Mitigation Strategies and Costs of Climate Protection: The Effects of ETC in the Hybrid Model MIND

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MIND is a hybrid model incorporating several energy related sectors in an endogenous growth model of the world economy. This model structure allows a better understanding of the linkages between the energy sectors and the macro-economic environment. We perform a sensitivity analysis and parameter studies to improve the understanding of the economic mechanisms underlying opportunity costs and the optimal mix of mitigation options. Parameters representing technological change that permeates the entire economy have a strong impact on both the opportunity costs of climate protection and on the optimal mitigation strategies e.g. parameters in the macro-economic environment and in the extraction sector. Sector-specific energy technology parameters change the portfolio of mitigation options but have only modest effects on opportunity costs e.g. learning rate of the renewable energy technologies. We conclude that feedback loops between the macro-economy and the energy sectors are crucial for the determination of opportunity costs and mitigation strategies.

1. SETTING THE SCENE

The Innovation Modeling Comparison Project (IMCP) explores the consequences of endogenous technological change (ETC) for the economics of stabilizing atmospheric carbon dioxide (CO_2) concentration. This paper contributes to the IMCP by presenting an analysis of technological change, both at different levels and in different sectors of the Model of Investment and technological Development (MIND). MIND combines an intertemporal endogenous growth model of the macro-economy with sector-specific and technological details taken

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from the field of energy system modeling. In particular, we explore the impact of endogenous technological change on opportunity costs and mitigation strategies within the framework of a social cost-effectiveness analysis.

We explore the impact of ETC in a social cost-effectiveness framework because we want to understand how technological change is induced by climate policy. Several studies have already incorporated aspects of ETC in this framework (Buonanno et al, 2003; Chakravorty et al, 1997; Goulder and Mathai, 2002; Kypreos and Barreto, 2000; Nordhaus and Boyer, 2000; Nordhaus, 2002; Popp, 2004a; 2004b). The added value of MIND arises mainly from two features. First, we incorporate a wide spectrum of relevant mitigation options, including improvement of energy efficiency, carbon capture and sequestration (CCS), renewable energy technologies, and traditional non-fossil fuels (exogenous time series for large hydropower and nuclear). Second, technological change in MIND has an endogenous formulation with R&D investments in labor and energy productivity, learning-by-doing, and vintage capital in the different energy sectors. We believe that including these features of ETC is essential for the assessment of macro-economic mitigation costs and the portfolio of mitigation options. MIND is a hybrid model merging features from bottom-up and top-down models. It resembles a bottom-up model because it comprises several energy sectors. However, compared to energy system models, the technologies are represented at a more aggregated level. In MIND, these sectors are embedded within a macro-economic environment, in order to evaluate the feedbacks between the macro-economy and the energy sector (see Manne et. al. 1995 for an example of a similar exercise). We will show that these feedbacks are crucial for an understanding of opportunity costs and mitigation strategies in an economy faced with climate policy.

The next section briefly introduces the model and its calibration, highlighting the improved treatment of CCS in MIND 1.1. Section 3 discusses technological change within MIND, forming the main part of this paper. Section 4 draws conclusions.

2. THE MODEL STRUCTURE OF MIND 1.1

The model equations of MIND are introduced and discussed in Edenhofer, Bauer and Kriegler (2005). The model version 1.0 presented therein has been extended by Bauer (2005), to replace exogenous scenarios of Carbon Capture and Sequestration (CCS) with a technologically detailed, endogenous treatment of the CCS option (model version 1.1). This study uses MIND 1.1, adapted slightly to meet the requirements of the IMCP, and enhanced by a more sophisticated carbon cycle (Hoos et al. 2001). The following section provides a summary of the model structure and parameter calibrations. Model equations are restricted to the parameters treated in the sensitivity analysis and parameter studies in this article; for a comprehensive discussion of the model structure we refer to Edenhofer et al. (2005) and Bauer (2005).

MIND is an integrated assessment model comprising a model of the world economy drawing specific focus on the energy sector, and a climate module computing global mean temperature changes. MIND therefore allows us to assess the impacts of constraints to climatic change on the economy in cost-effectiveness analysis.

