



ANALYSIS

# The impact of technological change on climate protection and welfare: Insights from the model MIND

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## Abstract

Avoiding dangerous climate change is likely to require policies to mitigate CO<sub>2</sub> emissions that are substantially more ambitious than those currently being considered. For such policies, the issue of endogenous technological change becomes important, both to estimate the overall costs and to identify the intertemporally cost-effective combination of mitigation options. In this paper, we first discuss the recent literature that evaluates the potential for endogenous technological change to reduce mitigation costs, and the efforts to incorporate endogenous technological change into pre-existing integrated assessment models. Then we formulate our own integrated assessment model, the Model of INvestment and Technological Development (MIND), which allows analysis of the relationship between specific mitigation options and the costs of ambitious climate protection objectives. Our model reveals two important results. First, the incorporation of technological change in a portfolio of mitigation options can reduce the costs of climate policies substantially. Achieving the ambitious policy goals necessary to avoid dangerous climate change becomes feasible without significant welfare losses. Second, the different mitigation options are of different importance in achieving climate protection goals: improving energy efficiency becomes too costly as a major mitigation option in the long run. In the long run, fossil fuels have to be substituted by renewable energy sources because a backstop technology with the potential of learning-by-doing has the strongest impact on reducing the welfare losses due to climate protection. Furthermore, Carbon Capturing and Sequestration can allow for further reduction in the costs of climate protection and can postpone the need to transform the energy system from a fossil-fuel-based one to a renewables one.

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## 1. Introduction

Climate scientists and an increasing number of policy-makers argue that avoiding “dangerous” climate change, a mandate of the United Nations Framework

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Convention on Climate Change (UNFCCC), will require the stabilisation of atmospheric carbon dioxide (CO<sub>2</sub>) concentrations at some level near, or below, 450 parts per million (ppm). Achieving this goal requires policies to reduce CO<sub>2</sub> emissions that are ambitious in comparison with any policy currently in effect or proposed. Many economists (for example, Nordhaus, 2002) argue that such policies have a large negative impact on economic growth, and hence on welfare, even if induced technological change in the direction of cleaner energy sources is taken into account. Others (for example Popp, 2004a,b) suggest that a reasonable climate policy would stimulate technological change to an extent that would make these policies inexpensive. Exploring the potential of technological change in reducing overall mitigation costs is a necessary prerequisite to developing a sound climate policy.

In this paper, we present results from a new model, the Model of INvestment and Technological Development (MIND), which addresses the issue of endogenous technological change. We follow the general approach of an intertemporal cost-effectiveness analysis, i.e. we calculate the impact of investments in different mitigation options on the overall macroeconomic costs of climate protection measured in terms of welfare losses.

Our results offer answers to two questions. First, what are the mitigation costs of ambitious climate protection goals if endogenous technological change is taken into account? Second, what is the relative importance of different mitigation options in reducing the costs of climate protection? We will show that endogenous technological change lowers the mitigation costs considerably; hence, even ambitious climate protection goals can be achieved without large negative impacts on welfare. Moreover, we will rank the mitigation options according to their potential for reducing the overall welfare losses of climate policy.

In the next section, we review the literature on endogenous technological change. Section 3 details the structure of our model, focusing in particular on the incorporation of endogenous technological change. Section 4 discusses the calibration of the model. In Section 5, we present simulation results and discuss the role of endogenous technological change in climate protection. Finally, Section 6 outlines some caveats of the analysis, and future challenges.

## 2. Integrated assessment models and endogenous technological change

In this section, we review empirical findings suggesting investment decisions as a primary cause of technological change. We also discuss current efforts in modelling technological change endogenously. These two themes are the foundation for our own modelling effort, presented in the next section.

### 2.1. Technological change as an outcome of investment decisions

It is a robust empirical finding that labour productivity grew faster than overall energy productivity over the last 200 years. This finding, albeit increasingly recognized as a stylized fact of economic growth, is not very well explained by economic models. One possible explanation of biased growth of factor productivities views technological change as an outcome of investment decisions. Investments, in turn, are viewed as reactions to scarcity of any given resource (such as labour, energy or capital) and a means to overcome these scarcities (Ruttan, 2001). Historically, entrepreneurs have invested more in increasing labour productivity because labour was a scarcer resource than energy. Union power, the welfare state and decreasing rates of population growth have enabled workers to limit their labour supply and to increase the wage rate.

In contrast to these dynamics in labour markets, exhaustible resources such as oil, coal and gas have become abundant and relatively cheap over the last 200 years, because technological progress in the exploration sector greatly reduced the marginal costs of using fossil fuels (Ruttan, 2001; Rogner et al., 1993). In the foreseeable future, fossil fuels will remain plentiful. Hence, the return on investment in renewable energy and in energy efficiency improvements will be too low to attract investments (see Bauer et al., *in press*). Our results imply that availability of relatively cheap exhaustible resources increase the opportunity costs of climate protection remarkably. Models ignoring these dynamics do not provide an appropriate framework for exploring the welfare implications of climate policy.

However, there is an important effect that reduces the opportunity costs of climate policy. It is a well-

known but often omitted fact that within the renewable energy sector, costs per unit of installed capacity (in kW, for instance) decrease with the cumulative installed capacity. The IEA (2000) report emphasizes that there is overwhelming empirical support for such learning-by-doing effects in all fields of industrial activity, including the sectors that transform or use energy. With every doubling of cumulative capacity or cumulative energy production, the costs fall by a constant fraction of the original costs. According to WEA (2000, 16), typical learning rates within the renewable energy sector are about 20% for photovoltaic (referring to cumulative installed capacity), 18% for wind energy (referring to cumulative installed capacity) and about 15% for electricity from biomass (referring to cumulative energy production; IEA, 2000, 21). It is open to debate whether learning-by-doing has the potential to outweigh technological progress in the exploration and extraction of coal, oil and gas. The models used in integrated assessment exhibit a broad range of answers.

To conclude, the net effect of technological change on the costs of climate protection is ambiguous. We believe that considering investment decisions as an engine of technological change is essential to a realistic understanding of these costs. In the next section, we give a short overview of ways in which technological change is incorporated in integrated assessment models.

## 2.2. *Incomplete understanding of endogenous technological change*

Nordhaus (2002) introduces the R&DICE model to enhance the global DICE model with induced technological change. He compares two cases. In the first, a carbon tax induces research and development (R&D) in the energy sector, leading to a decrease in carbon intensity (CO<sub>2</sub> per GDP). In the second case, the carbon tax induces a reduction in output while the carbon intensity is reduced exogenously at a constant rate. Nordhaus shows that improving energy efficiency through R&D investments is less efficient in reducing greenhouse gas emissions and minimizing welfare losses than output reduction induced by a carbon tax. It seems that this result is highly sensitive to the chosen parameters and therefore has only limited explanatory power in explaining how techno-

logical change can be induced by climate policy. Buonanno et al. (2003) introduce technological change into the RICE model. The model comprises only one R&D sector, whose accumulated stock has two effects. In contrast to R&DICE, R&D investments not only reduce carbon intensity but also create an external effect increasing the total productivity of the whole economy. Therefore, economic growth and emissions can only be decoupled if the parameters are chosen in such a way that the reduction in carbon intensity overcompensates the growth-enhancing effect of R&D investments.

