public domain, for which patents are expired so that their use is free from license payments. We assume that innovations are additive, which is

$$a_j = \int_0^1 a^{inn}_{j,h} \,\mathrm{d}h + a^{pub}. \tag{5}$$

Also, we assume that the firms have to pay a license fee $\theta_{h,t}$ for the innovations employed, for every unit of innovation $a^{inn}_{j,h,t}$, and for every unit of output $y_{j,t}$, so that for the firm *j*, expenditures on innovations amount to $\int_0^1 \theta_{h,t} a^{inn}_{j,h,t} y_{j,t} \,\mathrm{d}h$. Due to the assumed additivity of innovations (5), innovators face perfect competition and cannot earn monopoly rents. If one innovator charges the license fee θ_t, per output unit per innovation, then $\theta_t y_{j,t}$ presents the maximal value the firm *j* is willing to pay per innovation, also to other innovators, and the license fee contract precisely captures that value. No individual innovator can increase its revenues when it switches to another license system or charges a higher license fee. Hence, the license fee is clearing the market of innovations. The license fee is the same for all innovators and we drop the subscript *h*, and (5) becomes

$$a_j = a^{inn}{}_j + a^{pub}. \tag{6}$$

We return to the production of innovations at the end of this section.

The learning-by-doing knowledge stock b_t is based on cumulative experience, that is, the cumulative output level, with some depreciation δ_b,

$$b_{t+1} = (1-\delta_b)b_t + y_t, \tag{7}$$

where we omitted the subscript j for the output variable y_t, as in equation (4). Knowledge through a and b increases productivity, while the resource externality z decreases productivity, and when the former exceeds the latter, $\mu<\eta_a+\eta_b$, productivity increases over time, whereas in the other case, $\mu>\eta_a+\eta_b$, productivity decreases over time.

In addition to the license fees, firms pay for investment expenditures, $i_{j,t}$, and wages, $w_t l_{j,t}$. At time t, total expenditures thus amount to $i_{j,t} + w_t l_{j,t} + \theta_t a^{inn}{}_{j,t} y_{j,t}$, while revenues amount to $q_t y_{j,t}$. The firms maximize the net present value of their cash flows:

$$\max \sum_{t=1}^{\infty} \beta^t ((q_{j,t} - \theta_t a^{inn}_{j,t}) y_{j,t} - w_t l_{j,t} - i_{j,t}), \tag{8}$$

where (1/β)–1 is the real interest rate, subject to the production identity (3), the dynamics of resource depletion (4), and to the capital depreciation-investments relation (9),

$$k_{j,t+1} = (1-\delta_k)k_{j,t} + i_{j,t}. \tag{9}$$

where δ_k is the depreciation rate, and i_t is the investment flow. As expenditures on licenses are proportional to output and production has constant returns to scale, the firms operate in a competitive market pricing the output at marginal cost. This holds for all firms and we can as well omit firms' subscripts j. Appendix 1 presents the full set of first order conditions.

Next we turn to the supply of innovations. There are two externalities working in opposite direction. As a positive externality, knowledge about past innovations is public, that is, knowledge is non-rival when it is used to produce new knowledge. Research innovators use the 'library' of past inventions to produce new innovations, and thus, the flow of new innovations is increasing in the knowledge stock a. As a negative externality, research efforts r by one innovator negatively affect the finding of new innovations by other innovators, because of extraction of new innovations that are attainable from the current state of knowledge. The flow of new innovations for an individual innovator h is thus decreasing in the aggregate research flow r. Finally, the number of new innovations produced by an innovator h, Δa_h, is proportional to its research expenditures Δr_h ($\Delta r_h = r_h \Delta t$, research expenditures are equal to the research flow r_h times the time interval Δt), and a fraction δ_{inn} of innovations owned by the innovator leaks to the public domain because of patents that expire:

$$\Delta a^{inn}{}_h = \zeta\, r_h^{\pi-1}\, a^{1-\pi}\, \Delta r_h - \delta_{inn} a^{inn}{}_h. \tag{10}$$

where ζ is a scaling constant. Aggregation of innovations (10) over the innovators gives

$$a^{inn}_{t+1} = \zeta\ r_t^{\pi}\ a_t^{1-\pi} + (1-\delta_{inn})a^{inn}_t. \tag{11}$$

Public knowledge is fed through two channels. First, part of the property rights for innovations held privately by the innovators expires, $\delta_{inn}a^{inn}$, and public knowledge is also produced as a direct spinn-of of research, $\chi\zeta\ r_t^{\pi}\ a_t^{1-\pi}$, where the parameter $\chi \in (0,\infty)$ describes the relative contribution of research to public knowledge versus privately held innovations:

$$a^{pub}_{t+1} = (1-\delta_{pub})a^{pub}_t + \delta_{inn}\ a^{inn}_t + \chi\zeta\ r_t^{\pi}\ a_t^{1-\pi}. \tag{12}$$

Also, a small fraction δ_{pub} of knowledge becomes obsolete. Appendix 1 presents the full set of conditions characterizing the market for innovations.

3. Energy aggregation and climate change

So far we did not explicitly consider competition between technologies. In this section, we first extend the one-technology model with emissions and a simple representation of the carbon cycle, and we second consider two competing technologies that can be used for production.