MIND models economic dynamics by adopting an endogenous growth framework. It calculates time paths of investment and consumption decisions that are intertemporally optimal. The objective is to maximize social welfare, defined as the present value of utility (pure rate of time preferences is 1%), which is a function of per capita consumption exhibiting diminishing marginal utility. Most economic activity is subsumed in an aggregate CES production function (equation 1), the output Y_A of which describes the gross world product (GWP).[1]

$$Y_A = \phi_A[\xi_A^L(A * L_A)^{-\rho_A} + \xi_A^E(B * E)^{-\rho_A} + \xi_A^K \mathrm{K}_A^{-\rho_A}]^{-1/\rho_A} \tag{1}$$

The income share related parameters ξ_A are calibrated so that the actual income shares of labor L_A, energy E, and capital K_A relate to each other at the ratio of 66:4:30. Total factor productivity Φ_A is a fixed scalar calibrated to a value where the historical output of 2000 is reproduced. The elasticity parameter ρ_A determines the elasticity of substitution $\sigma_A = (1+\rho_A)^{-1}$. In some integrated assessment models, the elasticity of substitution between capital and energy is 0.4 for developed countries and 0.3 for developing countries (Manne et al, 1995). We have chosen an overall elasticity of substitution for all three factors of $\sigma_A = 0.4$. Labor L_A is described by an exogenous population scenario adopted from the common POLES/IMAGE baseline (CPI, Vuuren et al. 2003). Capital stock K_A is built up through investments and depreciates at a rate of 5 %. The initial value of K_A is derived from Y_A and an estimated capital coefficient. Capital coefficients were computed from the OECD database and from PWT6.1 for different countries. Their values agglomerate around 2.5. Since energy sector capital is separate from K_A, we assume a lower capital coefficient of 2.0. Variables A and B denote the productivities of labor and energy, respectively, and are stock variables determined by R&D investments according to equation (2):

$$\frac{\dot{A}}{A} = \alpha_A \left(\frac{RD_A}{Y}\right)^{\gamma_A}, \qquad with\ A(t = \tau_1) = A_0 \tag{2}$$

$$\frac{\dot{B}}{B} = \alpha_B \left(\frac{RD_B}{Y}\right)^{\gamma_B}, \qquad with\ B(t = \tau_1) = B_0 \tag{3}$$

RD_A and RD_B are investment flows controlled by the central planner. The parameters γ_A and γ_B (where $0<\gamma_A <1$. $0<\gamma_B <1$) model the decreasing marginal productivity of R&D investments. They are assumed to take the values of 0.05

1. MIND is implemented in discrete time steps of 5 years. In the model equations of this text we present the more intuitive continuous formulations, e.g. in case of derivatives.

and 0.1, respectively. Parameters α_A and α_B determine the productivity of R&D investments. They are calibrated at a rate such that spending 1 % of the GWP on energy R&D increases the energy efficiency parameter by 2.25 %; when 2.5 % of GWP is spent on labor R&D, the labor efficiency parameter increases by 2 %.

The energy input to aggregate production, E, is an additive composite of fossil energy, renewable energy, and traditional non-fossil energy, with the latter given exogenously. Fossil energy is produced from energy conversion capital and primary energy input in a CES production function. Fossil resources are converted to primary energy using an exogenous assumption about the carbon/energy ratio of the fossil fuel mix, its availability being described by a model of resource extraction. Resource R is extracted by capital K_{res}, the average productivity of which is subject to a scarcity effect ($\kappa_{res,s}$) and a learning-by-doing effect ($\kappa_{res,l}$):

$$R = \kappa_{res} K_{res} \tag{4}$$

$$\kappa_{res} = \kappa_{res,s}\, \kappa_{res,l} \tag{5}$$

The initial resource extraction is $R = 6.4$ GtC (SRES), assumed to be produced by a capital stock of $K_{res} = 5$ trillion \$US. This determines $\kappa_{res,l}$ because $\kappa_{res,s}$ is normalized to unity.

The scarcity effect $\kappa_{res,s}$ is determined by the marginal costs of resource extraction C_{res}^{mar}:

$$\kappa_{res,s} = \frac{\chi_1}{C_{res}^{mar}} \tag{6}$$

In equation 6, parameter χ_1 as well as the marginal costs in 2000 are set to \$113. During the simulation, marginal costs C_{res}^{mar} increase with cumulative resource extraction CR_{res} according to equations 7 and 8.

$$C_{res}^{mar} = \chi_1 + \chi_2 \left(\frac{CR_{res}}{\chi_3} \right)^{\chi_4} \tag{7}$$

$$CR_{res}(t) = \int_{\tau_1}^{t} R(t')dt', \text{ with } CR_{res}(t = \tau_1) = 0 \tag{8}$$

Parameter χ_1 denotes initial costs of the fossil resource, the exponent χ_4 captures the curvature of the function (i.e. the timing of increasing costs), and χ_2 gives the marginal costs once the amount described by χ_3 has been extracted. We parameterize this function according to Rogner's (1997) empirical assessment of world hydrocarbon resources, and arrive at the values $\chi_2 = 700$, $\chi_3 = 3500$ and $\chi_4 = 2$.