In his model ENTICE, Popp (2004a) overcomes these shortcomings by including a representative energy technology whose efficiency parameter can be improved by R&D investments without further externalities. In a refined version – called ENTICE-BR – Popp (2004b) includes a backstop technology. He shows that introducing a backstop technology has greater potential for reducing the costs of climate protection than the improvement of energy efficiency. However, these results are derived using an exogenous time path for total factor productivity—not a very convincing assumption because the time path of total factor productivity is determined by investment decisions. Moreover, the resource extraction sector, albeit crucial for determining the opportunity costs of climate protection, is omitted completely.

If learning-by-doing is incorporated in integrated assessment models, the effect is unambiguous. All models that include learning-by-doing find large welfare gains from induced technological change (Chakravorty et al., 1997; Goulder and Mathai, 2002; Manne and Richels, this volume; Gerlagh and van der Zwaan, 2003). This result is confirmed by many bottom-up energy system models—learning-by-doing within the renewable energy sector reduces the costs of meeting specific concentration targets (Manne and Barreto, 2004; Kypreos and Barreto, 2000).

The existing studies clearly show that learning-by-doing in backstop technologies reduces macroeconomic mitigation costs. The studies reviewed in this section also show that there is some conceptual ambiguity in the potential pay-offs of R&D in enhancing labour and energy efficiency. Moreover, to our knowledge, there is no modelling effort

evaluating the impact of learning-by-doing and R&D investments in different sectors in one coherent framework. In this paper, we evaluate how the entire portfolio of mitigation options performs in reducing welfare losses (i.e. the opportunity costs of climate protection policy) in comparison with isolated mitigation options.

### 3. The structure of MIND

The model MIND represents an improvement over past efforts to incorporate endogenous technological change in three respects. First, it includes separate R&D sectors for both labour and energy efficiencies. Second, it differentiates the physical capital stock in the energy sector, which allows us to study the internal dynamics of this sector. Third, it enables a comparison of all relevant mitigation options: energy efficiency, renewable energy sources, and Carbon Capturing and Sequestration (CCS). CCS has rarely been assessed together with the other mitigation options within macroeconomic integrated assessment models. At its current stage of development, the model treats the world as one unit, with no regional differentiation. While this prevents us from examining the effects of interregional trade, this is not an issue that we are exploring at this stage. Fig. 1 depicts the general structure of the model, and Appendix A describes the parameters used. In the remainder of this section, we describe the model structure and justify our choices of variables and functional forms.

#### 3.1. Welfare function and control variables

Like many other integrated assessment models, MIND maximizes an intertemporal, aggregated social welfare function (Eq. (1)).

$$W = \int_{t_1}^{t_2} e^{-\rho(t-t_1)} L(t) \ln \frac{C(t)}{L(t)} dt; \quad (1)$$

$$\text{Max}_{I_A, I_{\text{ren}}, I_{\text{res}}, I_{\text{fos}}, RD^A, RD^B} W!$$

The utility per period is determined by per-capita consumption  $C(t)/L(t)$ , which is discounted at the rate

of pure time preference  $\rho$ . We assume inelastic labour supply given by an exogenous population scenario. The former implies that there is no trade-off between labour and leisure time. The latter neglects the impact of an ageing population on growth, saving rates and innovation dynamics. While it seems obvious that an ageing population ought to have a potentially large impact on the costs of climate protection, we leave this aspect to other simulation studies. Population growth follows the SRES B2 scenario (Nakicenovic and Swart, 2001), whereby the world population reaches 10.4 billion people in the year 2100, roughly stabilizing at this level. We also assume that all factors used in production are fully utilized. For the remainder of this paper, time indices are omitted if no confusion results from so doing.

The control variables are:

1. investment in the economy-wide physical capital stock ( $I_A$ );
2. investment in the renewable energy sector ( $I_{\text{ren}}$ );
3. investment in the fossil resource extraction sector ( $I_{\text{res}}$ );
4. investment in the fossil energy sector ( $I_{\text{fos}}$ );
5. investment in R&D improving labour productivity ( $RD^A$ );
6. investment in R&D improving energy productivity ( $RD^B$ ).

The costs of Carbon Capturing and Sequestration ( $C_{\text{CCS}}$ ) and of energy production from traditional non-fossil energy sources ( $C_{\text{TNF}}$ ), which includes nuclear energy, large hydropower and traditional biomass, are included as exogenous paths. The CCS sector will be endogenized in future studies. The model fulfils a macroeconomic budget constraint (2) at every point in time.

$$Y_A = C + I_A + I_{\text{ren}} + I_{\text{res}} + I_{\text{fos}} + RD^A + RD^B + C_{\text{CCS}} + C_{\text{TNF}} \quad (2)$$

As Eq. (2) shows, the economy produces one generic output ( $Y_A$ ) that can be used for consumption ( $C$ ) or as a capital good for specific purposes in the different sectors of the economy.

For the sake of readability, we use continuous formulae in this section. In the numerical implementation, they are transformed into difference equations.