Carbon emissions, expressed as a function of time by E_t, are proportional to the use of fossil-fuel-based energy, y_t, via the aggregate carbon emission factor ε_t:

$$E_t = \varepsilon_t\ y_t, \text{ where } \varepsilon_t = \max(0.8, 0.998^t)\varepsilon_1 \tag{13}$$

The factor ε_t is assumed to be time-dependent, and declines by 0.2% per year and cannot drop below 80% of total output, to be able to account for a gradual de-carbonization process. Fossil-fuel consumption has been subject to such a process since the early times of industrialization, by a transition –in chronological order– from the use of wood to coal, from coal to 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. The carbon cycle dynamics assumed here are simple, and follow the approximations supposed in DICE (Nordhaus, 1994). Carbon emissions are linked to the atmospheric carbon-dioxide concentration, Atm_t, which in turn determines the global average surface temperature, Temp_t, using a "1-box representation":

$$\text{Atm}_{t+1} = \text{Atm}_0 + (1-\delta_M)(\text{Atm}_t - \text{Atm}_0) + (1-\delta_E)(\text{E}_t + \bar{\text{E}}), \tag{14}$$

$$\text{Temp}_{t+1} = (1-\delta_T)\text{Temp}_t + {}^2\log\left(\frac{\text{Atm}_{t+1}}{\text{Atm}_0}\right)\overline{T}\ \delta_T, \tag{15}$$

where δ_M is the atmospheric CO_2 depreciation rate, $1–\delta_E$ the retention rate, $\bar{E}$ are emissions not linked to energy production, δ_T the temperature adjustment rate resulting from the atmospheric warmth capacity, and $\overline{T}$ is the long-term equilibrium temperature change associated with a doubling of the atmospheric CO_2 concentration.

Population (POP_t) grows logistically as follows:

$$POP_{t+1} = POP_t\left(1 + g_{POP}\left(1 - \frac{POP_t}{POPLT}\right)\right), \tag{16}$$

where g_{POP} is the initial population growth rate and POPLT is the long term population number.

Now we turn to two competing technologies. Goods produced by both technologies have their own characteristics but are substitutes; we use the same parameter σ as above in equation (1), now to denote the constant elasticity of substitution between technologies. For convenience, we assume inelastic demand on the aggregate level, $\hat{y}_t$, which grows at a rate γ,[3] so that we can focus on the substitution effects between the two technologies. The technologies are denoted by g=1,2. We do not assume that energy produced by both technologies has constant elasticity of substitution, but we assume a linearly homogeneous and variable elasticity of substitution (VES) aggregation function.

In this context, the symbol σ denotes the elasticity of substitution between the two technologies and not the elasticity of demand as in the previous section. Though, we notice that if one technology has a minor share in total output, and if total demand for both technologies is constant, then σ approximately describes the elasticity of demand for that particular technology. Energy system models (e.g. Peck and Teisberg 1992) typically assume that carbon-free technologies are perfect substitutes for fossil fuel technologies, but have limited maximum supply and relatively high production costs that do not decrease over time. Such a set of assumptions does not facilitate an explanatory description of a continuous diffusion over time of carbon-free technologies, since under perfect substitution demand is zero for all but the cheapest technology, unless positive demand is explicitly included as a volume constraint. More generally, perfect substitution between different technologies cannot explain that relatively expensive new technologies can develop before they become fully competitive with mature technologies. In contrast, models with a neo-classical point of reference typically assume complementarity between energy technologies. In Stephan *et al* (1997) and Goulder and Schneider (1999), carbon-free technologies and fossil fuel based technologies are relatively poor substitutes, that is, they

[3] More specifically, we let $\hat{y}$ grow exogenously as follows: $\hat{y}_t = POP_t/POP_1(1+g_{ypc})^{t-1}\hat{y}_1$. This means that energy demand per capita grows at g_{ypc} per period, while the total energy demand also accounts for the relative increase in population.

have substitution elasticity of unity, or less[4]. Under this assumption, carbon-free technologies will not reach a substantial market share, irrespective of future decreases in production costs.

In this paper, we specify an aggregator function that bridges the two views on substitutability. We assume that σ is constant along an expansion path, that is when both y_1 and y_2 increase by the same factor, but σ varies along an isoquant for constant $\hat{y}_t$. Specifically, the two technologies are considered moderate substitutes, σ≈1, when one technology is dominant and demand for the other technology is best described through niche markets. The two technologies are considered good substitutes, σ>1, when both technologies have substantial market share. Finally, as in the energy system literature, we assume that no energy source has an absolute comparative advantage in use, that is, we treat demand for both technologies symmetrically. We can thus write the elasticity of substitution as a function of the relative inputs of both technologies, $\sigma(y_1/y_2)$. In the literature, various VES-aggregation functions have been specified, see Nadiri (1982, Section 3.1.2) for an overview. Most VES functions, however, assume that the elasticity of substitution is monotonically increasing in the share of one of the production factors, while we treat both technologies symmetrically, that is, we assume $\sigma(y_1/y_2)=\sigma(y_2/y_1)$. Our aggregation function is based on the symmetric VES aggregator function proposed in Kadiyala (1972). We have specified the aggregator function

$$y_{1,t}{}^{\vartheta} y_{2,t}{}^{\vartheta} (y_{1,t}^{(\sigma-1)/\sigma} + y_{2,t}^{(\sigma-1)/\sigma})^{(1-2\vartheta)\sigma/(\sigma-1)} = \hat{y}_t, \tag{17}$$

such that it satisfies the following features. The elasticity of substitution is unity if one technology is dominant, $\sigma\to1$ for $y_1/y_2\to0$, or $y_1/y_2\to\infty$. Also, the elasticity of substitution exceeds unity, signifying more intense competition, when both technologies are comparable in size. Thus, when one technology is in its infancy with high production costs, its elasticity of demand is about minus unity, and it has an almost constant value share ϑ. Appendix 1 presents the condition when prices are equalized to marginal productivity. *FIGURE 3* shows the output aggregation, as explained above.

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[4] Note that the elasticity of substitution measures the inverse of the curvature of the production isoquant. It divides the percentage change in the factor ratio (that is the change in the angle of the input vector) by the percentage change in the prices (the change in the slope of the isoquant). See, for example, Varian, 1992.