The learning-by-doing effect of capital productivity $\kappa_{res,l}$ depends on the ratio of actual resource extraction $E_{res,l}$ to initial resource extraction $E^0_{res,l}$.

$$\dot{\kappa}_{res,l} = \frac{\kappa_{res,l}}{\tau_{res,l}\,\kappa^{max}_{res,l}} (\kappa^{max}_{res,l} - \kappa_{res,l}) \left(\left[\frac{E_{res,l}}{E^0_{res,l}} \right]^{\beta_{res,l}} - 1 \right) \tag{9}$$

$$with \;\; \kappa_{res,l}\,(t = \tau_1) = \kappa^0_{res,l}$$

The factor $\beta_{res,l} = 0.4$ dampens the learning-by-doing effect: a rapid increase in extraction induces a loss in productivity gains relative to the same increase in extraction spread over a longer time period. Furthermore, productivity gains from learning saturate when productivity approaches its maximum value $\kappa^{max}_{res,l}$ which is set to twice its initial value. Parameter $\tau_{res,l}$ determines the speed of learning and is set to 100 years.

Renewable energy E_{ren} is produced by capital Kap_{ren} which is employed at $FLH_{ren} = 2190$ full load hours per year.

$$E_{ren}\,(t) = FLH_{ren} * Kap_{ren}\,(t) \tag{10}$$

$$Kap_{ren}\,(t) = \int_{t_0}^{t} \omega\,(t - t')\,\kappa_{ren}(t')\,I_{ren}(t')dt' \tag{11}$$

The available renewable energy capital stock in each point in time is determined by summing over the investments into renewable energy I_{ren} in preceding time steps multiplied with the productivity of installed capital κ_{ren}. Depreciation is modeled by weights ω which determine the fraction of capital that still remains. ω_1 to ω_7 are set to 1.0, 0.9, 0.8, 0.7, 0.5, 0.15, 0.05, and $\omega_i = 0$ if $i > 7$. This allows to model different capital productivities for different vintages of the capital stock. Capital productivity κ_{ren} indeed changes in time because the costs of renewable energy equipment c_{ren} decrease, subject to learning-by-doing.

$$\kappa_{ren} = \frac{1}{c_{ren}\,(t) + c_{floor}} \tag{12}$$

The inverse of floor costs $c_{floor} = 500$ US\$/kW constrains capital productivity from above, while c_{ren} starts out at $c_{ren} = 700$ US\$/kW and decreases with cumulative installed capital $CKap_{ren}$:

$$CKap_{ren} = \int_{\tau_0}^{t} Kap_{ren}(t')dt' \tag{13}$$

The following equation describes the dynamics of learning-by-doing in the renewable sector:

$$c_{ren,t} - c_{ren,t-1} = c_{ren,0}\, CKap^{-\mu_{ren}}_{ren,0}\, (CKap^{-\mu_{ren}}_{ren,t} - CKap^{-\mu_{ren}}_{ren,t-1})$$

$$\times \left(\frac{CKap_{ren,t-1}}{CKap_{ren,t}} \right)^{\beta_{ren}} \tag{14}$$
$$with\ c_{ren}(t=0) = c^0_{ren},$$

The learning parameter μ_{ren} determines the learning rate lr and reflects a learning rate of 15 %, i.e. investment costs decrease by 15 % with every doubling of cumulative installed capacity. Parameter β_{ren} within the last factor of the right hand side of the equation causes a dampening similar to $\beta_{res,l}$ in the learning-by-doing equation of the fossil resource extraction (equation 9). Set to $\beta_{ren} = 0.4$, it prevents learning that is too fast.

There are three sources of carbon dioxide emissions: fossil fuel combustion, leakage from sequestered CO_2, and emissions from land-use and land-use change. The latter are described by an exogenous time series. Since fossil resources are measured in tons of carbon, resource use R and emissions Em coincide, except for land-use emissions and Carbon Capturing and Sequestration (CCS):

$$Em(t) = R(t) + LULUC(t) - R_{cap}(t) + LEAK(t), \tag{15}$$

where R_{cap} denotes the amount of CO_2 captured in a given year and $LEAK$ denotes leakage.

CCS is modeled as a chain process distinguishing six steps: CO_2 is captured at point sources (1) and transported via pipelines to sequestration sites (2). There, the CO_2 needs to be compressed (3) before it is injected into the sequestration site (4). Then, it either remains in the site (5) or leaks into the atmosphere (6). Processes 1-4 are capital intensive and are modeled as capital stocks representing available capacities for the individual processes. Capacities are built up by investments according to the following equation:

$$K_{pq}(t) = \int_{t_0}^{t} \omega_q(t-t')\, \iota^{-1}_{pq}(t')\, I_{pq}(t')dt' \tag{16}$$

Variables K_{pq} denote the capacities, index p denotes the process step, and the index q denotes different investment alternatives such as one of five distinct capture technologies or one of six distinct sequestration alternatives. Weighting parameters ω introduce a depreciation scheme for different vintages of the capital stocks, similar to equation (11) in case of renewable energy. Investments are denoted I_{pq} and the investment costs are ι_{pq}. Investment costs for capturing capacity range from ~100 \$US/tC to ~450 \$US/tC depending on the specific capture technology. When the productivity of CCS investments is varied in parameter studies later on in this paper, the same relative change is applied to the investment costs for each technology.