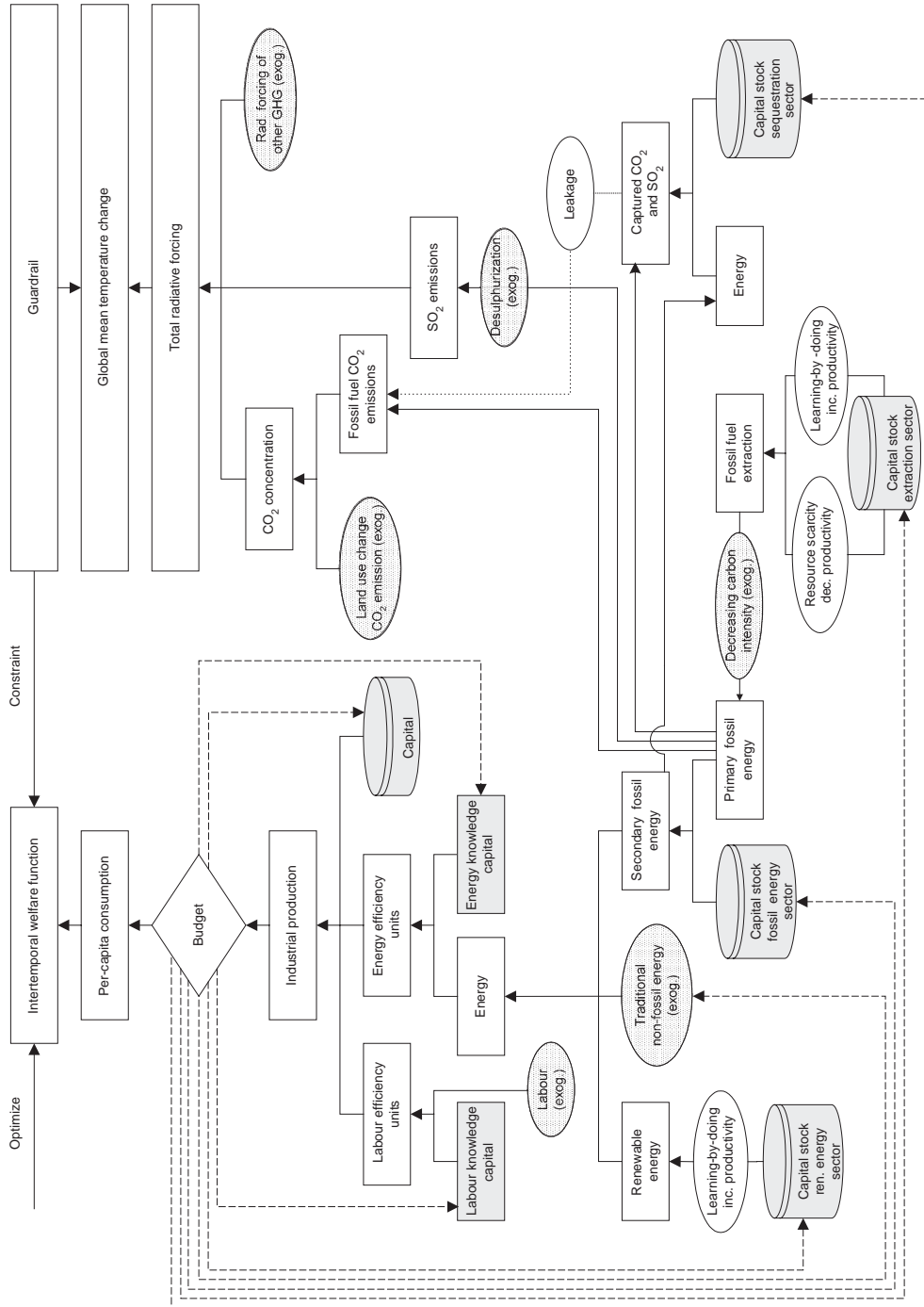


Fig. 1. Sketch of the MIND model.

For that purpose, the intertemporal welfare function is optimized for the period 1995 to 2300. The time step,  $\Delta t$ , is 5 years.

### 3.2. Macroeconomic production function

We assume a macroeconomic production function with a constant elasticity of substitution (CES) between the three factors used in production (see Eq. (3)) – labour ( $L_A$ ), capital ( $K_A$ ) and energy ( $E$ ). The substitution parameter ( $\rho_A$ ) is determined by the elasticity of substitution ( $\sigma_A$ ). We choose a value greater than zero and less than one ( $0 < \sigma_A = 1/(1 + \rho_A) < 1$ ) using the plausible assumption that all factors are essential in production, hence none can be fully substituted. Consequently, a Cobb–Douglas function would not be appropriate for analysing the macroeconomic aspects of energy use, because it allows energy to be asymptotically replaced by capital stock.

$$Y_A = \Phi_A [\zeta_A^L (A^* L_A)^{-\rho_A} + \zeta_A^E (B^* E)^{-\rho_A} + \zeta_A^K (K_A)^{-\rho_A}]^{1/\rho_A} \quad (3)$$

In most integrated assessment models, technological change is parameterized by total factor productivity, which enhances the productivity of all production factors. If a CES function is used, Harrod-neutrality is no longer compatible with a constant growth rate of total factor productivity. Therefore, we distinguish efficiency parameters for labour and energy. Firms have to choose the growth rate of labour productivity ( $A$ ) and energy efficiency ( $B$ ). The parameter  $\Phi_A$  is solely used for scaling the inputs to the dimension of the output. It is not assumed here that  $\Phi_A$  is increasing in time. This way, our model allows analysis of a potential bias in technological progress—firms can increase labour productivity more than energy productivity and vice versa. The distribution parameters ( $\zeta_A^L$ ,  $\zeta_A^E$  and  $\zeta_A^K$ ) determine the relative factor shares of labour, energy and capital respectively.

In Eq. (4), the process of capital accumulation is described with a constant depreciation rate ( $\delta_A^K$ ), as is common in economic growth theory.

$$\dot{K}_A = I_A - \delta_A^K K_A, \text{ with } K_A(t = t_1) = K_A^0 \quad (4)$$

### 3.3. Energy system

According to Eq. (5), at every point in time, the energy supply  $E$  comprises three components:

$$E = E_{\text{ren}} + E_{\text{fos}} + E_{\text{TNF}} \quad (5)$$

As Fig. 1 shows, energy can be delivered from fossil fuels (coal, oil and gas), from modern renewable energy sources (e.g. wind, biomass, solar and geothermal energy) and from traditional non-fossil energy sources (e.g. nuclear energy, traditional biomass and large hydropower).

For energy production from the traditional non-fossil energy sector  $E_{\text{TNF}}$ , we adopt an exogenous scenario from WBGU (2004), in which nuclear energy is phased out by 2050; the scenario does not include nuclear power as a backstop technology because of its unresolved problems, such as the deposition of nuclear waste and nuclear proliferation. In the scenarios presented in this paper, the traditional non-fossil energy sector only plays a marginal role in future energy production. Its total share declines continuously from approximately 14% in 1995, depending on the increase in total primary energy consumption.

#### 3.3.1. Fossil energy generation sector

As Eq. (6) shows, secondary energy ( $E_{\text{fos}}$ ) is produced from two factors: primary energy from fossil fuels ( $PE_{\text{fos}}$ ) and capital ( $K_{\text{fos}}$ ). We assume that labour and land are not limiting factors in producing energy from fossil fuels. The production of secondary energy is modelled by a CES function with a substitution parameter ( $\rho_{\text{fos}}$ ) and a total factor productivity  $\Phi_{\text{fos}}$  that describes the conversion efficiency of the energy system. This latter parameter is held constant over time. The parameter  $\Gamma$  is a scaling factor.