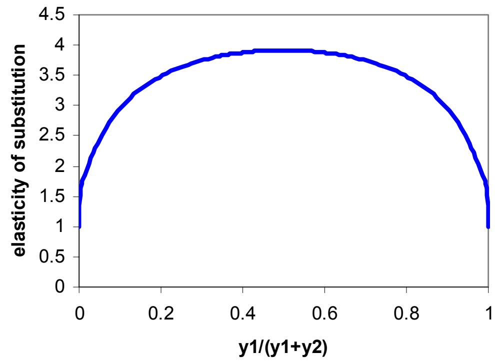

FIGURE 3. *Elasticity of substitution between fossil fuel and non-fossil energy sources, based on parameter values σ=5, ϑ=0.037.*

It is difficult to come up with aggregate energy prices for both technologies. Since, in 2000, the estimated ratio between the volumes for fossil fuel and non-fossil energy has been 24:1, an elasticity of substitution of σ=5 is approximately consistent with a price ratio of 1:2.8, reflecting the price ratio (2.5 \$/GJ and 7.0 \$/GJ) chosen for the current energy prices (see *p*(fossil fuel) and *p*(non-fossil energy) in TABLE 3). The assumed substitution possibilities of the carbon-free technology for the fossil fuel technology, reflected in the value of σ, is of crucial importance for the speed of market penetration. A high elasticity implies that market shares react strongly to even a modest decrease in future production costs, due to gained experience. A low elasticity, on the other hand, implies a relatively slow penetration rate.

4. Calibration and methodology

We also carried out a numerical simulation based on approximate real-world data. As a reference scenario, we constructed a business-as-usual path that follows common assumptions on future energy consumption and prices. The model runs for 45 time steps of 5 years each, representing the period 2000-2250, though the presentation of data and figures will be restricted to the first two centuries 2000-2200. On the basis of the database developed for the IIASA-WEC study (Nakicenovic *et al*., 1998), final commercial energy consumption in 2000 is estimated to be 320 EJ.[5] From the same database, the share of fossil fuel technologies in energy production (in 2000) is estimated at 96 %. This corresponds to 307 EJ. The remaining share of 13 EJ is non-fossil energy. Future energy consumption is assumed to increase by 1 per cent per capita (=g_{ypc}). In 2000, the population (POP_t) is assumed to be 5.89 billion (POP_1) and its growth rate 1.45%

[5] This excludes non-commercial biomass use, as well as traditional carbon-free sources such as nuclear and hydropower.

(World Bank, 1999). The population is assumed to logistically reach 11.4 billion by the end of the simulation period (POPLT), as in the IIASA-WEC study (Nakicenovic *et al*, 1998).

Since our model represents the two energy resources in an aggregate way, we have to make reasonable estimates for the average initial energy prices required. Because of the variability and volatility of these prices, this is not straightforward. In addition, the literature provides insufficient evidence on the elasticity of substitution between the two energy technologies, σ, to justify a certain choice. As our model serves mainly for analyzing the dynamics of the energy system, approximate estimates suffice.

Prices for final energy derived from natural gas technologies vary in a range from 2 to 3 \$(1990)/GJ.[6] 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 2000.

The two-technology model includes a non-fossil energy technology, competing with the fossil fuel technology as described in (17) and (41), which replaces the demand equation (1). A large spread exists in production costs for energy from wind, solar and biomass options. Prices for commercial final electricity from wind turbines varied in 1995 between 5 and 20 \$(1990)/GJ, in the highest-cost and lowest-cost production cases, respectively.[7] Whereas electricity production costs for photovoltaics are still significantly higher than that for wind energy, costs of electricity derived from biomass are comparable to that of wind energy.[8] The average price of final energy by the non-fossil energy is taken to be 7.0 \$/GJ, in the year 2000. This value is merely taken as an example from the range of current feasible wind electricity prices; it represents a realistic figure of the current cost of a particular non-carbon energy alternative, generically speaking.

We furthermore assume that both the fossil fuel and non-fossil energy have the same technology parameters, the value of which is taken from the one-technology model. Since we choose σ=5, the equilibrium converges to a non-fossil energy dominated balanced growth path. Parameters and first-period values for state variables have been chosen such that, in the benchmark scenario, also referred to at the Business as Usual (BAU) scenario, the share for the non-fossil energy increases from 4% in 2000 to 11% in 2100 and 98% in 2200 (*FIGURE 5*). Related to the non-fossil energy gain in market share, the non-fossil energy benefits from

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

[7] See, for example, IEA/OECD 2000, p.54. In fig.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 ECU(1990)/kWh. Assuming an approximate equivalence between the ECU and \$, as well as the conversion factor of 3.6 in going from GWh to TJ (that is, 0.0036 from kWh to GJ), one obtains the range quoted here.

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

economies of scale more than the fossil fuel energy source and its price decreases over time, while the price for the fossil fuel energy technology slightly increases (*FIGURE 6*).

5. Simulation results

This section presents and discusses the results with the calibrated model. *FIGURE 4* shows the level of emissions in the period 2000–2200 for three cases, namely BAU, a steady 20 $/tC tax without ITC and with ITC. *FIGURE 5* shows how the share of renewables changes over time in the same three cases.