In addition to the limitation inflicted by the necessity to build up capacity, the amount of carbon that may be captured is limited by a static and a dynamic constraint. The static constraint limits the amount of carbon which can be captured from a large power plant as a fraction of the resource use in the business-as-usual scenario. The dynamic constraint defines an upper limit of investments into the specific capture technologies in each period. The upper limit is defined as a share of the investments in the power generation sector. The rationale is that the capability of retrofit investments in large power plants depends on the total amount of investments undertaken in the power generation sector.

The injection of CO_2 into particular sequestration sites demands two types of facilities: compressors and injection wells (steps 3 and 4). The modeling approach takes into account that both facilities demand investments and secondary energy. In steps 5 and 6, the modeling approach considers the capacity constraint of each sequestration alternative *j* and leakage of sequestered carbon: Leakage is described by a rate, and the capacity of each sequestration alternative is the upper bound for the cumulative amount of CO_2 that is injected into each sequestration alternative.

3. THE ROLE OF ENDOGENOUS TECHNOLOGICAL CHANGE IN MIND

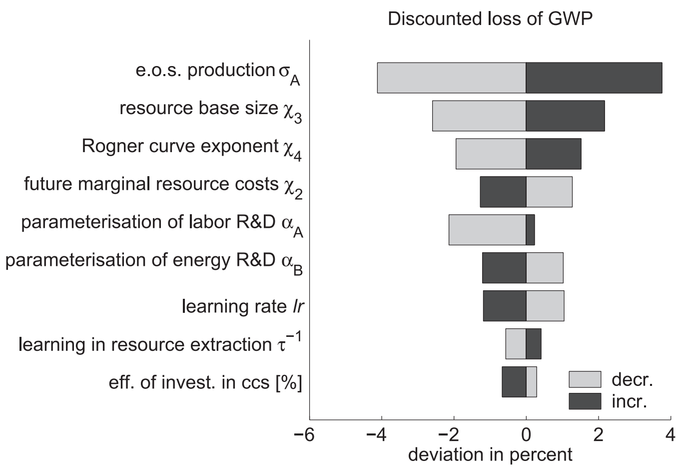
In what ways does endogenous technological change matter in policy scenarios computed with MIND? In the following sections, we explore this question using sensitivity analysis and miscellaneous parameter studies (see Bauer et al, 2005 for initial parameter studies with MIND). In the sensitivity analysis, we rank important technology-related model parameters according to their influence on two model outputs: the opportunity costs of climate protection and the mix of options used for CO_2 mitigation. We then study the effect of parameter variations on the same model outputs and analyze the underlying economic dynamics. All model runs stabilize atmospheric CO_2 concentration level at 450 ppm.

3.1 Local Sensitivity Analysis

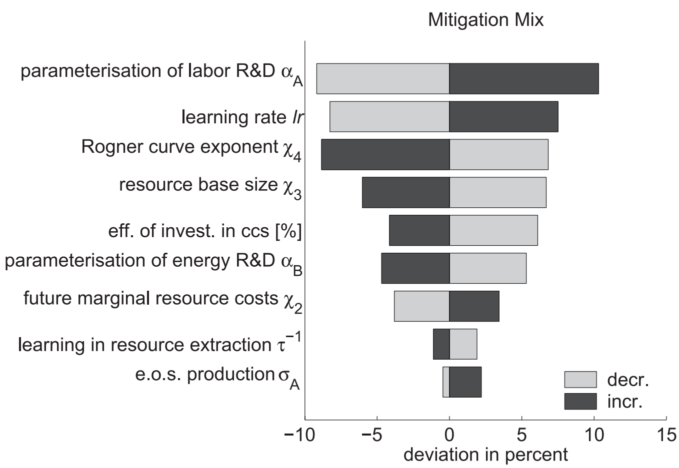
Figure 1a and 1b show the influence of important parameters of MIND on opportunity costs of climate policy (1a) and on the mix of mitigation options (1b). The former are measured as losses of gross world product (GWP), accumulated from 2000 to 2100 and discounted to present value at a rate of 5 %, relative to the business-as-usual scenario. The latter is represented by the ratio of the two dominant options, renewable energies and CCS, where a ratio of unity implies that the same amount of CO_2 reductions may be attributed to each of the mitigation options. Parameter influence is measured by the response of the model to a 5 % variation of the parameter. Taking the set of parameters from the model calibration as the starting point, we vary one parameter at a time, hence the effects reflect local sensitivity. As local sensitivity analysis assesses parameter sensitivity at only one point in parameter space it neglects the fact that sensitivities may vary tremendously at other points in parameter space. Using a measure of global sensitivity, i.e. a measure that takes into account simultaneous variation of several parameters, is preferable as it provides a remedy to this shortcoming.