$$E_{\text{fos}} = \Phi_{\text{fos}} (\zeta_{\text{fos}}^{PE} (\Gamma PE_{\text{fos}})^{-\rho_{\text{fos}}} + \zeta_{\text{fos}}^K K_{\text{fos}}^{-\rho_{\text{fos}}})^{1/\rho_{\text{fos}}} \quad (6)$$

$$\dot{K}_{\text{fos}} = I_{\text{fos}} - \delta_{\text{fos}}^K K_{\text{fos}}, \text{ with } K_{\text{fos}}(t = t_1) = K_{\text{fos}}^0 \quad (7)$$

$$PE_{\text{fos}} = R/M \quad (8)$$

In Eq. (7), capital accumulation in the fossil fuel system is modelled analogously to capital accumu-

lation in the macroeconomy. In Eq. (8), primary energy consumption equals the amount of extracted fossil resources ( $R$ —in units of extracted carbon) divided by the carbon intensity  $M$ . As MIND does not resolve different fossil fuels, we have adopted the fossil fuel mix scenario specified in WBGU (2004) to prescribe  $M$  exogenously. The scenario assumes that over the next century, coal and oil will be partially substituted by gas, leading to a decrease in carbon intensity of 20% (WBGU, 2004). This scenario has been constructed for the case of an ambitious climate protection goal as assumed in this paper. In the further development of MIND, it would be desirable to derive the change in the fuel mix endogenously, enabling firms in the power generation sector to choose the fuel carriers according to their relative prices, which will be influenced by climate protection goals.

### 3.3.2. Fossil fuel extraction sector

The extraction of fossil fuels determines the opportunity costs of renewable energy production. If technological progress in this sector is high, and secondary energy derived from coal, oil and gas becomes less expensive, then climate protection policies will become a more costly option. Eq. (9) calculates the amount of resources that can be extracted by a specific amount of capital. It assumes that fossil resources are only extracted by capital, and no other non-reproducible input is needed. This assumption can be justified by the fact that this sector is indeed highly capital intensive. In order to calculate the average productivity of capital  $\kappa_{res}$ , two opposing effects have to be analysed, as shown in Eq. (10).  $\kappa_{res}$  is determined by a *scarcity effect* ( $\kappa_{res,s}$ ) and a *learning-by-doing effect* ( $\kappa_{res,l}$ ).

$$R = \kappa_{res}K_{res} \tag{9}$$

$$\kappa_{res} = \kappa_{res,s}\kappa_{res,l} \tag{10}$$

The scarcity effect is caused by increasing marginal costs of extraction of coal, oil and gas; marginal costs increase because coal, oil and gas are exhaustible resources. The learning-by-doing effect improves capital productivity as cumulative production increases. In MIND, we do not assume – as

opposed to many other integrated assessment models – that the fossil fuel sector has no potential for learning-by-doing. The time path of the marginal costs of extracting fossil fuels emerges from the interplay between the learning-by-doing effect and the scarcity effect.

*3.3.2.1. The scarcity effect.* The marginal extraction costs ( $C_{res}^{mar}$ ) decrease capital productivity according to Eq. (11). The accumulated amount of extracted resources ( $CR_{res}$ ; see Eq. (13)) increases the marginal extraction costs (see Eq. (12); the equation and its parameters are adopted from Nordhaus and Boyer, (2000, 54)). The rationale behind the functional form is an optimal sequence to exploit deposits — from low-cost deposits to more and more expensive fossil fuel reserves. The parameter  $\chi_1$  specifies the present-day marginal extraction costs. The parameter  $\chi_2$  scales the increase in marginal costs, while the parameter  $\chi_4$  determines its non-linear acceleration. The parameter  $\chi_3$  refers to the remaining fossil fuel base as projected today. It is estimated to contain around 3500–6000 GtC (Rogner, 1997). Moreover, Eq. (12) in combination with Eq. (13) reproduces the technological assessment of Rogner et al. (1993) and Rogner (1997). He shows that marginal extraction costs increase with the cumulative amount of extracted fossil fuels. The Rogner curve implicitly assumes that there is technological progress within the extraction sector of 1% which increases the amount of carbon available.

$$\kappa_{res,s} = \frac{\chi_1}{C_{res}^{mar}} \tag{11}$$

$$C_{res}^{mar} = \chi_1 + \chi_2 \left( \frac{CR_{res}}{\chi_3} \right)^{\chi_4} \tag{12}$$

$$CR_{res}(t) = \int_{t_1}^t R(t')dt', \tag{13}$$

with  $CR_{res}(t = t_1) = 0$

*3.3.2.2. The learning-by-doing effect.* We assume that the capital productivity of the extraction sector can be increased by learning-by-doing. This is expressed by

Eq. (14), which determines the change in the productivity factor  $\kappa_{res,1}$  which depends on the ratio of actual resource extraction to initial resource extraction. The factor  $\beta_{res,1} (\leq 1)$  in Eq. (14) dampens the learning-by-doing effect. In the case of  $\beta_{res,1}=1$ , learning-by-doing would only be determined by the cumulative resource extraction, as can be seen by integrating Eq. (14). In the case of  $\beta_{res,1}<1$ , energy production also depends on the time path of the extracted fossil fuels: a rapid increase in extraction induces a loss in productivity gains relative to the same increase in extraction spread over a longer time period.

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

with  $\kappa_{res,1}(t = t_1) = \kappa_{res,1}^0$  (14)

The term  $((E_{res,1}/E_{res,1}^0)^{\beta_{res,1}} - 1)$  becomes negative if actual resource extraction drops below the initial amount of extraction. This means that productivity can decrease if actual resource extraction falls below a critical limit, because part of the accumulated knowledge will depreciate. Thus, if extraction of fossil fuels is phased out, capital productivity could drop below the initial value  $\kappa_{res,1}^0$ . If a climate protection policy were to lead to a phase-out of fossil fuel extraction, some of the current knowledge about resource extraction would then cease to exist.

Maximum productivity in the extraction sector is limited at the value  $\kappa_{res,1}^{\max}$ . Eq. (14) shows that the increase in productivity approaches zero as productivity itself approaches its maximum value. The time scale  $\tau_{res,1}$  determines the speed of learning in the extraction sector.

Eq. (15) describes capital accumulation in the extraction sector.

$$\dot{K}_{res} = I_{res} - \delta_{res}^K K_{res}, \text{ with } K_{res}(t = t_1) = K_{res}^0 \quad (15)$$

### 3.3.3. Renewable energy sector

The learning-by-doing effect is expressed in Eq. (16), where the costs per unit of output decrease approximately with the learning rate  $lr$  if the cumulative installed capacity is increased by 1%.

The learning rate is directly related to  $\lambda_{ren}$  according to Eq. (17).

$$\text{cost}(t) = \text{cost}(t_0) \left( \frac{CKap(t)}{CKap(t_0)} \right)^{-\lambda_{ren}} \quad (16)$$

$$\lambda_{ren} = - \frac{\ln(1 - lr)}{\ln 2} \quad (17)$$

Eq. (16) describes the fundamental form of cost reduction due to learning-by-doing as it is observed for various renewable energy technologies. However, it is by no means clear what kind of investment decisions and market conditions are responsible for such a stable relationship between cost reduction and cumulative installed capacity, and how this relationship for individual technologies affects overall learning-by-doing in the renewable energy sector.