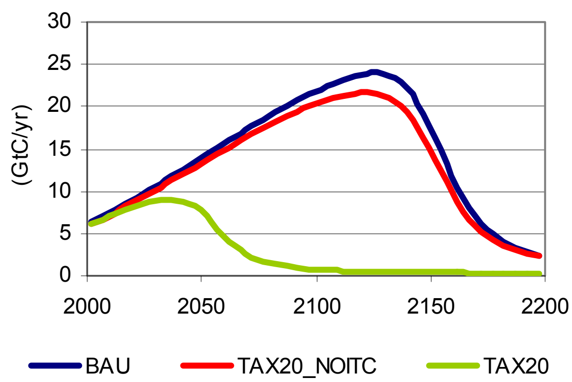

FIGURE 4. *Emissions for benchmark BAU scenario, a 20 $/tC tax without technological adjustment, and a 20 $/tC tax with endogenous technological change*

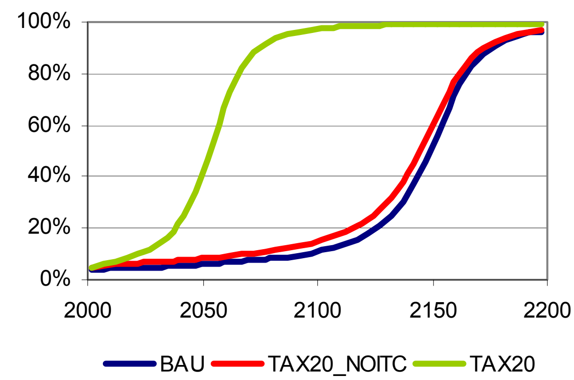

FIGURE 5. *Share for non-fossil energy for benchmark BAU scenario, a 20 $/tC tax without technological adjustment, and a 20 $/tC tax with endogenous technological change*

We can derive the following conclusions from *FIGURE 4* and *FIGURE 5*. Our model appears to reasonably represent the common BAU scenario as a benchmark. After 2140, emissions sharply drop because the energy system makes an endogenous transition towards the non-fossil energy technology. When we abstract from the impact of carbon taxes on technology, a carbon tax of 20 $/tC advances the shift towards the non-fossil energy modestly by about 20 years, and thus reduces emissions modestly. However, when we include ITC in our calculations, the effect of a carbon tax is amplified. The transition is advanced by about ninety years, it takes off at around 2030, and emissions drop substantially during the second half of the 21st century. The next figures present the cause for this advance in transition. *FIGURE 6* plots the energy production costs for fossil fuels and renewables, while *FIGURE 7* shows these costs for the case with a steady 20 $/tC tax and ITC.

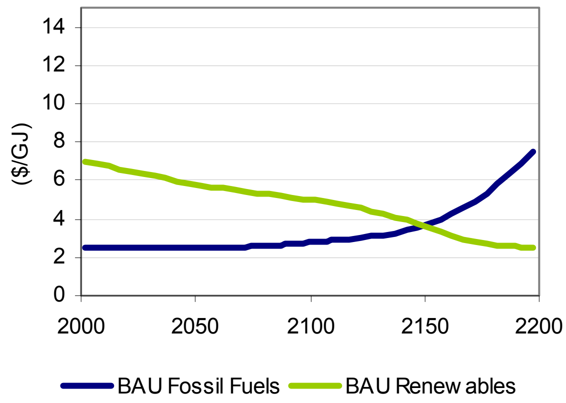

FIGURE 6. *Energy production costs for fossil fuels and non-fossil energy benchmark BAU scenario.*

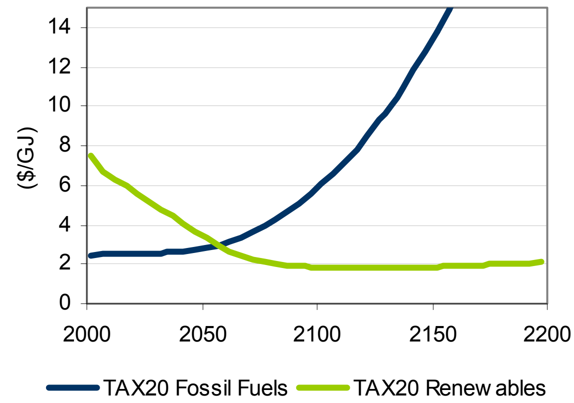

FIGURE 7. *Energy production costs for fossil fuels and non-fossil energy, 20 $/tC tax scenario with ITC.*

We can derive the following conclusions from *FIGURE 6* and *FIGURE 7*.[9] Under BAU (*FIGURE 6*), production costs for non-fossil energy steadily decrease, until, by 2150, they equal production costs of fossil fuels. From that point on, fossil fuels face decreasing market shares, the output levels for fossil fuels decreases, R&D effort and learning by doing decreases and the growth of innovations slows down. Technological development becomes insufficient to compensate for resource exhaustion and the increase in wages and fossil fuel prices increase. This is also the reason why production costs for fossil fuels increase much earlier in the 20 $/tC tax scenario (*FIGURE 7*), that is, immediately after non-fossil energy sources take over as the dominant energy source in 2060. The carbon tax stimulates the use of non-fossil energy, and this leads to an earlier decrease in production costs. Thus, ITC acts as a multiplier for a policy that aims at a transformation from carbon-based to carbon-free energy sources.

In the bottom up literature, this phenomenon is known as the learning curve. We will investigate whether our model can reproduce it. Thereupon, we plot the logarithmic production cost to the logarithmic installed capacity for fossil fuels in *FIGURE 8* and renewables in *FIGURE 9*.

[9] While it is not presented in the figures, the energy production costs under the TAX20_NOITC scenario match the BAU levels.