Figure 1. Sensitivity Analysis

1a.



1b.



Figures 1a and 1b show the influence of important technological parameters on opportunity costs and mix of mitigation options, respectively. Metric is the deviation of the output in response to an up to 5% increase (decrease) of the parameter. The parameter "e.o.s. production" refers to the elasticity of substitution σ_A in aggregate industrial production, i.e. production of the gross world product.

However, local sensitivity analysis is used in this paper for the following two reasons. Firstly, the model response to a change in a single parameter, *ceteris paribus* , is an intuitive measure. Secondly, the computational burden for a local analysis is much lower. To emphasise, while this analysis sheds light on the influence of parameters and the potential influence of their uncertainties on model results, we do not explicitly test parameter uncertainties. Therefore, we make no statements about the relative importance of parameters in contributing to the uncertainty of computed results, but rather, about the ir potential to impact results themselves.

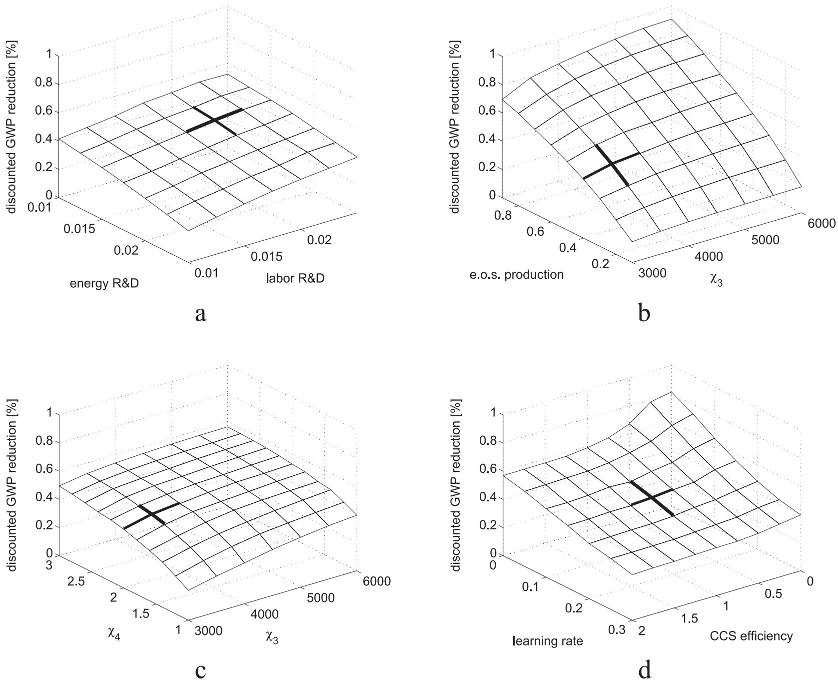
As Figure 1a indicates, the greatest influence on opportunity costs is exerted by the elasticity of substitution σ_A, followed by the parameters describing the availability of fossil resources, and the effectiveness of R&D investments in labor productivity. The latter and the top three parameters have a positive effect on costs, i.e. costs increase with the parameters, whereas the assumption of high marginal future fossil resources costs have a negative effect. Productivity of energy efficiency R&D and the learning rate of the renewable energy technologies rank next, followed by two more sector specific parameters, the learning parameter in fossil resource extraction and the efficiency of investments in CCS. Overall, the relatively small responses of the model to parameter variations (less than 5%) improves the confidence in the robustness of the computed opportunity costs. In the next two sections we will explore the reasons for this observation, and evaluate the role of technological change in deriving these results.

Figure 1b depicts the influence of parameters on the mix of mitigation options. It is immediately evident from a comparison between Figure 1a and Figure 1b that the ranking of parameters has changed. Most notably, the elasticity of substitution has dropped to the bottom rank, and two resource related parameters, χ_2 and χ_3, also emerge to fall in ranking. Conversely, the parameterization of labor R&D, the learning rate of renewable technologies, and the efficiency of CCS investments have risen in the hierarchy. Overall, the mitigation mix is more sensitive (with variations up to 10 %) than the mitigation costs in Figure 1a. This result comes as no surprise. Since GWP losses are closely related to social welfare, the maximization of which is the objective of MIND, GWP loss is deliberately kept to a minimum. The mix of mitigation options, on the other hand, is endogenously determined to minimize costs. It is intuitive that a change in the parameter values alters the competitiveness of mitigation options, hence its impact on the mitigation mix is significant.