We have used capital productivity as the vehicle to link learning-by-doing effects with investment decisions in the renewable energy sector. We assume that renewable energy is only produced by capital, which is justified if neither labour nor land is a limiting factor in production. Obviously, land could turn out to be a limiting factor, either globally or in specific regions, for several of the renewable energy options, such as biomass, wind, tidal or solar. Considering the limits to renewable energy posed by land availability and suitability would require examination of regional climate conditions and the potential to store energy for long periods of time or transmit it over long distances. This is beyond the scope of the paper.

Due to learning-by-doing, capital productivity in the renewable energy sector grows with accumulated installed capacity. We assume that its increase is inversely proportional to the decrease in costs for a unit of installed capacity associated with increasing cumulated capacity (see Eq. (18)). In the long run, we assume that productivity saturates at a maximum value  $1/c_{floor}$ . Far from this saturation value, the decrease in the reducible part  $c_{ren}$  dominates the increase in capital productivity. The change in  $c_{ren}$  between two subsequent time steps is described in Eq. (19). It is easy to see that for  $\beta_{ren}=0$ , Eq. (19) can be directly derived from the fundamental form of cost



reduction due to learning-by-doing as given in Eq. (16).

$$\kappa_{\text{ren}}(t) = \frac{1}{c_{\text{ren}}(t') + c_{\text{floor}}} \quad (18)$$

$$\begin{aligned} c_{\text{ren},t} - c_{\text{ren},t-1} &= c_{\text{ren},0} CKap_{\text{ren},0}^{\mu_{\text{ren}}} \\ &\times \left( CKap_{\text{ren},t}^{-\mu_{\text{ren}}} - CKap_{\text{ren},t-1}^{-\mu_{\text{ren}}} \right) \\ &\times \left( \frac{CKap_{\text{ren},t-1}}{CKap_{\text{ren},t}} \right)^{\beta_{\text{ren}}}, \end{aligned} \quad (19)$$

with  $c_{\text{ren}}(t = t_1) = c_{\text{ren},0}$  (19)

We have chosen  $\mu_{\text{ren}}$  as the learning factor and  $1 > \beta_{\text{ren}} > 0$  in order to capture path dependence of the learning-by-doing effect on investment decisions. The factor  $\beta_{\text{ren}}$  in Eq. (19) induces a penalty for a rapid expansion of cumulative capacity between two subsequent time periods. The rationale behind this assumption is that the learning effects are reduced if the installed capacity is increased very fast. For example, this effect has been observed in the German wind energy sector, which has experienced a phase of rapid growth because of public subsidies (Neij et al., 2003). However, further research is needed to estimate the penalty parameter.

It is important to note that interaction between the learning parameter  $\mu_{\text{ren}}$  and the path-dependent penalty  $\beta_{\text{ren}}$  gives rise to the observed relationship between costs per unit capacity and cumulated installed capacity described by Eq. (19).

Within the renewable energy sector, we assume a vintage structure of capital. As Eq. (20) shows, the capacity installed ( $Kap_{\text{ren}}$ ) in a given year  $t'$  is derived by multiplying the amount of investment  $I_{\text{ren}}(t')$  by the productivity  $\kappa_{\text{ren}}(t') = 1/(c_{\text{ren}}(t') + c_{\text{floor}})$  at  $t'$ . Thus, the productivity of an investment depends on its age. Learning-by-doing has an impact only on the most recently installed capital.

$$Kap_{\text{ren}}(t) = \int_{t_0}^t \omega(t - t') \kappa_{\text{ren}}(t') I_{\text{ren}}(t') dt' \quad (20)$$

$$E_{\text{ren}}(t) = FLH_{\text{ren}} * Kap_{\text{ren}}(t) \quad (21)$$

$$CKap_{\text{ren}} = \int_{t_0}^t Kap_{\text{ren}}(t') dt' + CKap_{\text{ren},0} \quad (22)$$

As the capital stock depreciates, only a proportion  $\omega(t - t')$  of the vintage at  $t'$  is available for energy production (Eq. (20)) at time  $t$ . By multiplying the installed capacity by the full load hours ( $FLH$ ), we get the amount of energy  $E_{\text{ren}}(t)$  which can be produced within the renewable energy sector (see Eq. (21)). The cumulative installed capacity is derived from Eq. (22).

### 3.4. R&D investments

As in endogenous economic growth models, we introduce an R&D sector in order to model the improvement of labour and energy efficiency. Eqs. (23) and (24) show that we assume the same functional form for both sectors. According to Eq. (2), the R&D sectors are financed from the generic output that is produced with a specific capital, labour and energy intensity. Implicitly, we assume that the R&D sector shares the same capital and energy intensity as the aggregated output, a conservative assumption given that some endogenous economic growth theorists argue that the R&D sector is less capital and energy intensive than the economy as a whole. Because of this assumption, the R&D sector is at the same time a growth engine that does not induce additional energy consumption. Climate protection would induce a reallocation of resources from energy-intensive sectors to the R&D sector. Therefore, in the long run, climate policy could enhance the growth rate of the economy because the R&D sector can grow without inducing additional energy demand.

The factors  $\alpha_A^{RD}$  and  $\alpha_B^{RD}$  in Eqs. (23) and (24) parameterize the productivity of the R&D investments. The parameters  $\gamma_A$  and  $\gamma_B$  are understood as the “stepping-on-toes” effect, which decreases the marginal productivity of R&D due to unproductive work, unproductive patent races and unproductive scientists.

$$\frac{\dot{A}}{A} = \alpha_A^{RD} \left( \frac{RD^A}{Y_A} \right)^{\gamma_A}, \quad \text{with } A(t = t_1) = A_0 \quad (23)$$

$$\frac{\dot{B}}{B} = \alpha_B^{RD} \left( \frac{RD^B}{Y_B} \right)^{\gamma_B}, \quad \text{with } B(t = t_1) = B_0 \quad (24)$$

MIND calculates the social returns to R&D investments, implying that the intertemporal spillovers are

already internalized. In contrast to the R&DICE (Nordhaus, 2002) model, we have not tried to approximate the extent to which markets fail to achieve the social optimal returns on investment. In MIND, we derive a first-best solution.

### 3.5. Carbon Capturing and Sequestration (CCS)

In this analysis, the amount of carbon to be sequestered, and the related costs of capturing it, are given exogenously. The CCS scenario employed here has been adopted from WBGU (2004): over the next century, 200 GtC will be captured and sequestered. The amount of CCS increases up to 2050 and then declines until the end of the 21st century. Neither the time path of the amount of CCS nor the cost path is intertemporally optimal.