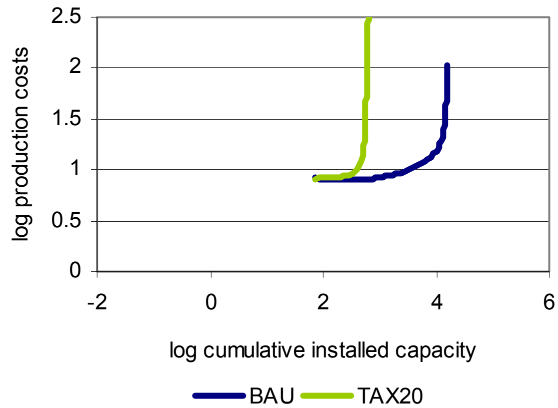

FIGURE 8. *Simulated learning curve for fossil fuels, BAU scenario and 20 \$/tC tax scenario with ITC.*

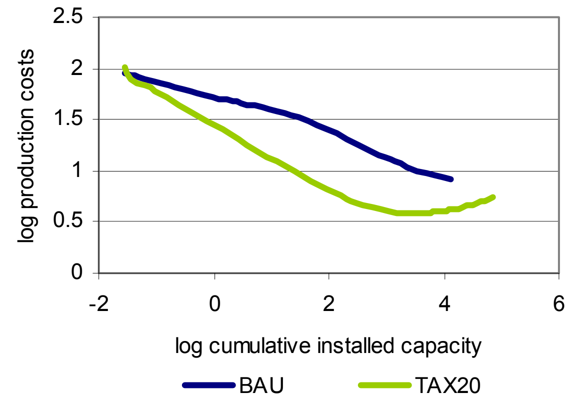

FIGURE 9. *Simulated learning curve for non-fossil energy, BAU scenario and 20 \$/tC tax scenario with ITC.*

FIGURE 8 shows that the production costs for fossil fuels are initially almost constant, until the effort to extract fossil fuels increases substantially, and as a result the production costs go up steeply, and it is no longer economically attractive to exploit these resources at a large scale. *FIGURE 9* shows that the production costs fall, when the output of renewable resources grows. In the steady 20 \$/tC tax case, the costs drop even further, until the costs of labor become a limiting factor in the production cost.

We can draw the following conclusions from these two figures. We have calculated, ex post, installed capacity per period as that part of production that uses newly installed capital stock. On the horizontal axis, we find the log of the cumulative value for this variable z. On the vertical axis, we have the log of the production costs q. In models that describe learning by doing through learning curves (e.g. MESSAGE, Messner 1997; DEMETER 1, van der Zwaan *et al*. 2002, Gerlagh and van der Zwaan 2003), typical for bottom up models, a constant learning rate (lr) is assumed at which the cost of investments or the costs of production per output unit declines for each doubling of cumulative production. This corresponds to

$$q_t = q_0 x_t^{\alpha-1}, \qquad (18)$$

where x_t is the cumulative experience or capacity installed, and $0<\alpha<1$ and q_0 are constants. 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

$$lr = 1 - 2^{\alpha-1}. \qquad (19)$$

In our model, there is no exogenous learning rate, but we can reproduce the learning curves that come out of our simulations. For the non-fossil energy sources, under BAU, we find an average learning rate of about 16% (*FIGURE 9*). Thus, our model reasonably captures the main insight from the energy system learning by doing literature.

However, the mechanisms underlying the curve in our model differ from the energy system models in an important way. First, in our model, technology advances through R&D and learning by doing, but it has to offset increasing wages for the non-fossil energy source, and increasing resource scarcity for the fossil fuels as well. Thus, production costs only decrease when technological advances are sufficient to offset the two forces that tend to increase prices. For fossil fuels, as becomes clear from *FIGURE 6* and *FIGURE 8*, initially technological progress is just sufficient to compensate increasing wages and increasing scarcity, but after a time, prices increase, even though the stock of technology keeps growing.

Second, in our model, while technological progress through learning by doing is based on past cumulative experience, technological progress through R&D is based on expected revenues from innovations. Thus, an anticipated increase in the market share for non-fossil energy sources increases current R&D effort and decreases production costs, before the rise in non-fossil energy materializes. This explains why in *FIGURE 9* the learning curve for the 20 $/tC scenario lies below and bends off compared to the BAU learning curve.

Finally, we turn to the question of the introduction whether transient carbon taxes can have permanent effects on emissions when they direct technological change. *FIGURE 10* and *FIGURE 11* show the effect of a transient tax of 20 $/tC for 20 years (2005–2025) (TAX20A), a transient tax of 20 $/tC for 40 years (2005–2045) (TAX20B), a permanent tax over the whole period (TAX20), and compare this to the BAU.

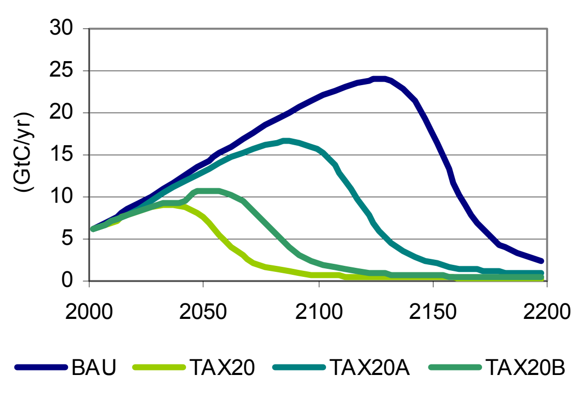

FIGURE 10. *Emissions for benchmark BAU scenario, a permanent 20 $/tC tax, and two transient 20 $/tC tax scenarios with endogenous technological change*

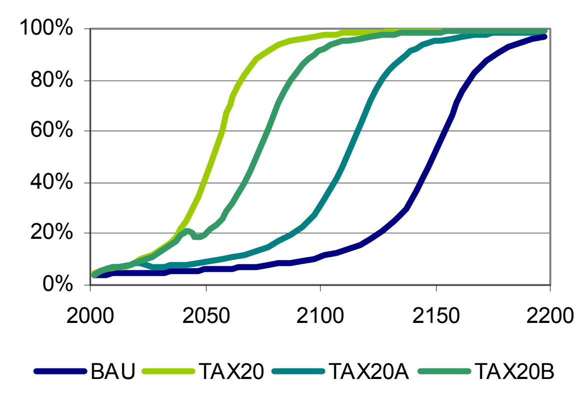

FIGURE 11. *Share for non-fossil energy for benchmark BAU scenario, a permanent 20 $/tC tax, and two transient 20 $/tC tax scenarios with endogenous technological change*

From *FIGURE 10* and *FIGURE 11* follows that a transient carbon tax of 20 $/tC for 20 years (2005-2025) advances the transition by about 55 years (*FIGURE 11*) and decreases cumulative emissions over 2000–2100 by 11%. A transient tax of about 40 years advances the transition by about 110 years and reduces cumulative emissions by 44%, while a permanent tax advances the transition by about 130 years and reduces cumulative emissions by 61%. From this extreme sensitivity of the model with ITC to taxes, also indicates that the BAU is surrounded with uncertainty on the date when renewables overtake fossil fuels. Small perturbations in say 2000-2050, can have a large and lasting impact, possibly changing the BAU.