3.2 Determinants of the Opportunity Costs

This section takes a closer look at the opportunity costs of climate protection. We present parameter studies varying two parameters simultaneously. This enables us to discuss the effects of varying these parameters, as well as analyzing the interdependencies between them, hence taking a first step beyond a local sensitivity analysis presented in Section 3.1. To an extent, this analysis remains very much local in character since many parameters remain fixed at their default levels. However, restricting the variation to two parameters at a time enables an intuitive graphical presentation of the results, which provides deeper and useful insights into the workings of MIND.

Figure 2. Parameter Studies of Mitigation Costs



Figures in this panel show discounted gross world product loss (discount rate is 5 %) for several parameter studies. In figure 2a, energy R&D and labor R&D refer to the productivity of investment into research that enhances the efficiency of the corresponding factor. In 2b, e.o.s. production refers to the elasticity of substitution in the aggregate industrial production sector. Parameters χ_3 and χ_4 in figure 2b and 2c refer to the size of the fossil resource base and the exponent of the Rogner curve, respectively. Figure 3d treats the learning rate of renewable technologies and the efficiency of investments in CCS technology. The pairs of default parameter values are indicated with a bold cross.

We start out by taking a look at the engine of endogenous growth in MIND: R&D investments that drive labor and energy efficiencies. Figure 2a displays the productivity of these investments. While the two parameters are similar with respect to the process they describe – accumulation of a knowledge stock increasing the productivity of an input factor to aggregate production – their effects on opportunity costs are contrary. An enhanced effectiveness of labor productivity R&D raises costs, while better energy efficiency R&D reduces GWP losses. This is due to opposite effects on the mitigation gap, i.e. the discrepancy of CO_2 emissions between business-as-usual and climate policy scenarios. More effective labor R&D stimulates additional economic growth and implies higher CO_2 emissions in the baseline. More effective energy R&D investments, on the other hand, facilitate much better energy efficiency in the baseline, and hence lowers CO_2 emissions.

The mitigation gap characterizes the challenge for the economy facing climate protection goals and manifests itself in the opportunity costs.

Figure 2b compiles two parameters with an effect of the second type: the elasticity of substitution in the aggregate production sector, and the estimated size of the available fossil resources. Figure 2b shows that costs increase with the elasticity of substitution. This too can be attributed to baseline effects: higher elasticity of substitution implies a more flexible production technology which induces higher economic growth in the business-as-usual scenario. Therefore, achieving 450 ppm requires a substantial departure from the baseline and is relatively costly. A variation of the resource base has a bigger impact on the mitigation costs if the elasticity of substitution is relatively high. Low values of the elasticity of substitution hinder economic growth and consequently imply a lower demand for energy. At low energy demand, relaxing the scarcity of the resource has a smaller effect. In general, a larger resource base allows higher economic growth in the business-as-usual case. When climate policy constrains resource use, it devaluates exhaustible resource as an economic asset and diminishes the rent income of their owners. The loss of rent income increases with the resource base because a relatively cheap and abundant resource can no longer be used as input in production.

We take yet a closer look at the fossil resource base. Figure 2c studies the variation of the size of the resource base χ_3 and parameter χ_4. Parameter χ_4 as well as the resource base are proxy variables for the technological progress in the extraction sector. Increasing χ_3, i.e. assuming more abundant resources, results in cheaper short to medium term supply of the fossil resource. Increasing χ_4 trades a slow and steady increase of the marginal costs for a steeper increase at a later time – thus making the resource cheaper and more easily available in the short to medium term. High values of χ_4 allow higher economic growth in the business-as-usual case and induce a relatively large mitigation gap. For high values of χ_4 the marginal costs of extraction are essentially constant. Under this condition, an increased resource base has moderate impact on macro-economic mitigation costs. For low values of χ_4, an increased resource base has a slightly higher impact on the macro-economic costs because marginal improvements in extraction already increase the shadow price of the resource. This parameter study shows that climate protection becomes relatively costly if there is a high rate of technological progress in the exploration and extraction of fossil fuels. Accelerated technological progress in the extraction sector makes climate policy more costly, because such policy devaluates assets (resources and capital stock in the corresponding sectors). Therefore, special attention ought to be paid to assumptions about resource availability and their uncertainties.

Contrary effects can be observed if technological progress decreases the costs of mitigation technologies. The impact on opportunity costs is shown in Figure 2d. We explore two parameters which are both closely related to mitigation options: the efficiency of investments into Carbon Capture and Sequestration technologies (CCS) and the learning rate of renewable energy technologies.