There is a remarkable lack of data for calibrating an endogenous model of CCS. We have assumed an energy penalty of 25% for capturing the carbon in geological formations and no leakage rate of carbon from the deposits. No reliable and valid empirical estimates of leakage rates from different geological deposits are available. We refer to our study that assesses the sensitivity of gross world product (GWP) losses and the amount of carbon to be sequestered to the leakage rate and the learning rate of the renewable energy sector (Bauer et al., *in press*). Investments in CCS as well as the energy penalty and the leakage rate are the crucial factors determining whether Carbon Capturing and Sequestration are an option to buy time (Edenhofer et al., *in press*). Nevertheless, the inclusion of the exogenously assumed carbon-capturing scenario already shows that CCS can be an important option.

### 3.6. Climate module

MIND includes a simple climate model that translates the anthropogenic emissions of carbon dioxide and sulphate aerosols into a change in global mean temperature. The emission of sulphates is directly linked to the combustion of fuels in the fossil energy sector. In addition, the model takes into account an exogenous scenario for the radiative forcing of greenhouse gases other than CO<sub>2</sub>. We use a simple energy-balance model to calculate the

response of global mean temperature to a perturbation of the radiation balance at the top of the atmosphere due to anthropogenic emissions of greenhouse gases. For the basic model equations, see Petschel-Held et al. (1999) and Kriegler and Bruckner (2004). The model is tuned to reproduce the short-term (100-year) behaviour of the climate model MAGICC satisfactorily. MAGICC was used as an emulator of complex atmosphere–ocean general circulation models as well as a scenario generator in the Third Assessment Report (TAR) of the IPCC (Cubasch and Mehl, 2001). The climate sensitivity of the model is set to 2.8 °C.

## 4. Calibration

We have chosen parameter values within plausible ranges as suggested by the empirical literature. This does not guarantee, however, that the whole system exhibits sensible properties. Therefore, we have ensured that MIND is able to reproduce the so-called stylized facts of economic growth given the chosen parameter setting. According to Kaldor (1963), labour productivity grows at a constant rate, capital productivity remains constant over time, and the income shares of labour and capital are constant in the steady state.

Unfortunately, these facts are not sufficient to ensure that the model has sensible properties, because energy as an input factor is completely neglected. Therefore, we have included an additional stylized fact that emerges from the macroeconomic growth pattern of the last two centuries: over the last 200 years, the growth rate of labour productivity ( $Y/L$ ) exceeded the growth rate of energy efficiency ( $Y/E$ ). This benchmark is reproduced by MIND for calibration.

We are convinced that this set of stylized facts is not comprehensive. A better understanding of the stylized facts on a sector-specific level is needed. Moreover, it would be necessary to develop a calibration procedure that ensures that the behaviour of the model is in accordance with a predefined comprehensive data-set. Therefore, a satisfactory calibration of MIND needs further methodological development. In the following, we justify our choice of parameters sector by sector.

#### 4.1. Aggregate production sector

The CES production function and calibration of its parameters play a central role in the model formulation. The dispute about the elasticity of substitution between production factors – especially between capital and energy – has been going on for some decades. In a review of several studies, [Thompson and Taylor \(1995\)](#) found that the average substitution elasticity identified in studies based on the so-called Allen partial elasticity of substitution between energy and capital is 0.17, while the so-called Morishima elasticity of substitution is 0.76 on average. We favour Morishima's concept, because Allen's concept is not applicable to a production function with more than two production factors ([Blackorby and Russell, 1989](#)). 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  $\sigma_A=0.4$ . We have set the ratio of the distribution parameters  $\xi_A^L:\xi_A^E:\xi_A^K=66:4:30$  equal to the ratio of the initial factor shares in 1995. The values of the other parameters  $\Phi_A$ ,  $A_0$  and  $B_0$  are chosen to reproduce the initial factor shares under the additional requirements for the initial period 1995 that  $Y_A=24.6$  trillion \$US,  $L_A=5.7$  billion people,  $E=271$  EJ and  $K_A=49.2$  trillion \$US (adopted from the SRES scenarios; see [Nakicenovic and Swart, 2001](#)). These values correspond to a capital coefficient for industrial capital of  $K/Y=2$ , which is adopted from the Penn World Tables 6.1 and the OECD database on capital formation. The aggregate capital stock is measured in monetary units. In order to aggregate heterogeneous capital goods in an index "capital", it is necessary to assume a regular economy, i.e. the price-weighted average of capital stock increments across steady-state equilibria always decreases with an increase in the interest rate ([Burmeister, 1980](#)). In the work presented, we make this regularity assumption.

#### 4.2. Fossil energy generation sector

For the production function of the energy generation sector, we set the ratio of the distribution parameters to  $\xi_{\text{fos}}^{\text{PE}}:\xi_{\text{fos}}^{\text{K}}=50:50$  and the elasticity of substitution to  $\sigma_{\text{fos}}=0.3$ . The parameters  $\Phi_{\text{fos}}$  and

$\Gamma$  are calibrated to reproduce the following data in 1995:  $PE_{\text{fos}}=320$  EJ contained in  $R=6.4$  GtC fossil fuels, and secondary energy  $E_{\text{fos}}=231$  EJ. The initial capital stock is assumed to be  $K_{\text{fos}}^0=6$  trillion \$US.

#### 4.3. Fossil fuel extraction sector

Following [Nordhaus \(2002\)](#), the marginal extraction cost curve is parameterized by  $\chi_1=113$  \$US/tC,  $\chi_2=700$  \$US/tC,  $\chi_3=3500$  GtC and  $\chi_4=4$ . The initial resource extraction is  $R=6.4$  GtC (SRES), assumed to be produced by a capital stock of  $K_{\text{res}}^0=5$  trillion \$US. This allows us to compute  $\kappa_{\text{res},l}(t=t_1)$ . We assume that  $\kappa_{\text{res},l}^{\text{max}}$  can achieve twice the initial value.

#### 4.4. Renewable energy sector

In order to estimate the initial vintage structure of capital in the renewable energy sector, we assume a total cumulative amount of modern renewable energy production until 1995 of 40 EJ and a growth rate of 20% p.a. for renewable energy production from 1960 to 1995 ([WEA, 2000](#)). This leads to renewable energy production of 8 EJ in 1995. In order to calculate the capacity that has to be installed in each period to achieve 8 EJ in 1995, we assume a depreciation scheme for capital (weights  $\omega$ ; see Appendix A) and constant FLH of 2190 h per year. In accordance with these assumptions, we calculate a cumulative capacity in 1995 of 411 GW. The learning curve is determined by two initial conditions—the cumulative installed capacity in 1995 and the investment costs of ~1200 \$US/kW (based on [Nakicenovic and Riahi, 2002](#)). These investment costs consist of floor costs and a reducible part. As a reasonable number for the floor investment costs, we have chosen 500 \$US/kW (also based on [Nakicenovic and Riahi, 2002](#)). Therefore the reducible part amounts to ~700 \$US/kW. We set the learning parameter  $\mu_{\text{ren}}$  to 15%. Because of a lack of empirical studies, we set parameter  $\beta_{\text{ren}}$  to 0.4, rather than calibrating it.