From *FIGURE 10* and *FIGURE 11* we can also derive the ITC impact factor, to find the significance of ITC for the responsiveness of cumulative emissions to constant carbon dioxide taxes. We measure this response as the reduction in cumulative carbon dioxide emissions over the period 2000-2100 following the steady carbon tax of 20 $/tC. We compare the reduction in cumulative emissions without ITC, and with ITC. This leads to an ITC impact factor of 2.4, which is even higher than the factor 2, which was found by Carraro and Galeotti (1997). They, however, only included learning by research and left out learning by doing. Our model clearly indicates that it is too pessimistic to assume technology as given in the long run.

6. Discussion

In this paper we have presented a model that is neo-classical in nature, but we have tried to get it in line with the results known from the system-engineering models, notably (i) the learning curve, and (ii) the S-curved transition towards new (renewable) technologies.

As for (i), we bridge a gap between the neo-classical economic literature that focuses on incentives for R&D as the driving force for productivity, and the energy systems models that more or less mechanically describe productivity as dependent on cumulative historic experience. We have presented results from applied numerical neo-classical model for the energy sector that can reproduce the learning curve typical for system engineering models. However, two comments are in order. First, production costs decrease because of both learning by doing and research. Research is not only affected by past output and knowledge levels, but also by anticipated output levels. Thus, an anticipated increase in the market shares for renewables will stimulate research that increases the productivity. Thus, an anticipated future increase in output for renewables will enhance the decrease of current production costs: the learning curve becomes steeper in a policy scenario that favors the use of renewables. Second, production costs tend to increase because of increasing wages. Production costs can only decrease insofar as the increase in productivity exceeds the productivity in wages. When, in the long term, fossil fuels are slowly replaced by renewables, research levels will drop for fossil fuels, and production costs will increase due to increasing wages. The fossil fuels will follow an inverted learning curve when fading out.

As for (ii), from energy system analysis, it is known that the process from invention, to demonstration projects, to significant market shares typically takes between five and seven decades (Nakicenovic *et al*. 1998). Energy system models incorporate these insights by explicitly setting constraints on the increase in market shares for new technologies. Our model does not have such market penetration constraints, but still it generates the same S-curve for the market share of renewables. Also, when climate change policy stimulates the transition towards non-carbon emitting energy sources, the transition is enhanced, but it is also realistic. See the discussion by Caldeira *et al*. (2003), O'Neill *et al*. (2003), Swart *et al*. (2003), Hoffert *et al*. (2003).

DEMETER 2E on the one hand simplifies DEMETER 1 (van der Zwaan *et al*. 2002, Gerlagh and van der Zwaan 2003) by only considering the production of energy, but on the other hand it extends DEMETER 1 by including learning by research and distinguishing between private and public innovations. In the future, we intend to extend DEMETER 2E with the production of non-energy consumer goods as well.

Besides the methodological insights, we have also presented some policy analyses, to verify whether as a weak impulse can have a long-term impact on emission levels and whether a weak impulse may change the learning curve too.

We have shown numerically that endogenous technological change has a very large impact on the responsiveness of emissions to carbon dioxide taxes. As measure of this response, we take the reduction in cumulative carbon dioxide emissions over the period 2000-2100 following a constant carbon tax of 20 \$/tC. Endogenous technological change enhances cumulative emissions reductions by factor 2.4. Without endogenous technological change, one has a much more pessimistic perspective on the possibilities of emission reductions than with ITC. Moreover, with ITC, even a temporary carbon tax has a lasting effect on CO_2 emission levels.

Acknowledgments

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Appendix 1. First order conditions for firms' profit maximization

The energy producers

In this appendix, we derive all first order conditions for the representative energy producer.

The Lagrangean for profit maximization (8) subject to (3), (4), and (9) reads:

$$\mathbf{L} = \Sigma_t \beta^t (qy - \theta a^{inn} y - wl - i + \lambda(\varsigma z^{-\mu} a^{\eta a} b^{\eta b} k^{\alpha} l^{(1-\alpha)} - y)$$

$$- \psi k + \beta\psi_{+1}(i + (1-\delta_k)k) + \kappa z - \beta\kappa_{+1}(z + y)) \tag{20}$$

Where $\beta^t\lambda_t>0$ is the dual variable for (3), $\beta^{t+1}\psi_{t+1}>0$ is the dual variable for (9), and $\beta^{t+1}\kappa_{t+1}>0$ is the reversed dual variable for (4). For convenience, we omitted time subscripts for the variables in the Lagrangean, and used shorthand notation ψ_{+1} to denote the forward time lap ψ_{t+1}. The first order conditions for y, a, l, i, k, and z are, respectively,

$$q = \theta a^{inn} + \lambda + \beta\kappa_{+1}, \tag{21}$$
$$\theta y = \eta_a \lambda y/a, \tag{22}$$
$$w = (1-\alpha)\lambda\, y/l\ , \tag{23}$$
$$1 = \beta\ \psi_{+1}\ , \tag{24}$$
$$\psi = \beta(1-\delta)\psi_{+1} + \alpha\lambda y/k, \tag{25}$$
$$\kappa = \beta\kappa_{+1} + \mu\lambda y/z. \tag{26}$$