Varying these two parameters shifts the competitive advantage between the two mitigation options and, consequently, the extent to which they are used. It turns out that the efficiency of CCS investments has no strong impact on the overall opportunity costs if the learning rate of renewable energy technologies is relatively high. The reason is that renewables are modeled as a backstop technology, i.e. as a carbon-free energy source, and need no non-reproducible input for energy production. In contrast to the renewables, CCS investments only bridge from the fossil fuel age to a carbon-free era. CCS makes the transition of the energy system smoother but has severe limitations if fossil fuels become more costly because of increasing marginal extraction costs at the end of the 21st century. At the same time, renewable energy becomes cheaper because of learning-by-doing. It is plausible that this effect cannot be altered by high efficiencies of CCS investments. At low learning rates of the backstop technology, CCS becomes more important.

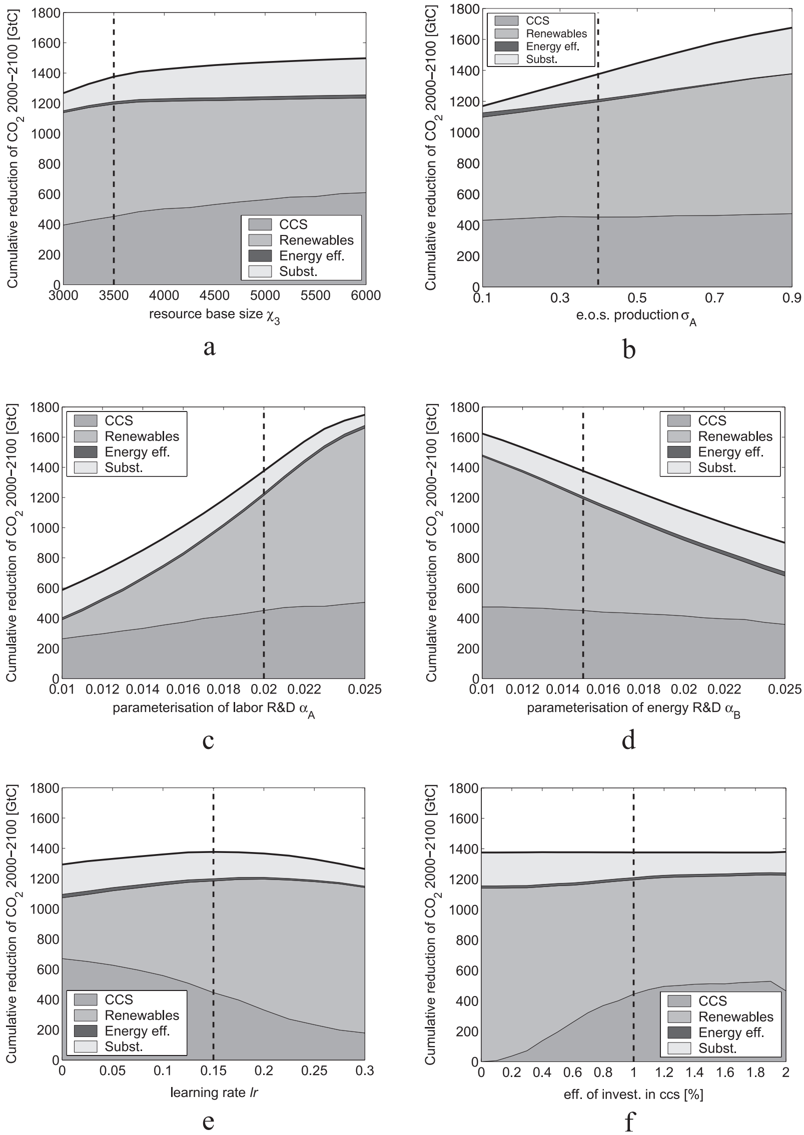
3.3 Mitigation Strategies

In this section we analyze the impact of the same parameters explored in the previous section on the option portfolio of an optimal mitigation strategy. Mitigation options are compared on the basis of the amount of CO_2 that they enable the economy to reduce. For the CCS option, this is straightforward: it is simply the amount of captured and sequestered CO_2 (less the amount that leaks from the sequestration site). In case of energy related mitigation options, i.e. renewable energy and energy efficiency improvements, the corresponding amount of "mitigated CO_2 emissions" was derived from the equivalent amount of energy from fossil fuels. In , the degree of efficiency on converting primary into final energy is determined endogenously in the production function of the fossil sector. In this ex post analysis, however, we estimate the "equivalent" amount of fossil energy by assuming a fix coefficient. The remaining mitigation options, namely energy savings by substitution of energy at the levels of energy transformation and aggregate production, are visualized as the difference to the total reduction of CO_2.

Figure 3a shows that the amount of CCS within the portfolio of mitigation options increases with the assumed resource base. The cumulative amount of CO_2 reduced by renewables within the next century decreases, energy efficiency remains constant and energy savings increase. An increasing resource base implies increasing rents for the owners. This increasing rent income makes CCS a more profitable option. Due to high economic growth and relatively cheap fossil fuels, the return on investment in renewables falls short of the returns on CCS investments.