#### 4.5. R&D sector

The calibration of the initial values of  $A_0$  and  $B_0$  is discussed above in the context of the industrial

production function. The parameters  $\alpha_i^{\text{RD}}$  for both R&D sectors are calibrated as follows. When 1% of GWP is spent on energy R&D, the energy efficiency parameter increases by 2.25%; when 2.5% of GWP is spent on labour R&D, the labour efficiency parameter increases by 2%. The parameters  $\gamma_i$  are estimated to be 0.1 and 0.05 for energy and labour R&D respectively. Estimates of the influence of R&D on productivity growth are usually based on Hicks-neutral technological progress (Griliches, 1998, chapters 9, 10 and 12). These estimations cannot be used to calibrate the R&D sector. Therefore, we have adopted parameter values for the improvement in labour productivity (see Appendix A) from our own preliminary calculations.

## 5. Welfare implications of technological change

In this section, we present the results of an intertemporal cost-effectiveness analysis. We study the optimal policy that achieves a predefined safe-minimum standard for the climate at the least cost and compare different assumptions about available technology options.

The safe-minimum standard is defined as follows: in order to avoid dangerous climate change, the increase in global mean temperature ( $\Delta\text{GMT}$ ) and its rate ( $\Delta\text{GMT}/\text{decade}$ ) are limited to 2 °C and to 0.2 °C/decade respectively. This is in accordance with a “guardrail” on climate change that was put forward by the German Scientific Advisory Board on Global Change (WBGU) in a special report for the first conference of the parties to the UNFCCC in Berlin (WBGU, 1995). Since then, the so-called WBGU climate window has been a controversial issue. Some regard it as being too ambitious from an economic point of view, while others claim that it is not strict enough to avoid dangerous anthropogenic interference with the climate system. In any case, the WBGU window provides an important example of a climate protection goal that can be used to study the impact of technological change on reducing emissions and associated GWP losses.

The starting point of our analysis is a comparison of a business-as-usual scenario (BAU) with a climate protection scenario (CPP). The CPP scenario respects the WBGU climate window which is comparable to

stabilizing the concentration of CO<sub>2</sub> at around 420 ppm. Hence, the CPP scenario optimizes overall welfare subject to the climate window.

Fig. 2a shows that in the CPP scenario, the constraint of achieving the climate protection goal induces a diffusion of renewable energy technologies after 2050 which is preceded by a shortage of secondary energy production and therefore by a substantial improvement in energy efficiency. Due to learning-by-doing, the opportunity costs of renewable energy technologies decrease and their share in the global energy mix increases substantially after 2050. Fig. 2b reveals that the changed energy mix is driven by a change in investment strategy. The share of investments in the renewable energy sector increases considerably after 2020 because the climate

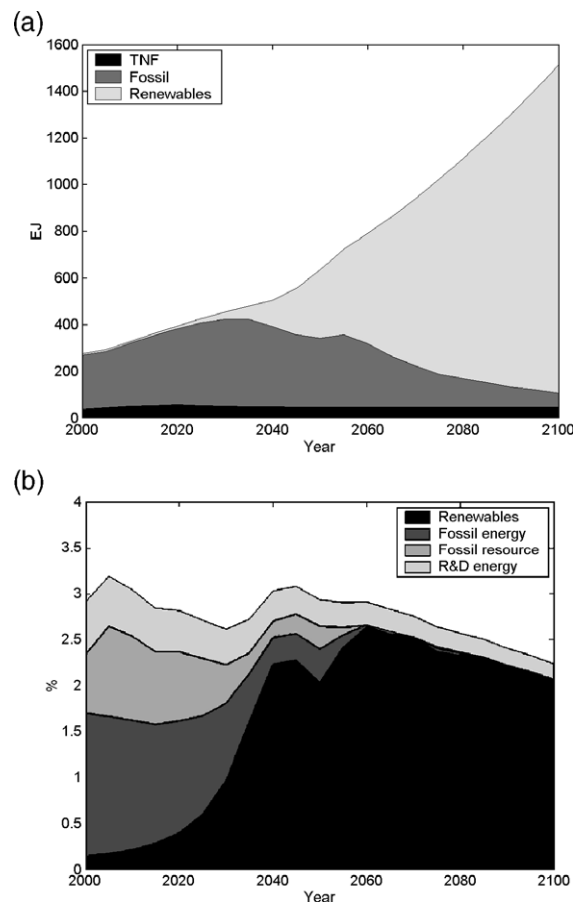


Fig. 2. Energy mix (a) and investment shares of GWP (b) in the CPP scenario.

protection goal reduces the social return on investment within the fossil fuel sector and increases it within the renewable energy sector. It is noteworthy that “early action” in climate policy in MIND does mainly refer to a change in investment strategy and not to an increase in the market share of renewables or emission reductions.

Fig. 3 shows the impact of different mitigation options on welfare losses, i.e. the relative difference in welfare between BAU and scenarios in which one or more mitigation options are activated. Economic theory convincingly suggests that welfare changes should be measured in terms of per-capita consumption and not GWP, yet in many integrated assessment studies GWP is used as a proxy for welfare. We display and discuss both measures to maintain compatibility with the integrated assessment literature.

In the *first scenario (CPP)*, all mitigation options are available and are used according to intertemporal cost-effectiveness. Relative to the BAU path, the per-capita consumption losses and the GWP losses are about 1.13% and 0.81% respectively.

In the *second scenario (EE)*, only the option to improve energy efficiency is switched on. If only investment in energy efficiency is possible, the discounted GWP losses reach about 6.5% (see Fig. 3). This indicates that improvement of energy efficiency becomes quite costly as a major mitigation option in the long run. In this scenario, per-capita consumption losses are lower than GWP losses: investment expenditures are reduced because their

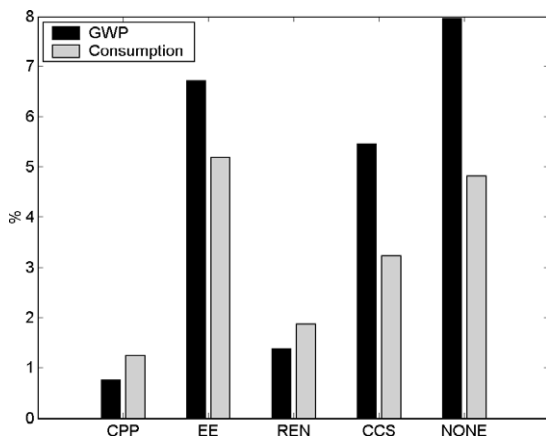


Fig. 3. Cumulated GWP and per-capita consumption losses for different mitigation options, discounted at a rate of 5%.

return – measured in terms of per-capita consumption – is substantially lowered by climate protection, and therefore consumption can be increased.