We can substitute equations (24) in (25) to derive a capital cost equation that shows capital costs to consist of interest and depreciation:

$$\delta_k + 1/\beta - 1\ = \alpha\lambda y/k\ . \tag{27}$$

The price of the output good, q, consists of three parts (21), the license fee θa^{inn}, the immediate production costs λ, and the resource scarcity rent $\beta\kappa_{t+1}$. From (21) and (22), we see that innovation costs make a constant mark up η_a on top of the immediate production costs net of the license fee, λ,

$$\theta a\ = \eta_a\lambda\ . \tag{28}$$

which enables us to give the price of innovations θ as:

$$\theta\ =\ \eta_a\ \xi\ z^{\mu}\ a^{-1-\eta_a}\ b^{-\eta_b}. \tag{29}$$

Substitution of (28) in (21) gives us output prices q as

$$q_t = (1+\eta_a\, a^{inn}/a)\lambda_t + \beta\kappa_{t+1}. \tag{30}$$

where λ_t is the marginal production costs per unit of output,

$$\lambda = \min \{(\delta_k+1/\beta-1)k+wl \mid 1\leq\varsigma\ z^{-\mu}a^{\eta_a}b^{\eta_b}k^{\alpha}l^{1-\alpha}\} = \xi_t\, z_t^{\mu}\ a_t^{-\eta_a}\ b_t^{-\eta_b}\ , \tag{31}$$

with ξ the price of the factor composite $(k_{j,t})^{\alpha}(l_{j,t})^{1-\alpha}$, dependent on capital costs, δ_k+1/β–1, and wages, w_t

$$\xi = \varsigma^{-1}\alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}(\delta_k+1/\beta-1)^{\alpha}\, w^{1-\alpha}, \tag{32}$$

which is exogenous to the firm. The term $\beta\kappa_{t+1}$ describes the resource rent for the future increase in resource exploitation efforts due to present exploitation levels. Equations (30) and (31) display that output prices are proportional to factor costs, as expressed in ξ, inversely proportional to the technological productivity, a^{η_a} and b^{η_b}, that there is a mark up $\eta_a a^{inn}/a$ for the costs of technology and for the resource rent.

For the renewable energy resource sector, we assume that there is no exhaustion and we assume μ=0; this does not change the first order conditions.

Innovators

Let φ^{inn}_{t} denote the asset price of an innovation, that is, the value of an innovation to its owner.

In equilibrium, this value, one period ahead, $\beta\varphi^{inn}_{+1}$, is equal to the production costs per unit of innovation, $\Delta r_h/\Delta a_h$, given by (10),

$$\beta\varphi^{inn}_{+1} = \zeta^{-1}\ r^{1-\pi}\ a^{\pi-1}. \tag{33}$$

Hence, equilibrium on the market for innovations requires that the costs of developing a new technology, that is, the costs of an increase Δa_h, equals the revenues the innovator can obtain by selling the license fees.

We obtain the overall research effort r,

$$r = (\zeta\beta\varphi^{inn}_{+1})^{1/(1-\pi)}\ a. \tag{34}$$

The revenues from an innovation are equal to the net present value of future license fees:

$$\varphi^{inn}_{t} = \sum_{t=s}^{\infty}(\beta(1-\delta_{inn}))^{(s-t)}\theta_s y_s\ , \tag{35}$$

In terms of a recursive equation, we write

$$\varphi^{inn}_{t} = \theta_t y_t + (1-\delta_{inn})\beta\varphi^{inn}_{t+1}. \tag{36}$$

Private and social returns on research do not match. The social returns of an innovation held by the innovator are given by

$$\varphi^{soc}{}_{t} = \theta_t y_t + (1-\delta_{inn})\beta\varphi^{soc}{}_{t+1} + \delta_{inn}\beta\varphi^{pub}{}_{t+1} \tag{37}$$

where the first two terms on the right-hand-side are the same as for the private returns, but the third term reflects the fact that those innovations that leak from the private sector to the public domain also contribute to the social value of the privately held innovations. In turn, the social value of knowledge in the public domain, in terms of a recursive equation, is given by

$$\varphi^{pub}{}_{t} = \theta_t y_t + (1-\delta_{pub})\beta\varphi^{pub}{}_{t+1}. \tag{38}$$

Given these three values for innovations, we can calculate the social rate of return on research in period t (SRR_t). For the individual firm, the private value of an innovation is equal to the production costs per unit of innovation, $\beta\varphi^{inn}{}_{+1}=\mathrm{d}r_h/\mathrm{d}a_h$, as described in (33). Public returns, however, fall short of private returns because of the extraction of innovations. The extraction factor is given by the ratio between marginal productivity of research, $\Delta a^{inn}/\Delta r$, as described by (11), and the private productivity of research, $(\Delta a^{inn}{}_h/\Delta r_h)$, given by (33). For this factor, we find

$$\lim_{\Delta\downarrow 0} (\Delta a^{inn}/\Delta r)(\Delta r_h/\Delta a^{inn}{}_h) = \pi. \tag{39}$$

At the same time, public returns exceed private returns because of the spill-over from privately held knowledge to publicly available knowledge. First, the social value of privately held innovations exceeds the private value, $\varphi^{soc}{}_{t+1}/\varphi^{inn}{}_{t+1}>1$, and second, research leads to a direct spin of on public knowledge, $\chi\varphi^{pub}{}_{t+1}/\varphi^{inn}{}_{t+1}$. The *SSR* is now given by

$$SRR_t = \pi(\varphi^{soc}{}_{t+1}+\chi\varphi^{pub}{}_{t+1})/\varphi^{inn}{}_{t+1}. \tag{40}$$

When the *SRR* exceeds unity, $SRR>1$, the social returns on research exceed the costs, and policies are warranted that stimulate research above its equilibrium level. Typically, from empirical studies, the *SRR* is found to be in the order of four, $SRR\approx 4$.