In figure 3b, energy savings (reduction of energy consumption by substituting energy by capital in different sectors) become more profitable if the elasticity of substitution increases; at the same time, the importance of energy efficiency decreases.

Figure 3. Parameter Studies of Mix of Mitigation Options



Figures 3a-f show how the mix of mitigation options varies in parameter studies. CO_2 reductions caused by avoiding the use of fossil fuels (renewable energy, energy efficiency improvements, and substitution) are estimated from the alternative use of fossil fuels. Dashed lines indicate the default parameter value.

A more surprising result is obtained in figure 3c and 3d. In figure 3c an increasing productivity of R&D investment in labor enhancing activities also increases the share of renewables in the mitigation portfolio. The explanation is as follows: economic growth induces additional energy demand that is met by carbon-free technologies. Due to high economic growth, marginal extraction costs of fossil fuels increase sooner, and thus CCS is less competitive compared to renewables. In contrast, when R&D investments in energy efficiency become more productive, the mitigation gap shrinks, and the share of renewables within the mitigation portfolio decreases (3d). Interestingly, changes in the productivity of energy R&D investments affect the baseline rather than providing a more attractive mitigation option. In this study, the energy efficiency parameter varies from 63 to 245 % of its regular value in 2100 in the baseline, the latter implying that energy use in 2100 is decreased by 60%. Climate policy, however, only induces 0.4 to 2.7 % additional increases of the efficiency parameter. To sum, higher energy efficiency and a lower baseline for economic growth reduce the demand for renewables. The importance of the renewable energy option depends heavily on the underlying economic growth path.

As figure 3e shows, high learning rates in the renewable energy sector reduce the optimal amount of CCS substantially. In that sense CCS can be seen as a joker-option if the learning rate of the renewables is relatively low. It is also remarkable that energy savings are less important when the learning rate is relatively high because the energy demand can be met by the carbon-free renewables. Learning-by-doing reduces the price of electricity produced by renewables and increases the demand for renewables which reduces their costs further. This feedback loop makes CCS less important. As figure 3f indicates, this effect can be counteracted by an increasing efficiency of CCS-investments.

4. CONCLUDING REMARKS

In what ways does technological change matter? Our analysis shows that technological change works in two "directions": we identify technological progress that permeates the entire economy and technological progress that is restricted in its effects to a single sector. Examples for such sector-specific technological change are learning-by-doing effects associated with renewable energy technologies and resource extraction, as well as technological progress in CCS, here modeled via its investment efficiency. In , parameters associated with such sector specific technological change have a significant impact[2] on the optimal mix of mitigation options. For example, an increased learning rate increases the share of renewables, and improved investment efficiency in CCS increases the share of CCS within the entire portfolio of mitigation options (Figures 1b and

2. We refer to the impact of a parameter in terms of a relatively large potential influence, i.e. a large sensitivity of results to changes of this parameter. Recall, however, that the actual uncertainty about parameters is not taken into account.

3ef). However, these parameters are less important in determining the overall opportunity costs of climate protection which measure the impact on the overall economy (Figure 1a).

In contrast, there is technological change with significant impact on the macro-economic growth process, evident in its influence on opportunity costs. Such technological change is described by parameters of the macro-economic environment, like the elasticity of substitution, and the parameters characterizing the effectiveness of labor- and energy R&D investments. Labor R&D investments in particular have a strong influence on macro-economic growth as well as the mix of mitigation options. Progress in resource extraction is an example of sector-specific technological change with a macro-economic impact. This progress is characterized by the parameters of Rogner's scarcity curve and has been shown to exert a significant influence on opportunity costs. The most prominent effect of these parameters is their impact on the baseline.

We conclude that feedbacks between the macro-economy and the energy system are crucial for determining mitigation costs and the development of the mitigation portfolio in time. The case of technological change in resource extraction shows how sector-specific processes may exert significant influence on the macro-economy, while the impact of labor R&D productivity on the share of renewable energy is an example of macro-economic influence on a distinct sector.

This has strong implication for policy. A sector-specific policy that fosters technological change in the extraction sector induced by increasing prices in the oil or gas market would increase the opportunity costs of climate protection. A policy that increases the economy-wide energy efficiency in all energy related sectors would reduce the costs of climate protection substantially. Enhancing technological change in the extraction sector makes sense, if decision makers intended only to increase energy security. Analysis here highlights that the impact of such a policy on the opportunity costs of climate protection must also be taken into account.

The results presented here indicate that partial-equilibrium models omitting intertemporal and inter-sectoral aspects can be misleading for designing a climate and energy policy. Thus, they stress the utility of hybrid models incorporating endogenous technological change at the sector level as well as at the macro-economic level. Moreover, hybrid models pose a coherent framework not only for the assessment of the opportunity costs and portfolios of mitigation strategies, but also for the design of climate and energy policy instruments.

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