In the *third scenario (REN)*, only the backstop option with learning-by-doing is enabled. Fig. 3 shows that the substitution of fossil fuels by renewable energy is the most important single option for reducing GWP and consumption losses. If the substitution of fossil fuels by renewables can enter the portfolio of mitigation options, welfare losses can be reduced to a degree that makes climate protection economically viable.

In the *fourth scenario (CCS)*, only Carbon Capturing and Sequestration is switched on. This exhibits some potential for reducing the welfare losses. It turns out that CCS is an option that is used temporarily, with the benefit of postponing the transformation of a fossil-fuels-based to a renewables-based energy system, and consequently allowing for a smoother transition (not shown).

In the *fifth scenario (NONE)*, none of the mitigation options is activated, which leaves only factor substitution (which is available per se) as a means to conform to the climate window. Time paths in the renewable energy sector and in the R&D energy sector are prescribed to follow the BAU scenario, i.e. we assume that investment decisions in these sectors will not be changed by a climate protection goal. The CCS option is not available here; firms only have the option of substituting energy by labour and capital.

These results confirm to some extent those of Popp (2004b), who concludes from the ENTICE-BR model that adding a backstop technology (without learning-by-doing) has the largest potential for reducing the welfare losses of climate protection. In the scenarios above, the impact on GWP is greatest for the backstop technology, followed by CCS and then by energy efficiency improvements. A fortiori, a backstop technology with learning-by-doing further reduces the GWP losses and welfare losses, measured in terms of per-capita consumption, of climate protection.

## 6. Conclusion

Calculations with the MIND model show that technological change in different sectors reduces the

costs of climate protection substantially. Technological change is triggered by investments in sector-specific capital stocks. Reallocation of investment, especially in the renewable energy sector and in the CCS sectors, enables an economy to successfully implement ambitious climate protection goals while at the same time guaranteeing stable economic growth.

Backstop technology has a large impact on welfare losses. Emission reductions imply much more severe welfare losses in a situation without backstop technology and without learning-by-doing, because the climate protection goal can only be achieved via a reduction in economic output and by enhancing energy efficiency. In the long run, improving energy efficiency is too costly to be an exclusive option. Limiting technological change to R&D investments that improve only the efficiency parameters, as is done in the top-down macroeconomic models reviewed in this paper, is therefore inappropriate.

The results indicate that a better understanding of technological change should be a priority on the research agenda. In particular, it is open to debate whether the concept of a “learning rate” can serve as a valid predictor of future development. More empirical work, in cooperation with engineers, may enhance the understanding of the underlying processes, such as the interplay between path dependencies and learning-by-doing, as well as learning-by-doing at the micro and macro levels. We think that the MIND model presented here is an important step forward in assessing mitigation costs.

However, as it currently stands, the MIND model has an important limitation: it is designed as a social planner model. If the conditions of the welfare theorems are fulfilled, equivalence exists between social planner and market solutions (Becker and Boyd, 1997, 213–241). There are at least two reasons why the MIND model does not fulfil these conditions: first, the private return on R&D investment diverges from the social return on R&D investment; second, there are increasing returns to scale within the energy sector because of learning-by-doing. Decentralized agents in the renewable energy market are not able to realize the socially optimal rate of cost reduction because learning-by-doing creates positive externalities for other producers. Therefore, designing a general intertemporal equilibrium version of MIND for a comparison with the social planner solution

would be the natural next step. With both versions at hand, the design of optimal policy instruments becomes a feasible task.

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## Appendix A. List of parameters

Welfare function	$\rho$	0.01	Pure time preference rate
	$t_0$	1960	First year of calibration
	$t_1$	1995	First year of optimization
	$t_2$	2300	Last year of optimization
	$\Delta t$	5	Time step [years]
Production function	$\sigma_A$	0.4	Overall elasticity of substitution of production factors
	$\xi_A^L$	0.66	Distribution parameter for labour
	$\xi_A^K$	0.3	Distribution parameter for capital stock
	$\xi_A^E$	0.04	Distribution parameter for energy
	$\delta_A^K$	0.05	Capital stock depreciation rate
	$K_A^0$	49.2	Initial capital stock [trillion \$US]
R&D function	$\alpha_A^{RD}$	0.024	Parameterization of R&D investments in labour
	$\gamma_A$	0.05	Stepping-on-toes effect for labour
	$\alpha_B^{RD}$	0.036	Parameterization of R&D investments in energy
	$\gamma_B$	0.1	Stepping-on-toes effect for energy
Fossil energy sector	$\sigma_{fos}$	0.3	Elasticity of substitution
	$\xi_{fos}^{PE}$	0.5	Distribution parameter for primary energy
	$\xi_{fos}^K$	0.5	Distribution parameter for capital stock
	$\delta_{fos}^K$	0.05	Capital stock depreciation rate
	$K_{fos}^0$	6	Initial capital stock [trillion \$US]

Extraction sector	$\tau_{res,1}$	100	Year
	$\kappa_{res,1}^{\max}$	3.22	Maximum capital productivity [GtC/trillion \$US]
	$\kappa_{res,1}^0$	1.61	Initial capital productivity [GtC/trillion \$US]
	$\beta_{res,1}$	0.4	Damping factor for learning-by-doing effect
	$\chi_1$	113	Scaling of marginal cost curve [\$US/tC]
	$\chi_2$	700	Scaling of marginal cost curve [\$US/tC]
	$\chi_3$	3500	Resource base [GtC]
	$\chi_4$	4	Slope of marginal cost curve
	$\delta_{res}^K$	0.05	Capital stock depreciation rate
	$K_{res}^0$	5	Initial capital stock [trillion \$US]
Renewable energy sector	$CKap_{ren,0}$	0	Cumulative capacity in 1960 [GW]
	$c_{floor}$	500	Floor investment costs [\$US/kW]
	$c_{ren}^0$	700	Initial learning investment costs 1995 [\$US/kW]
	$\mu_{ren}$	15	Learning parameter [%]
	$\beta_{ren}$	0.4	Penalty factor
	$FLH_{ren}$	2190	Full load hours p.a.
	$\omega_1$	1	Weight of vintage installed in current period
	$\omega_2$	0.85	Weight of vintage installed 1 period ago
	$\omega_3$	0.7	Weight of vintage installed 2 periods ago
	$\omega_4$	0.5	Weight of vintage installed 3 periods ago
	$\omega_5$	0.3	Weight of vintage installed 4 periods ago
	$\omega_6$	0.15	Weight of vintage installed 5 periods ago
	$\omega_7$	0.05	Weight of vintage installed 6 periods ago

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