The dynamic two-technology model consists of equations (2), (3), (4), (6), (7), (9), (11), (12), (21), (23), (24), (26), (27), (28), (32), (34), (36), (37), (38), (40), both for fossil fuels and non-fossil energy; equations (17) and (41) are used for aggregation. The impact of energy production on the global carbon cycle is calculated ex post via equations: (13), (14) and (15).

Parameters have been chosen such that the balanced growth solution corresponds to the data; see TABLE 1–TABLE 3 for all parameter and variable values.

Energy aggregation

From equalization of prices and marginal productivity in (17), $p_1/p_2 = y_1/y_2$, we have

$$\left(1-\vartheta\right)\left(y_2 p_2 y_1^{(\sigma-1)/\sigma} - y_1 p_1 y_2^{(\sigma-1)/\sigma}\right) = \vartheta\left(y_1 p_1 y_1^{(\sigma-1)/\sigma} - y_2 p_2 y_2^{(\sigma-1)/\sigma}\right), \tag{41}$$

Appendix 2. Model parameters and variable values in calibration procedure

TABLE 1. *Calibration parameters and variable values in first period (2000-2004) for fossil fuels*

Parameters	per period	per year	*Endogenous variables*	Per period	Per year
α	0.3		y [ZJ]	1.536*	0.307
β	0.784	0.952	p [$/GJ]	2.500*	
δ_k	0.35	0.07	a	10.208	
δ_{inn}	0.25	0.05	a^{inn}	1.000*	
δ_b	0.1	0.02	a^{pub}	9.208	
δ_{pub}	0.1	0.02	b	7.731	
χ	4.530*		z	15.566	
μ	0.027*		q	2.500	
η_a	0.321*		λ	2.401	
η_b	0.260		l	2.582	0.516
π	0.5		i	0.793	0.159
σ	0.4		k	1.767	
ς	0.200*		ξ	7.994	
ζ	0.394*		r [trillion $]	0.0768*	0.0154
			κ	0.030	
Exogenous. Variables			ψ	1.276	
w	1		φ^{inn}	0.281	
$\hat{y}$	2.216*	0.443	φ^{pub}	0.393	
			φ^{soc}	0.468	
			θ	0.075	
			SRR	4*	
Exogenous variables growth rates			*Variables growth rates*		
$g_{\hat{y}} = \gamma$	0.0987*	0.019	g_p	0*	0
g_w	0.0773	0.015	g_φ	0	0
			g_y	0.0987*	0.019
			g_a	0.0987	0.019
			g_l	0.0199	0.004

* *Empirical data for y and p, a normalization for a*=1, *research expenditures that make 2 per cent of total value of output, and a social rate of return on research of SRR=4, and growth rates* g_p=0, g_y=0.0987 *are used to calculate the parameters* χ, η_a, ς, ζ, μ, *variable* $\hat{y}$, *and growth rate* γ; *parameter* $\beta=1.05^{-\text{years}}$.

TABLE 2. *Calibration parameters and variable values in first period (2000-2004) for non-fossil energy*

Parameters	Per period	per year	*Endogenous variables*	Per period	Per year
α	0.3		y [ZJ]	0.064*	0.0128
β	0.784	0.952	p [$/GJ]	7.000*	
δ_k	0.35	0.07	a	1.100	
δ_{inn}	0.25	0.05	a^{inn}	0.112	
δ_b	0.1	0.02	a^{pub}	0.988	
δ_{pub}	0.1	0.02	b	0.273	
χ	4.530		z	0.476	
μ	0		q	7.000	
η_a	0.321		λ	6.779	
η_b	0.260		l	0.304	
π	0.5		i	0.097	
σ	2		k	0.208	
ς	0.321*		ξ	4.986	
ζ	0.394		r [trillion $]	0.010	
			κ	0.000	
Exogenous. Variables			ψ	1.276	
w	1		φ^{inn}	0.307	
$\hat{y}$	3.136*	0.627	φ^{pub}	0.429	
			φ^{soc}	0.511	
			θ	1.978	
			SRR	4	
Exogenous variables growth rates			*Variables growth rates*		
$g_{\hat{y}} = \gamma$	0.0987	0.019	g_p	–0.0159	–0.0032
g_w	0.0773	0.015	g_φ	0	0
			g_y	0.1345	0.0256
			g_a	0.1164	0.0223
			g_l	0.0363	0.0072

* *Empirical data for y and p, are used to calculate the parameter* ς, and variable $\hat{y}$, *no resource exhaustion for renewables* μ=0, *elasticity adjusted for renewable energy* σ=2; $\beta=1.05^{-years}$.

TABLE 3. *Two-technology model additional parameter, exogenous variable (value at first period, 2000-2004), and state variable values at beginning of first period (2000)*

Endogenous variables	per period	per year	*Climate parameters*	per period	per year
y (fossil fuels)	1.536	0.3072	ε_1	0.0205	
y (non-fossil energy)	0.064	0.0128	Atm_0	0.590	
p (fossil fuels)	2.500		δ_M	0.0408	0.0083
p (non-fossil energy)	7.000		δ_E	0.36	
			$\bar{E}$	0.00665	0.00133
Exogenous variable			δ_T	0.096	0.02
$\hat{y}$	1.491		$\overline{T}$	3.0	
			g_{ypc}	0.051	0.01
Integration parameters			g_{POP}	0.149	0.0282
σ	5.0		POP_1	5.89	
ϑ	0.037		POPLT	11.36	

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